ESSAYS ON PRODUCT RECALL DECISION AND EFFECT

Khimendra Singh

A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the Kenan-Flagler Business School.

Chapel Hill
2021

Approved by:

Katrijn Gielens

Rajdeep Grewal

Shijie Lu

Shrihari Sridhar

Sriraman Venkataraman

© 2021
Khimendra Singh
ALL RIGHTS RESERVED

ABSTRACT

Khimendra Singh: Essays on Product Recall Decision and Effect
(Under the direction of Rajdeep Grewal)

Product recalls are pervasive events across many industries, such as automobile and consumer product. Notably, the cost of these product failures could be astronomical. Therefore, these adverse events are of considerable interest to academics, policymakers, and practitioners. My dissertation contributes to this literature by investigating two different yet related aspects of recalls. The first two essays explore underlying elements that affect the recall decision-making process (pre-recall phase). The third essay explores the impact of these adverse events (post-recall phase).

In essay 1, I examine whether corporate lobbying influences recall decisions. Lobbying as a political mechanism is widely studied in social science research but remains relatively unexplored in the marketing literature. I find that a firm with higher lobbying expenditures is less likely to initiate a recall, such that approximately $417,014 more in lobbying expenditures is associated with one less voluntary recall by the firm. Results also suggest that a firm's political influence also led the regulatory agency to adopt a bias that favors the lobbying firm. In essay 2, I capture the game-theoretic strategic interaction between an automaker and its supervising regulatory agency recall decision-making process. By modeling one player's decision as a function of another player's expected decision, I examine whether the regulator's presence affects an automaker's decisions after controlling for other relevant factors (e.g., defect and product-level characteristics). Results suggest a significant strategic interaction such that

automakers act proactively in anticipation of the regulator's actions, highlighting an underlying trade-off in their decisions.

In essay 3, I study how recalls transcend business-to-business (B2B) secondary markets (i.e., used products) by examining recalls' effects on intermediary B2B buyers' purchases. By conceptualizing vehicle recalls as exogenous shocks to the automobile secondary market, I find that the transaction prices for recalled products reduce by about 10% in the B2B used vehicle market. The price for recalling automaker's non-recalled vehicles, which belong to the same segment (e.g., compact) as the recalled vehicle, also declines by 5.54% (negative spillover). In contrast, the price of recalling automaker's non-recalled vehicles belonging to a different segment increases by 4.91% (positive spillover). Other automakers also experience a negative spillover.

To my amazing parents Nandan Singh and Sarla Devi;
To my sisters Asha and Deepa and brother Vikram;
Thank you for your encouragement, love, and support throughout my life.

ACKNOWLEDGEMENTS

First and foremost, I express my gratitude to my advisor, Professor Rajdeep Grewal, for his guidance and patient support during the last five years. I thank Raj for his invaluable time, input, and unwavering support throughout this journey. I could not have asked for a better advisor. Raj's approach towards high-quality research inspires me to follow in his footsteps. Specifically, his support during my job market process has been a lifesaver. I would also like to thank Professor Jan-Benedict Steenkamp and Professor Katrijn Gielens for having accepted me to the UNC doctoral program, where I have experienced a great learning curve. A big thanks to Professor Sriram Venkataraman for his time and inputs whenever I needed some research feedback. I also thank Professor Pranav Jindal for his valuable inputs. I am also thankful to other members of my dissertation committee, Professor Shrihari Sridhar and Professor Shijie Lu, for their support. I have also benefited from my discussion with other faculty members in the marketing group, including Barry Bayus, Kyuhong Han, Kristopher Keller, Minkyung Kim, Fei Long, Daniel Ringel, and Longxiu Tian. I also thank the UNC staff, Laura Howe, Erin Mitchell, and Kim Yates, for their sincere support. A special thanks to Professor Manish Gangwar for providing me a research opportunity at ISB, which was my first step into the research world.

I wholeheartedly thank my parents, Nandan Singh and Sarla Devi. Their affection and wisdom have been my guiding light. Any success in my life has been and would always be a direct result of their sacrifices throughout their lives. I am grateful to my sisters, Asha and Deepa, and my brother, Vikram, for their affection and encouragement, which helped me achieve this milestone. A special thanks to my friend Marialinda Papi, who has always provided her support despite being thousands of miles away. Her cheerfulness and encouraging words always lift me up. I am also grateful to my fellow students, Evgeniya and Michael, for their friendship. Finally, I thank Almighty for giving me the opportunity, strength, and perseverance to undertake this research and complete my Ph.D. successfully.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

2SLS	Two-stage least squares
3SLS	Three-stage least squares
B2B	Business-to-business
B2C	Business-to-consumer
BMW	Bayerische Motoren Werke AG
CAPEX	Capital expenditure
CMP	Conditional mixed-process
CRP	Center for Responsive Politics
DiD	Difference-in-differences
FCF	Free cash flow
FDA	Food and Drug Administration
FEC	Federal Election Commission
GDP	Gross domestic product
GM	General Motors
GMM	Generalized method of moments
IV	Instrumental variable
LDA	Lobbying Disclosure Act
NHTSA	National Highway Traffic Safety Administration
OEM	Original equipment manufacturer
TA	Total assets
US	United States
USD	United States dollar

CHAPTER 1: INTRODUCTION

Product recalls are inevitable in many industries (e.g., medical equipment, consumer products). Examples of prominent recalls include Johnson & Johnson's Tylenol recall, Pfizer's Bextra recall, Volkswagen's diesel emission recall, and Mattel's toy recall. For the automotive industry, recalls are especially pervasive. In 2016, recalls affected 50.5 million vehicles and cost automotive firms almost $22.1 billion (Jibrell 2018). Due to such impact, academics, policymakers, and practitioners have paid considerable attention to product recalls (Cleeren, Dekimpe, and Heerde 2017). Extant empirical research, however, has primarily focused on the post-recall phase, which includes the impact of recalls on financial and non-financial elements (e.g., Chen et al. 2009; Liu and Shankar 2015; Thirumalai and Sinha 2011); it is mostly silent on the pre-recall phase (i.e., strategic decision-making to initiate a recall). For example, which underlying factors or mechanisms affect firms' recall decisions? Recalls have a direct (e.g., reduced sales) and indirect (e.g., reputation loss) impact, which would prompt firms to think carefully before deciding whether to initiate a recall. Despite such decisions being endogenous, most studies in the literature have considered a recall an exogenous shock while examining its post-recall impact (e.g., Borah and Tellis 2016; Chen et al. 2009; Germann et al. 2014). Shedding light on factors that could influence recall decisions (voluntary or mandatory) by concerned entities (firms and the regulatory agency) is important from strategic marketing and policy perspectives.

One potential strategy, which could influence recall decisions could be a firm's corporate lobbying, through which the firm attempts to create political connections and alter the regulatory landscape (Bertrand, Bombardini, and Trebbi 2014). In 2009–2010, after Toyota acted slowly to accidents reports, which suggested its vehicles' sudden acceleration flaws, a US Congressional report, examining this case, alleged lobbying influences by automotive firms (Kirchhoff and Peterman 2010), citing an internal Toyota document (dated July 6, 2009), in which the chief operating officer highlighted several "wins," such as delaying final safety rules by National Highway Traffic Safety Administration (NHTSA). For example, Toyota's internal document suggested that the negotiated equipment recall on its Camry model saved the company $100 million. This report raises some important questions: Does lobbying influence product (i.e., automobile) recall decision-making? Do a firm's voluntary recall decisions change significantly as the firm's lobbying expenditures change? Does lobbying influence the regulatory agency's (i.e., NHSTA in the case of automobiles) mandatory recall decisions? Conventionally, objective product quality should be the only factor influencing recall decisions. However, the anecdotal evidence discussed above may suggest otherwise. Product defects have severe societal impacts (e.g., loss of lives, economic loss). Therefore, any element that may bias necessary corrective actions to address product defects needs scrutiny.

In essay 1, I find that automotive firms that engage in lobbying are less likely to initiate a recall voluntarily. In particular, approximately $417,014 more in lobbying expenditures is associated with one fewer voluntary recall, on average. A quick calculation indicates potential benefits to the firm: An average recall in our data involves 247,305 vehicle units. With an average conservative cost of $50 per vehicle (e.g., repair or replacement, loss of revenue), one fewer recall implies approximately $12 million in savings. Results suggest that political influence through lobbying might also bias the regulatory agency's decisions. Firms with higher lobbying are likely to face fewer mandatory recalls; approximately $1.55 million more in lobbying expenditures is associated with one less mandatory recall. These results seem to validate the concerns raised in the congressional report about lobbying influence on recalls. Results suggest that the recall decision process is susceptible to political influence, a channel not yet unexplored in this context. Importantly, this study finds that lobbying is an important (marketing) tool used by automotive companies to influence vehicle recalls.

In essay 2, I further scrutinize the recall decision-making process by modeling the game-theoretic structure of interaction between the automaker and the regulator agency. Specifically, I consider one player's recall decision (e.g., automaker) an endogenous choice influenced by another player (the regulatory agency). In the automobile industry, the regulatory agency (NHTSA) also has the authority to initiate a recall besides the automaker. For example, an automaker may decide to initiate a recall (defined as a voluntary recall) based on the underlying factors (e.g., consumer complaints, fatality reports) and corresponding tradeoff. For example, a voluntary recall allows stakeholders to retain a positive impression of the firm (Souiden and Pons 2009). Therefore, on the one hand, the desire to create/retain a positive image may motivate an automaker to initiate a voluntary recall. On the other hand, substantial recall costs (e.g., defect repair, loss of revenue) may prompt automakers to avoid a voluntary recall. However, if the automaker decides to take no action, the regulatory agency NHTSA may step in and recommend a recall if required. The possibility of a recall authorized by the regulator (defined as a mandatory recall) brings additional complexity to the automaker's decision-making process because now the automaker's strategic decision depends not only on consumers' complaints/fatality reports but also on the expected action of another player (NHTSA).

Incorporating the belief of one player's expected action into another player's decision-making creates a strategic interaction (dependency) between players' decisions. Such interaction between an automaker and its supervising regulatory agency is of substantial managerial and policy import because this would help us understand whether one decision-maker changes its decision in the presence of another decision-maker. I model this strategic interaction as a discrete game and calibrates this model using rich datasets that include vehicle recalls of 15 automobile firms and defect complaints and death reports by vehicle owners during a fourteen-year period (2003–2016) in the US.

Results suggest that automakers are more likely to initiate a voluntary recall in the presence of the regulatory agency. This change in automaker's behavior impacts society because fewer recalls would result in more complaints and crashes and impose additional costs on society. I also consider that the automaker and the regulator might exchange relevant information (e.g., defect details) before making any decision. An information exchange could reduce a player's uncertainty regarding the defect and thus affect recall decisions. Such common information, often not observed by the researcher, can lead to biases in the model if not considered. I use an exogenous variable, the distance between an automaker headquarter and the regulator office, as a proxy for this information exchange. Prior research in economics and finance literature (e.g., Giroud 2013; Lerner 1995; Petersen and Rajan 2002) has used geographical distance as a proxy for the information exchange and the ease of monitoring. Following this research, I use the geographical distance between an automaker's headquarter and the regulator's office to indicate the cost of information exchange and examine whether variation in common information through the exchange could significantly impact recall decisions. Results show that more effective information exchange could lead to additional voluntary recall actions.

Several other characteristics (defect, product, and entity-level) also impact recall decisions. For example, an automaker with a wider dealership network, which highlights an automaker's recall handling capability, is more likely to initiate a voluntary recall. Among defect characteristics, I find that a greater geographical dispersion of complaints (denoted by the number of US states in complaints) increases the probability of a recall action.

Recalls could significantly impact firms, both financially and non-financially; a plethora of studies have already examined various elements of this impact such as loss in sales (e.g., Freedman et al. 2012), change in advertising effectiveness (Liu and Shankar 2015), stock market (e.g., Chen et al. 2009), consumer loyalty (e.g., Souiden and Pons 2009), firm learning (e.g., Haunschild and Rhee 2004), and used product market (e.g., Che et al. 2020) among others. However, notably, these studies revolve around business-to-consumer (B2C) transactions. They do not examine transactions further upstream from the end-consumer involving business-to-business (B2B) intermediaries (e.g., auto dealers in the automobile industry). As a result, few insights are available regarding the impact of product recalls on B2B markets. As described in Table 4.1, extant research on product recalls emphasizes markets with consumers as the end-users, despite the significant value and size of B2B markets. Lilien (2016) notes that B2B transactions account for $10.7 trillion, i.e., 42% of all US revenues, and calls for rigorous empirical research of the B2B buying process. Recently, Cleeren et al. (2017) also assert the lack of empirical research on product recall effects in B2B markets.

In essay 3, I examine the impact of recalls on the B2B used product market. Specifically, I study whether and how B2B buyers (e.g., auto dealers) alter their demand for recalled products in response to product recalls. What short-term changes do B2B buyers make in their product purchases? How do these B2B buyers adjust the prices they are willing to pay if the used product faces a recall? How do recalls influence buyers' demand for non-recalled products? In particular, do B2B buyers switch to another non-recalled product offered by the same firm or a different firm? Do they buy a non-recalled product within the same product segment or a different segment if they switch? Furthermore, do we observe any heterogeneity in these effects due to product or buyer characteristics? Answers to these managerial and policy-relevant questions would provide insights into product recall effects on B2B buyers' transactions and corresponding inventory management. I propose a descriptive causal inference model and calibrate it with individual-level B2B sales data of used vehicles to establish causal effects.

I find that, due to a recall, the demand for recalled products decreases, which in turn leads to about 10% (~ $1,043) lower prices in the B2B used vehicle market. Specifically, a government-mandated recall is associated with greater damage to recalled products (~ $1,098 lower price). I also find that the adverse effect is more damaging for older vehicles than younger vehicles with fewer miles; an increment of 1000 more miles on the odometer reading is associated with a loss of about $21 in used vehicle's transaction prices. Consistent with the contagion effect (Roehm and Tybout 2006), I also find that the demand for non-recalled vehicles that belong to the same vehicle segment (e.g., compact) as the recalled vehicle declines. Essentially, this negative spillover suggests a 5.54% (~$574) drop in prices of the non-recalled vehicles that belong to the focal automaker (which experiences the recall). In contrast, consistent with the competitive effect (Ozturk et al. 2019), demand for non-recalled vehicles that belong to a different vehicle segment (e.g., midsize) increases, which leads to 4.91% (~$509) higher prices. Such positive spillover highlights that B2B buyers adjust their planned product purchases by switching to non-recalled vehicles from a different segment but within the same focal automaker. Prices of other automakers' vehicles that belong to the same segment as the recalled model also decrease, highlighting a broader negative spillover effect within the recalled product's segment.

My dissertation contributes to three strands of literature on product recalls. The first contribution is to work on the decision-making process of recalls. Most studies in this literature have focused on the post-recall phase, which includes exploring the impact of product recalls on firms or consumers. In comparison, two essays in my dissertation focus on the pre-recall phase, which includes examining the recall decision-making process and exploring underlying factors that affect this process. Most importantly, many studies in the recall literature consider a product recall as an exogenous shock when investigating the impact of recalls on different elements (e.g., financial or non-financial). My research, however, considers a recall decision as an endogenous choice and examines the role of critical factors such as corporate lobbying and regulatory oversight in the recall decision-making process.

The second contribution is to the marketing-politics interface, a critical but yet underdeveloped research area in marketing. With few exceptions, a handful of empirical studies exist in this domain, especially in the context of regulatory oversight over various industries, which many executives acknowledge to be a powerful political factor impacting their operations. Lobbying could create influence on the regulatory agency and thus lead to fewer corrective actions. Therefore, my research highlights the complexities involved in decisions due to a channel beyond typical marketing and financial indicators. These findings are highly relevant from a policy perspective.

The third contribution is to the literature on business-to-business (B2B) markets. Recall literature has primarily studied markets with consumers as the end-users, despite the significant value and size of B2B markets. Consistent with prior research (Cleeren et al. 2017), I know of no studies that quantify the impact of product recalls in B2B buyers' markets (primary or secondary). In response, I examine managerially relevant questions related to short-term changes in B2B buyers' product purchases in response to recalls. Specifically, focus on the used vehicle market provides pertinent insights into auto dealers' inventory management. These findings are also timely and policy-relevant because this research can directly inform the ongoing policy debate surrounding the recently proposed Used Car Safety Recall Repair Act (Congress 2019).

In today's time, when adverse events, such as product recalls, keep causing significant damages to businesses and society, I believe that my dissertation essays explore some important elements regarding political influence, government regulation, and the B2B market in the automobile category. I discuss these essays in the following three chapters.

REFERENCES

Bertrand, Marianne, Matilde Bombardini, and Francesco Trebbi (2014), "Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process," *American Economic Review*, 104 (12), 3885–3920.

Borah, Abhishek and Gerard J. Tellis (2016), "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research*, 53 (2), 143–160.

Che, Xiaogang, Hajime Katayama, Peter Lee, and Nan Shi (2020) "Willingness to pay for brand reputation: Lessons from the Volkswagen diesel emissions scandal," Working Paper, University of London.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises," *Journal of Marketing*, 73 (6), 214–226.

Cleeren, Kathleen, Marnik G. Dekimpe, and Harald J. van Heerde (2017) "Marketing Research on Product-Harm Crises: A Review, Managerial Implications, and an Agenda for Future Research," *Journal of the Academy of Marketing Science,* 45 (5), 593–615.

Congress (2019) S.1971 - Used Car Safety Recall Repair Act, (accessed December 17, 2020), [available at https://www.congress.gov/bill/116th-congress/senate-bill/1971/text].

Freedman, Seth, Melissa Kearney, and Mara Lederman (2012), "Product Recalls, Imperfect Information, and Spillover Effects: Lessons from the Consumer Response to the 2007 Toy Recalls," *Review of Economics and Statistics*, 94 (2), 499–516.

Germann, Frank, Rajdeep Grewal, William T. Ross Jr., and Rajendra K. Srivastava (2014), "Product Recalls and the Moderating Role of Brand Commitment," *Marketing Letters*, 25 (2), 179-91.

Giroud, Xavier (2013), "Proximity and Investment: Evidence from Plant-Level Data," *The Quarterly Journal of Economics*, 128 (2), 861–915.

Haunschild, Pamela R. and Mooweon Rhee (2004), "The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls," *Management Science*, 50 (11), 1545–1560.

Jibrell, Anisa (2018), “Auto Recall Bill Grew 26% to $22 Billion in 2016, Study Says,” *Automotive News*, (January 30), (accessed June 17, 2020), [available at https://www.autonews.com/article/ 20180130/RETAIL05/180139974/auto-recall-bill-grew-26-to-22-billion-in-2016-study-says].

Kirchhoff, Suzanne M. and David R. Peterman (2010), “Unintended Acceleration in Passenger Vehicles,” *Congressional Research Service*, (April 26), (accessed June 17, 2021), [available at https://fas.org/sgp/crs/misc/R41205.pdf].

Lerner, Josh (1995), “Venture Capitalists and the Oversight of Private Firms," *Journal of Finance*, 50 (1), 301–318.

Lilien Gary (2016), “The B2B Knowledge Gap,” *International Journal of Research in Marketing,* 33 (3), 543–556.

Liu, Yan and Venkatesh Shankar (2015), “The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry,” *Management Science*, 61 (10), 2514–2535.

Ozturk, O. Cem, Pradeep K. Chintagunta, and Sriram Venkataraman (2019), “Consumer response to chapter 11 bankruptcy: Negative demand spillover to competitors,” *Marketing Science,* 38 (2), 296-316.

Petersen, Mitchell A. and Raghuram G. Rajan (2002), “Does Distance Still Matter? The Information Revolution in Small Business Lending,” *Journal of Finance*, 57, 2533–2570.

Roehm, Michelle L. and Alice M. Tybout (2006), “When Will a Brand Scandal Spill Over, and How Should Competitors Respond?” *Journal of Marketing Research,* 43 (3), 366–373.

Souiden, Nizar and Frank Pons (2009), “Product Recall Crisis Management: The Impact on Manufacturer’s Image, Consumer Loyalty and Purchase Intention,” *Journal of Product & Brand Management*, 18 (2), 106–114.

Thirumalai, Sriram and Kingshuk K. Sinha (2011), “Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences,” *Management Science*, 57 (2), 376–392.

CHAPTER 2: LOBBYING AND PRODUCT RECALLS: A STUDY OF THE US AUTOMOBILE INDUSTRY

Introduction

In 2009–2010, Toyota responded slowly to hundreds of reported accidents involving its vehicles, potentially linked to sudden acceleration flaws. A 2010 U.S. Congressional report, examining the case, openly alleged lobbying influences by automotive firms (Kirchhoff and Peterman 2010), citing an internal Toyota document (dated July 6, 2009), in which the chief operating officer highlighted several "wins," such as delaying final safety rules by National Highway Traffic Safety Administration (NHTSA) and persuading NHTSA officials to impose smaller sanctions. The internal document, for example, suggested that the negotiated equipment recall on its Camry model saved the company $100 million. The report raises important questions that motivate the current research: Does lobbying influence product (vehicle/automobile) recalls? Can we observe significant differences in voluntary recall by firms based on their lobbying expenditure levels? Does lobbying influence public agencies' (i.e., regulators, NHSTA in the case of automobiles) mandatory recalls? The answer to these questions is not obvious. In an environment where objective product quality should be the only factor influencing product recall, lobbying should have no impact on recall decisions as lobbying does not alter product quality. However, the anecdotal evidence provided above suggests otherwise. Uncovering whether there is a relationship between lobbying and product recalls (voluntary and mandatory) is important from strategic marketing and public policy perspectives.

Product recalls are inevitable in many industries (e.g., medical equipment, consumer products). Examples of some of the prominent recalls include Johnson & Johnson's Tylenol recall, Takata airbags recall, Pfizer's Bextra recall, Volkswagen's diesel emission recall, and Mattel's toy recall. For the automotive industry, recalls are especially pervasive. In 2016, 919 recalls due to defects and compliance issues affected 50.5 million vehicles and cost firms almost $22.1 billion (Jibrell 2018). Recalls have a direct (e.g., reduced sales) and indirect (e.g., brand reputation loss) cost prompting firms to try to avoid/reduce recalls.

One strategy for reducing recalls relies on corporate lobbying, through which firms attempt to create political connections and alter the regulatory landscape (Bertrand, Bombardini, and Trebbi 2014). Blanes i Vidal, Draca, and Fons-Rosen (2012) refer to the U.S. lobbying industry as a market for political connections; firms invest and hire lobbyists to gain access to politicians, then extract returns in different forms (Alexander, Mazza, and Scholz 2009). For example, drug makers lobby intensely to avoid bills that aim to curb drug prices. In 2015, companies within the pharmaceuticals and health products sector spent $240 million on lobbying (Chon 2016). Table 2.1 provides examples of lobbying activities across diverse industries. It is important to understand whether and how political influence might bias critical policies, including recall decisions as they can lead to loss in revenue or reputational damage. We study the relationship between recall and lobbying in the automotive industry, which contributes almost 3% of U.S. gross domestic product and generates more manufacturing jobs than any other U.S. sector.[1] Further, the automotive industry is subject to close regulatory supervision, making it an ideal setting for our study.

[1] See http://www.americanautocouncil.org/us-economic-contributions, accessed February 2020.

A recall process (Figure 2.1) generally starts with consumer complaints about vehicle defects, but a firm's own tests also might reveal defects. The firm analyzes complaints or potential issues and may decide to initiate a voluntary recall. The NHTSA also has access to consumer complaints, so the regulatory agency may recommend a mandatory recall if the firm does not initiate a voluntary recall. However, if firms can influence the NHTSA using lobbying connections, the firms could influence the recall process, as indicated by anecdotal evidence in the popular press.[2]

As a government agency, the NHTSA functions in a politically active environment. The President of the United States nominates its chief, and oversight committees consist of members from the Senate and House of Representatives (Figure 2.2). With this structure, multiple political actors actively interact with the NHTSA, and accordingly, automotive firms can use lobbying as a political channel to build connections with various actors and potentially exert influence. These activities might lead the agency to make choices that favor the lobbying firm, such as limiting investigations into consumers' complaints or not recommending recalls, as well as issuing lax regulations. These choices may favor the lobbying firms that may then adopt a passive response to vehicle defects. We investigate this dimension of influence in firms' recall decision-making.

(Please see Table 2.1, Figure 2.1, and Figure 2.2)

To investigate the causal relationship between a firm's lobbying expenditures and automotive recalls, we consider the U.S. passenger vehicle market. We gather recall and lobbying expenditure data for major automotive firms, which reveal that lobbying expenditures

[2] For example, "GM Turns to Holland & Knight for Post-Recall Lobbying Push," https://www.law.com/nationallawjournal/almID/1202657819376/?slreturn=20190907230356, accessed June 2020; "Toyota's Lobbying Power Primed for Test as Congressional Scrutiny Mounts," https://www.opensecrets.org/news/2010/02/toyotas-lobbying-power-primed/, accessed June 2020; and "Takata's Tab for U.S. Lobbying Rises 22% as Recall Scrutiny Intensifies," https://www.autonews.com/article/20150805/OEM11/150809915/takata-s-tab-for-u-s-lobbying-rises-22-as-recall-scrutiny-intensifies, accessed June 2020.

and recalls are negatively associated. It seems that a reduction in voluntary recalls drives this negative effect as increase in lobbying expenditures reduces voluntary recalls. This finding seems to suggest a change in firm's recall behavior as it changes its lobbying expenditures. The recall process suggests that a reduction in voluntary recalls due to increase in lobbying expenditures should offer regulators more opportunities for mandatory recalls, but regulators do not compensate for change in firm recall behaviors. In fact, results suggest that regulator's tendency to recommend mandatory recall also goes down as lobbying expenditures increase. Thus, benefits of increased lobbying expenditure for a firm seem to be two fold, reduced voluntary and reduced mandatory recalls. First, the lobbying firm itself reduces the number of recalls and second the regulator seems to issue fewer recalls. In deriving these findings, we also note an empirical challenge in the form of an omitted variable bias, in that an omitted variable influences both the decisions to lobby and to recall by a firm. To address this issue, we use an instrumental variable (IV) approach and affirm the robustness of the results with several alternate model specifications and robustness tests.

With these findings, our study contributes to empirical literature on lobbying by addressing its influence on product recalls. We empirically establish the validity of lawmakers' concerns about lobbying influences, especially for the automotive industry, in which vehicle defects can have severe consequences. More broadly, we highlight the regulatory dimension of recalls and study an extension beyond existing literature that mainly adopts a business orientation. The interface of marketing and politics is a critical but underdeveloped research domain (e.g., for exceptions, Han et al. 2019; Jung and Mittal 2020; Martin et al. 2018) especially in the context of regulatory oversight over various industries, which many executives acknowledge to be a powerful political factor impacting their operations (KPMG 2015). By combining research into recalls and lobbying expenditures, we specify how firms work to manage their regulatory environment.

Institutional Background

We detail critical institutional factors for automotive recalls and corporate lobbying activities, then note the mechanisms by which corporate lobbying expenditures can influence regulatory agencies.

Automotive Recalls

Recalls are common in the automobile industry; even a minor defect among the many vehicle components can trigger recalls. The NHTSA is responsible for oversight of vehicle safety in the United States, such that it can initiate recalls if necessary and is responsible to monitor the effectiveness of ongoing recalls. It also maintains multiple channels for consumers to submit complaints (e.g., phone, email, and website, among others), through which it receives approximately 4,000 complaints every month.[3] Depending on the type of complaint, the NHTSA assigns any complaint to one of 37 categories (e.g., power train, suspension); a complaint about leaking engine oil belongs to the engine and engine cooling category for example. In this study, we consider the seven original equipment manufacturer (OEM) complaint categories:[4] electrical systems, fuel systems (gasoline), power train, engine (engine cooling), suspension, exterior lighting, and structure, as we detail in the Data section. Complaints also may be specific to a specific manufacturer (e.g., Honda) or make (e.g., Lexus). In addition to consumer complaints, NHTSA collects and tracks automotive-related injuries, deaths, fires, and crashes; these data are

[3] See https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/810552.pdf, accessed June 2020.

[4] Each of these seven complaint categories contribute at least 2% recalls to entire OEM categories recalls in our data set. Cumulatively, the seven included categories capture approximately 94% of OEM recalls. Each of the excluded categories captured less than 2% recalls (these included Engine (other), Equipment Adaptive, Forward Collision Avoidance, Fuel System (other), Hybrid Propulsion System, and Traction Control System).

available to manufacturers too. Using available information (e.g., complaints, deaths, private information such as firm's financial health), the firm decides whether to recall or not (voluntary recall). Simultaneously, NHTSA also has the authority to recommend a mandatory recall (based on the available information such as consumer complaints and death reports). Note that NHTSA does not have access to the firm's private information. This process (Figure 2.1) occurs in each decision interval, which usually is a calendar quarter, as is also reflected in the quarterly reporting of firms' lobbying expenditures (see the Data section).

Political Influence

Political science literature discusses the "iron triangle" mechanism through which political capital influences regulatory agencies and bureaucracies (Adams 1981). The triangle reflects the aligned actions and interests of three key actors in public policy making: (1) the regulated industry (e.g., the automotive industry), (2) legislative oversight committees (e.g., Committee on Transportation and Infrastructure, Committee on Commerce, Science and Transportation), and (3) the regulatory agency (e.g., NHTSA). The resulting alliance aims to control government policy, within the agency's jurisdiction, for the mutual benefit of the three sides of the triangle. For example, Freeman (1965) describes exchanges of favors among agencies, special interest groups, and congressional committees that earn the agencies more funding and power, if they cater to the interest groups, which then influence politicians, who ultimately exert pressure on the regulatory agency (Correia 2014).

Legislative and executive bodies can exert political control over regulatory agency's activities through mechanisms such as budget setting, appointments, and oversight. Weingast (1984) details how politicians use budgets to reward (or sanction) agency decisions that increase (decrease) their political support. For the NHTSA, the president nominates its head, and then Senate panel approve the nomination. The appointed administrators often enter lobbying careers after leaving the agency (e.g., former head of the NHTSA David Strickland became a lobbyist at a law firm that deals with automobile regulations). To maximize their future career prospects in a regulated industry, regulatory agency administrators may act in accordance with congressional interests, but they also represent attractive candidates for lobbyist because of their inside knowledge of how agencies work that can help muster political support. As one lobbying firm founder notes: “People who are experienced in Washington tend to be better at doing this kind of work than people who have never worked in the government before” (Farnam 2011). Finally, Congressional committees have investigative oversight (Correia 2014), and their investigations may uncover and publicize agency abuses that in turn might prompt legislative responses or policy changes. During hearings, Congress also can clarify for the agency how they believe it should function. This mechanism also depends on institutional powers (Weingast and Moran 1983), in that Congress delegates responsibilities to monitors, and appropriates budgets of agencies to create incentives for them to act in accordance with its goals (De Vault 2002).

Research examining the link between political influence and regulatory agencies reveals several influences. For example, pertaining to tax benefits, Richter, Samphantharak, and Timmons (2009) find that firms that spend more on lobbying pay lower effective tax rates the next year. Among firms subject to class action lawsuits, those that lobby more achieve longer class-action periods, such that lobbying appears to delay fraud detection (Yu and Yu 2011). On average, politically connected firms also are less likely to be involved in enforcement actions and face lower penalties (Correia 2014). These empirical findings imply that lobbying expenditures may be associated with favorable treatment by regulatory agencies.

Corporate Lobbying

Lobbying Disclosure Act. The Lobbying Disclosure Act (LDA) (1995), which governs lobbying activities in the United States, requires firms to disclose lobbying expenses. The LDA defines "lobbying activities" as contacts and efforts in support of such contacts, including preparation and planning activities, research and other background work, and coordination with others' lobbying activities.[5] It further defines a "lobbyist" as a person or entity that has one or more employees who (1) are employed or retained by a client for financial or other compensation, (2) offer services that include more than one lobbying contact, and (3) engage in lobbying activities for at least 20% of the services provided for that client over any three-month period. Lobbying firms must file separate reports for each client, containing substantial information about their lobbying activities, such as the revenue generated and the issues for which the firm lobbied on that client's behalf during that period. The only exceptions are if a client does not spend more than $3,000 in a quarter for lobbying. If lobbying income is $5,000 or more, a lobbying firm also must provide a good faith estimate of actual amount, rounded to the nearest $10,000. Firms with in-house lobbyists may file a single registration; they must register if their total expenses for lobbying activities exceed $13,000 in a quarter.[6] The Honest Leadership and Open Government Act of 2007 required firms to start report lobbying expenditures quarterly as of 2008; previously, they filed semi-annual reports to the Senate's Office of Public Records.

Lobbying Process. Firms might rely on internal (in-house) lobbyists or external, professional lobbying firms. Lobbyists usually are insiders with extended networks of political contacts, who interact with politicians and their appointees to further the interests of their client firms. In many cases, they have held positions in government agencies (revolving door phenomenon) which increases access to government and their lobbying effectiveness (Ridge, Ingram, and Hill 2017). Lobbying constitutes an investment that firms make in the political

[5] See https://www.senate.gov/legislative/Lobbying/Lobby_Disclosure_Act/3_Definitions.htm, accessed June 2020.

[6] See https://lobbyingdisclosure.house.gov/ldaguidance.pdf, accessed June 2020.

arena, such that they hire lobbyists to support or contest specific legislative proposals, which in the United States mostly take the form of proposed bills. Because the resulting legislation determines the policy landscape and macro-environment for firms, they have an interest in lobbying for selected bills (Borghesi and Chang 2015).

Even if firms fail to achieve their immediate policy goal, they may introduce novel ideas to the policy-making community, because lobbyists also help facilitate information transfers, particularly when they can claim special expertise (Bertrand, Bombardini, and Trebbi 2014). Lobbyists' expertise can be valuable if legislators lack the technical background or resources to undertake an in-depth analysis of a proposed bill. In some cases, lobbyists even create draft versions of the bills for lawmakers to introduce (Chang 2013), in which case the client firms exert strong influences on policy changes, which can benefit the firms in myriad ways.

Lobbying as Political Activity. We emphasize lobbying for this study, instead of other forms of political activities like campaign contributions, due to three key features of lobbying. First, legal limits constrain political contributions, whereas lobbying expenditures are not subject to any limits, leading them to become, in monetary terms, the largest form of corporate political activity in the United States (Milyo, Primo, and Groseclose 2000). In 2012, lobbying of the federal government accounted for $3.5 billion in expenditures, substantially more than the estimated $750 million spent on campaign contributions (De Figueiredo and Richter 2014). Second, lobbying exists to support or oppose legislative bills, and it takes place throughout the year. Firms also can hire as many lobbyists as they deem necessary. In contrast, campaign contributions usually go to a particular candidate during election seasons. Third, because laws limit the roles that corporations may play in supporting political candidates, firms establish political action committees to raise money from third-party sources (e.g., employees, shareholders), such that most campaign contributions come from individuals, not corporations (Adelino and Dinc 2014; Ansolabehere, De Figueiredo, and Snyder 2003; Chen, Parsley, and Yang 2015).[7] Therefore, we use lobbying to assess a firm's political influence.

Related Literature

Product Recalls

Marketing studies of product recalls span many different areas, as Table 2.2 summarizes. Some studies focus on tangible performance aspects, revealing that recalls negatively affect a firm's value and performance indicators, such as sales and profits (e.g., Chu, Lin, and Prather 2005; Dranove and Olsen 1994; Salin and Hooker 2001). Another set of studies explore strategic aspects, such as the effectiveness of advertising and other marketing mix variables following a recall (e.g., Van Heerde, Helsen, and Dekimpe 2007; Zhao, Zhao, and Helsen 2011). For example, in comparing proactive and passive recall response strategies, Chen, Ganesan, and Liu (2009) determine that the stock market responds negatively if a firm initiates a recall before receiving any reports of injuries. Studies also investigate intangible outcomes (e.g., loyalty, image, reputation) of a product recall. Cleeren, Dekimpe, and Helsen (2008) argue that brand advertising can counter the negative effects of a recall and enhance consumers' first post-recall purchase decisions According to Souiden and Pons (2009), if manufacturers contest recalls, it negatively affects their image and consumer loyalty. Product recalls help firms learn though, and a greater recall magnitude can diminish the number of future recalls and injuries (e.g., Haunschild and Rhee 2004; Thirumalai and Sinha 2011).

Recalls could also create spillover effects on different products produced by the same manufacturer, competitors in the category, and the industry as a whole (e.g., Bala et al. 2017;

[7] In the 2010 elections, individual direct donations to Congressional candidates accounted for more than 60% of total funding. See https://www.opensecrets.org/resources/dollarocracy/04.php, accessed June 2020.

Jarrell and Peltzman 1985; Marsh et al. 2004). Liu and Shankar (2015) identify negative spillover effects on choices and market shares of other sub-brands with the same parent brand name as a recalled product, and Borah and Tellis (2016) observe that negative online chatter about a recalled car model increases negative chatter for others with the same brand. Freedman et al. (2012) establish sizable, negative impact of recall on entire industry sales. Studies have also explored factors (e.g., product scope, supply chain proximity, political spending, poor financial conditions), which could affect product quality and subsequent recalls (e.g., Bray et al. 2019; Kini et al. 2017; Rayfield and Unsal 2019; Thirumalai and Sinha 2011). Product recalls could also impact secondary markets. Hartman (1987) finds that safety recalls by General Motors (GM) diminish the resale value of the recalled products but do not affect the values of other GM products. Ater and Yosef (2018) and Strittmatter and Lechner (2020) study the supply-side implications of product recalls in secondary markets, using the Volkswagen emission scandal; they both find statistically significant negative impact of recalls on the supply of recalled products. We seek to build on this foundation by studying the effect of a political dimension on recall decisions.

(Please see Table 2.2)

Corporate Lobbying

Firms use corporate lobbying as a strategic tool to create political connections and gain benefits, as demonstrated by various studies. De Figueiredo and Silverman (2006) identify large returns to lobbying by universities for academic earmarks, and Alexander, Mazza, and Scholz (2009) find that firms that lobbied for the American Jobs Creation Act of 2004 earned returns of greater than $220 for every $1 spent lobbying. Studying the mortgage industry, Igan, Mishra, and Tressel (2012) determine that lenders that lobby more intensively engage in riskier lending practices *ex ante*, then benefit more from bailout programs. To determine if financial markets value corporate lobbying, Borisov, Goldman, and Gupta (2016) analyze the impact of an exogenous event that influenced lobbying processes and discover that firms that lobby more experience losses after the event. Chen, Parsley, and Yang (2015) cite a positive association of lobbying with market measures of financial performance.

Such influences likely stem from the access that corporate lobbyists offer to lawmakers. As Blanes i Vidal, Draca, and Fons-Rosen (2012) determine, lobbyists formerly employed by the federal government generate the most lobbying revenues; those who were formerly staff members of U.S. senators experience a 28% ($182,000 at the median) drop in lobbying revenues when that senator leaves office. But firms also seek private information, tips, and predictions from lobbyists (Mullins and Scannell 2006). As Gao and Huang (2016) find, hedge fund managers connected to lobbyists trade more heavily in politically sensitive stocks and thereby outperform the managers of unconnected funds.

Data Description

The data for this study come from multiple sources. For information about recalls and consumer complaints, we refer to the NHTSA database.[8] For firms' lobbying expenditures and categorizations across lobbied issues, we rely on the U.S. Senate database.[9] We use Compustat to obtain financial indicators (e.g., capital expenditures, liability), Automotive News data (sales), and Consumer Reports to determine vehicle quality ratings (Table 2.3).

(Please see Table 2.3)

[8] See https://www.nhtsa.gov/recalls#vehicle, accessed July 2021.

[9] See https://lda.senate.gov/system/public/, accessed July 2021.

Recall

The automotive industry regulator NHTSA maintains records of recall data and makes them accessible for public reference. The NHTSA website provides detailed information about both consumer complaints and vehicle recalls, including the name of the firm, make, and model; the number of affected units; and a brief description of the defect.[10] Our balanced panel over a nine-year period (2008–2016, with the starting year determined by when quarterly lobbying expenditure data are available) features data related to 14 automotive firms (BMW, Daimler, Ford, General Motors, Honda, Hyundai, Jaguar, Kia, Mazda, Nissan, Porsche, Tesla, Toyota, and Volkswagen). These firms were involved in 636 vehicle recalls,[11] and over the nine-year period, General Motors faced the highest number of recalls (97), as well as the highest number of incidents linked to deaths (19) in a quarter. The complaint data set also identifies consumer complaints received by the NHTSA, according to the automobile firm's name; the make, model, and model year; and a brief description of the complaint. We obtain the number of complaints and reported deaths from this data, with the descriptive statistics listed in Table 2.4 (panel A).

(Please see Table 2.4)

In this data set, the number of quarterly voluntary recalls ranges from 0 to 15 per firm; the number of quarterly mandatory recall ranges from 0 to 5 per firm. The mean quarterly number of complaints is 437 per firm. We observe 556 voluntary recalls and 80 mandatory recalls during nine-year period. In Figure 2.3, we highlight some notable data distributions. The bar graphs of the frequency distribution of voluntary and mandatory recalls indicate that, on an

[10] We also verify the recall event details from other two sources (https://www.kbb.com/ and https://www.cars.com/). Examples are provided in Figure WB 2.2 (Appendix).

[11] We consider unique recalls to establish this count. For example, different makes of the same firm (e.g., Honda, Acura) could have recalls at different times for the same reason in the same recall campaign. We use unique recall campaign numbers to avoid double counting.

aggregate firm level, voluntary recalls span 53.37% of the total data points. On the aggregate firm level, mandatory recall events are sparse and occur for 12.30% of the total data points. The line graph also indicates variation in lobbying expenditures and voluntary recalls, aggregated over firms for 36 quarters (nine-year period).

(Please see Figure 2.3)

The complaint data set reveals 37 complaint categories[12] (e.g., airbag, suspension, steering), which we classify into issues attributed to the original equipment manufacturer (OEM; e.g., powertrain) or not (e.g., air bags), with the assistance of automotive industry experts (not associated with this study). Each third-party–supplied part (i.e., non-OEM group) could be present in several car makes, so a defect in a non-OEM part would likely trigger recalls for multiple firms, thereby creating an indirect correlation. We instead focus on the OEM group, which represents 44% of the total recalls, and thereby avoid this co-dependency. Specifically, we consider seven OEM complaint categories, each of which represent at least 2% of all OEM recalls in our data set (electrical system, fuel system [gasoline], powertrain, engine [engine cooling], suspension, exterior lighting, and structure), and together these seven categories account for more than 94% of all OEM recalls.

The number of complaints and deaths are primary determinants of recalls; they indicate the defect's severity and thus the seriousness of the consequences from a consumer safety standpoint. Accordingly, severe recalls attract more negative responses from stakeholders, with a stronger impact on sales (e.g., Hoffer, Pruitt, and Reilly 1988; Liu and Shankar 2015). Ni, Flynn,

[12] These categories are: Air bags; Back over prevention; Child seat; Communications; Electrical system; Electronic stability control; Engine; Engine and engine cooling; Equipment; Equipment adaptive; Exterior lighting; Forward collision avoidance; Fuel system diesel; Fuel system gasoline; Fuel system; other; Hybrid propulsion system; Interior lighting; Latches/locks/ linkages; Other; Parking brake; Power train; Seat belts; Seats; Service brakes; Service brakes air; Service brakes electric; Service brakes hydraulic; Steering; Structure; Suspension; Tires; Traction control system; Trailer hitches; Vehicle speed control; Visibility; Visibility/wiper; Wheels.

and Jacobs (2014) also find that severity of recalls relates positively to financial penalties by the stock market, and Thomsen and McKenzie (2001) find that recall severity negatively influences a firm's financial value. To represent severity, we use the reported number of complaints and deaths as key covariates. More reported deaths represent personal losses to consumers; more complaints indicate a widespread vehicle defect (Eilert et al. 2017). Injuries leading to deaths, even if associated with relatively few complaints, can trigger a product harm crisis and recalls. These complaint characteristics control for recall size and defect severity, which inform our assessment of the direct and indirect costs of the recall.

Lobbying Expenditures

We collect corporate lobbying expenditures from the U.S. Senate website, including spending by firms and their subsidiaries through internal (in-house) lobbyists and external, professional lobbying firms. As we noted previously, the LDA of 1995 offers definitions and requirements for lobbyists and lobbying activities; it mandates that each lobbyist indicate for which issues it lobbied in any period. The resulting reports reveal that firms invest in lobbying to address diverse issues (e.g., Accounting, Aerospace, Automotive Industry, Energy/Nuclear, Homeland Security, Immigration, Tobacco, Transportation). Table WB 2.1 (Appendix) contains a complete list of these lobbying issues.[13] Figure WB 2.1 (Appendix) depicts a section of the lobbying report submitted by BMW for its lobbying expenditures for October–December 2016. Senate records contain lobbying expenditures at the parent firm or holding company level, so we only observe firm-level lobbying expenditures.

Since 2008, cumulative U.S. lobbying expenditures have exceeded $3 billion, with a peak of $3.51 billion in 2009. In our study, the 14 focal automotive firms spent $338.55 million over

[13] See https://lda.congress.gov/LD/help/default.htm?turl=Documents%2FAppCodes.htm, accessed June 2020.

nine-year period (2008–2016). Median value of quarterly lobbying spending is $250,000. General Motors ranked highest during this period, with $99.95 million in spending. 2008 marked the year these firms spent the most ($44.90 million). Ford Motors spent highest quarterly expenditures in the fourth quarter of 2013 ($7.86 million). The issue category that attracted the most investments, or 11.5% of spending, was the broad “automotive industry,” followed by “taxation” (10.4%).

In the 36 quarters we study, Subaru did not incur any lobbying expenditure, and for Mitsubishi, we observe only one non-zero observation, so we exclude these firms. We also exclude Chrysler, which underwent multiple, different mergers (Daimler, Fiat); the management changes and corresponding regulatory exposure make it a potentially unstable data point for our study.

Lobbying expenditures below some reasonable threshold appear as zero values in the Senate data, but we expect this data limitation to have minimal impact. Firms primarily employ external lobbying firms, for which the reporting threshold is low ($3,000). In our data, the mean and median values of quarterly lobbying expenditures are $671,739 and $250,000, respectively, and 99% of firm-quarter observations with positive lobbying expenditures include amounts greater than $20,000. Similar to Kerr, Lincoln, and Mishra (2014), we also do not observe any clustering around the thresholds. Therefore, the potential measurement error due to reporting requirements should be minimal.

Control Variables

We include control variables to capture factors that might affect the firm’s recall decision and the effectiveness of lobbying. First, we consider the geographical dispersion of defect complaints. We count the unique number of US states where the defect complaints were registered. This variable would help us control for how widespread potential defect is beyond its sheer magnitude (number of complaints and deaths). Second, we note the firm's liabilities, measured as its total liabilities normalized by sales. Kini, Shenoy, and Subramaniam (2017) show that firms with higher leverage experience greater recall probabilities; if they struggle with weak financial conditions, firms may lower their discretionary investments in quality, leading to more risk of subsequent recalls. A lack of resources also may limit the firm's tendency to provide remedy and encourage it to avoid initiating recalls. Moreover, such liabilities may affect the extent of lobbying activities and determine the firm's political activity.

Third, we control for capital intensity, or a firm's capital expenditures (CAPEX) (Steven, Dong, and Corsi 2014). These expenditures include investments for purchases, improvements to, or maintenance of long-term assets to enhance the firm's efficiency or capacity. For example, if a firm introduces a new product or builds a new plant, its capital expenditures rise. Investing in fixed assets should enhance the firm's product quality and reduce the number of defective products, so it may be associated with fewer recalls. We normalize this by firm sales.

Fourth, we control for potential agency issues that may arise. The firm aims to maximize its market value, but that goal might not align with managers' (agents') preference to maximize their own personal interests, potentially at the expense of firm owners. Misaligned interests can create value losses for shareholders (Jensen and Meckling 1976). For example, self-interest might drive a top manager to pursue political actions for private gain. Because we cannot observe all lobbying activity and all its outcomes completely (Richter, Samphantharak, and Timmons 2009), we account for potential agency issues, using a measure of the agency costs of free cash flows. That is, if a firm has excess cash flows to finance projects efficiently, firm managers should be more likely to invest in projects that enhance their personal utility (Jensen 1986). Such concerns may be more prevalent in low growth firms, which generally have substantial free cash flows for managers to invest. Following Jensen (1986) and Doukas, Kim, and Pantzalis (2000), we proxy for agency costs with the interaction of a poor growth opportunities indicator and free cash flows (FCF) standardized by total assets (TA). The FCF equals operating income before depreciation minus the sum of taxes, interest expense, and dividends paid (Lehn and Poulsen 1989). The growth indicator variable equals 1 if the firm's Tobin's q is less than 1 (poorly managed firm or poor growth opportunities) and 0 otherwise.

Fifth, we also control for firm size, measured as the number of vehicle units sold. The number of sold products may affect recall, because more vehicles on the road mean more potentially defective vehicles. Larger firms usually feature a more diversified, complex product base, which also could be associated with more recalls (Steven, Dong, and Corsi 2014). Firm size may determine lobbying and political power too (Kerr, Lincoln, and Mishra 2014); politics likely is more important to larger, more visible firms that must represent themselves on multiple fronts (Agrawal and Knoeber 2001). We control for the vehicle quality by using Consumer reports rating data. High/low quality of vehicles could be associated with high/low number of recalls. Thus, this variable would allow us to control for potential impact of vehicle quality on number of recalls. Since it may take some time for defects to appear, we use ratings with one lag (quarter) in the analysis.

Model Specifications

We estimate the recall process (Figure 2.1) with instrumental variable (IV) model and simultaneous equation system (specifically 3SLS). We run additional specifications including a non-linear model to ensure the robustness of our results.

Instrumental Variable Model

We could use ordinary least squares and exploit the between- and within-data dimensions to establish the link between recalls decisions and lobbying (Wooldridge 2002). However, this empirical model would potentially suffer from endogeneity bias. Endogeneity concerns arises from the firm-level, time-varying variables that correlate with both lobbying and product recalls. Studies have shown that failure to address endogeneity could lead to statistically inconsistent parameter estimates. Few solutions to address endogeneity could include field experiments (e.g., Johnson et al. 2017), natural experiments (e.g., Shapiro 2018), or instrumental variables (e.g., Pattabhiramaiah et al. 2018). We rely on an instrumental variable strategy. We consider two-stage least squares model (2SLS; Wooldridge 2012) in an attempt to identify a valid instrument that meets relevance and exclusion restriction conditions (with conceptual justification).

Time-Varying Omitted Variable Bias. Lobbying activities and expenditures are strategic decisions for firms, and investments in lobbying result from their beliefs about the potential benefits for recall episodes. An omitted variable bias, or endogeneity, might arise if a time-varying omitted variable influences both the decisions to lobby and to recall, such as the firm's strategic philosophy about regulatory risk management. That is, the prominence and dynamism of regulations across markets creates a situation in which the regulatory environment is a primary risk for business (Ernst & Young 2011; Ross 2005). Consulting agencies thus offer regulatory risk management products (e.g., Dannemiller et al. 2017). In the automotive industry, dynamic factors such as product safety disputes (e.g., orders for unrepaired recalls),[14] societal developments (e.g., reducing greenhouse gas emissions),[15] or politically induced scenarios (e.g., appointment of new administrators)[16] all can drive regulatory changes. In turn, the link between

[14] See https://www.ftc.gov/news-events/press-releases/2017/03/ftc-approves-final-orders-settling-charges-used-auto-dealers, accessed June 2020.

[15] See https://obamawhitehouse.archives.gov/the-press-office/2012/08/28/obama-administration-finalizes-historic-545-mpg-fuel-efficiency-standard, accessed June 2020.

[16] See https://www.detroitnews.com/story/business/autos/2019/04/03/trumps-pick-nhtsa-chief-clears-u-s-senate-panel/3353494002/ accessed June 2020.

a firm's regulatory risk management strategy and its lobbying is likely. Firms prefer to avoid recalls and harsher regulatory actions; a firm with political clout could potentially exert this influence on the NHTSA and thereby reap undue benefits.[17] In anticipation of future recalls, firms also might invest proactively in lobbying to influence key stakeholders and create a potential safeguard. For example, more than 30 lobbyists worked for Toyota in 2009 (one year before its unintended acceleration recall) to represent its interests before Congress and federal agencies (Krumholz and Levinthal 2010). In 2014 (during an ongoing ignition switch recall debate), General Motors hired two new lobbying firms to assist with its "product and safety recall issues" (Tau 2014). Other industries also observe similar lobbying ramp up practice when regulatory scrutiny grows (Tracy 2019).

Such a strategy flow from organizational mindset and likely embed throughout the organization, such as in managerial experience and business knowledge, which makes it difficult to quantify. The absence of a measure of regulatory risk management, which correlates with both recalls and lobbying, thus creates an omitted variable bias that also raises endogeneity concerns (Wooldridge 2002). Using 2SLS, we seek to identify an IV that meets the relevance and exclusion restrictions to address this concern.

Instrumental Variable (IV). The quarterly aggregated political contributions of residents living in counties where a firm has its headquarters or production facilities provide a potential IV. In the United States, individual contributors may donate to any political candidate or committee; the Federal Election Commission (FEC) maintains a database of all contributions. For example, Toyota has a presence in seven counties (headquarters in Los Angeles County,

[17] Many reports assert that former regulators hired by Toyota helped halt the probes. See https://www.denverpost.com/2010/02/12/regulators-hired-by-toyota-helped-halt-probes/, accessed June 2020.

Calif.; plants in Madison County, Ala.; Gibson County, Ind.; Scott County, Kent.; Union County, Miss.; Bexar County, Tex.; and Putnam County, W.V.).[18] We sum individual contributions from these counties. With the prediction that a firm with a larger geographical footprint is more likely to be active in lobbying at both its headquarters location and in areas where its plants are located, we gather headquarters and plant information for each firm from various sources (e.g., company website, annual reports). Then we search websites maintained by the Office of Policy Development and Research and Department of Agriculture to find county codes and corresponding ZIP codes for each county. We enter these ZIP codes into the FEC website to identify individual contribution data over the nine-year study period.

Instrument Relevance. To satisfy the relevance criterion, the IV should correlate with the endogenous regressor, which is lobbying expenditures. We anticipate that they correlate negatively: If individuals, i.e., residents living in counties where a firm has its headquarters or production facilities, contributions increase (decrease), firms' lobbying expenditures should decrease (increase). In general, an individual might make political donations to signal her political engagement and share her views on various issues, related to local policies, jobs, infrastructure development, and so on; those issues also are relevant to firms with a presence in those local counties. When political donations increase, firms may be motivated to dedicate less money to lobbying activities, because they know their interests already are being represented by individual contributions in the political system. Donations also fund the political ambitions of elected officials, so those officials likely account for the signaled interests of contributors in their legislative decisions. As Hill et al. (2013) determine, if more politicians already represent the interests of the citizens of a state in which a firm is present, the firm's need to hire lobbyists'

[18] For the firms in our sample, county-level overlap across firms is minimal: Out of 49 counties (observed across all firms), 6 counties host more than one firm. See Table WB 2.3 (Appendix) for location details.

decreases. If instead individual donations decrease, firms may be motivated to allocate more money to lobbying to ensure adequate representation of their interests. Thus, conceptually, this instrument appears to meet the instrument relevance criterion.

Exclusion Restriction. The proposed instrument should not correlate with the omitted variable absorbed by the error term (Wooldridge 2010). Individual political contributions should not exhibit any association with variables (e.g., vehicle quality) that determine the recall decisions by a firm or regulator; rather, reasons to donate likely vary substantially across individual contributors (Powell 2012). For example, an individual might use political contributions to express her personal political orientation and ideology (Ansolabehere, de Figueiredo, and Snyder 2003) or out of a sense of civic duty; an environmentally conscious voter might contribute to a committee that is raising support for an environmental bill. Others might donate to align with the norms of their networks of friends or professional relationships. In all these cases, individual contributions are unlikely to be directly associated with variables that determine automotive recalls, so we conceptually argue that it meets the exclusion restriction criterion too.

Empirical Validity. We assess the empirical validity of the IV by examining its strength and exogeneity through different tests. Before doing so, we remove any contributions from individuals associated with any automotive firms, using employer information included in the FEC data. We consider many variations of firm names (e.g., General Motor, General Motor Co., General Motor Company, General Motors Corp., General Motors; see firms' names table in Table WB 2.2 (Appendix) to identify firms' employees. We observe significant heterogeneity in individuals' contributions across firms' locations. In our data, county-level median and maximum values of quarterly contributions are $81,912 and $74.90 million USD, respectively.

Over nine-year period (2008-2016), sum of all individuals' contributions is $2.73 billion. California's contribution, aggregated across its all locations, was the largest (48.9% of the total amount). West Virginia recorded the lowest aggregated contributions. Over nine-year period, Los Angeles County (California) was the biggest contributor among all counties ($845.77 million USD).

In Table 2.5, we report the first-stage results of the two-stage estimator, which show that our IVs are significant predictor of firm lobbying. For both set of equations, IV coefficients are significant and empirically support the proposed relationship with the endogenous variable. IV negative sign indicates that a greater (lower) degree of individual contributions lowers (increases) firms' need to hire lobbyists. For voluntary recalls, an F-test on the instruments rejects the null hypothesis of weak instruments ($\text{statistic} = 5.34\ (\text{df} = 2;\ 469), p < .05$). The first-stage equation also controls for other exogenous variables, including firm-, year-, and quarter-level fixed effects. A Wu-Hausman test suggests the presence of endogeneity in the system, in that it rejects the null hypothesis ($\text{statistic} = 6.10\ (\text{df} = 1;\ 469), p < .05$). Furthermore, a Sargan-Hansen test ensures the validity of the instruments; it does not reject the null hypothesis that the instruments are exogenous and thus valid ($\text{statistic} = .010\ (\text{df} = 1), \text{n.s.}$). We find similar statistics for mandatory recalls. An F-test on the instruments rejects the null hypothesis of weak instruments ($\text{statistic} = 5.27\ (\text{df} = 2;\ 473), p < .05$). A Wu-Hausman test suggests the presence of endogeneity in the system ($\text{statistic} = 4.97(\text{df} = 1;\ 473), p < .05$). A Sargan-Hansen test does not reject the null hypothesis that the instruments are exogenous ($\text{statistic} = .46\ (\text{df} = 1), \text{n.s.}$).

Two-Stage Least Squares (2SLS). After identifying a valid instrument that meets the relevance and exclusion restrictions, we can apply 2SLS. We first estimate lobbying expenditures as function of the instrument (individual contributions) and the other exogenous variables, then use the estimated value of lobbying expenditures in the second-stage regression for recalls. The 2SLS includes the following specification for the firm:

$$\mathrm{Lobbying}_{iyq} = \gamma_0 + \gamma_1 Z_{iyq} + \gamma_2\, XV_{iyq} + \varepsilon_{iyq}. \tag{2a}$$

$$\mathrm{Vol\_recall}_{iyq} = \beta_0 + \beta_1 \mathrm{Predicted\_lobbying}_{iyq} + \beta_2\, XV_{iyq} + \vartheta_{iyq}. \tag{2b}$$

Equation 2a represents the first stage of the 2SLS. $\mathrm{Lobbying}_{iyq}$ is the lobbying expenditures by firm i in quarter q of year y. Z_{iyq} is the instrument, which is exogenous in nature. To satisfy instrument relevance, the coefficient γ_1 must be significant and nonzero. Equation 2b represents the second stage of the 2SLS. Here, Z_{iyq} does not appear. To meet the exclusion restriction condition, Z_{iyq} must not correlate with the error term ($E(Z_{iyq} * \vartheta_{iyq}) = 0$). $\mathrm{Vol\_recall}_{iyq}$ is the number of voluntary recalls of firm i in quarter q of year y. XV includes covariates for voluntary recalls, namely, recall-specific covariates (number of consumer complaints, reported deaths, and number of states where the complaints were registered), firm-specific variables (liabilities and capex normalized by quarterly values of sales, agency costs, quality rating, and sales), and time-invariant factors (firm, quarter, and year fixed effects). Firm-level fixed effects capture firm-level time-invariant unobserved factors (e.g., organizational culture, managers' risk preferences). It corrects for the omission of time-invariant firm-level factors. Year-level and quarter-level fixed effects account for unobserved factors that vary over time and are common to all firms. Thus we can tease out any year-level fluctuations (e.g., economic cycles that influence all firms). Controlling for time-invariant factors removes time-invariant between-level variation; it relies only on within-level variation in the data. Similarly, the 2SLS specification for the regulator is as follows.

$$\mathrm{Lobbying}_{iyq} = \lambda_0 + \lambda_1 Z_{iyq} + \lambda_2\, XM_{iyq} + \epsilon_{iyq}. \tag{2c}$$

$$\text{Mand\_recall}_{\text{iyq}} = \alpha_0 + \alpha_1 \text{Predicted\_lobbying}_{\text{iyq}} + \alpha_2 \text{XM}_{\text{iyq}} + u_{\text{iyq}}. \tag{2d}$$

Equation 2c and 2d represent the first stage and second stage of the 2SLS model, respectively. $\text{Mand\_recall}_{\text{iyq}}$ is the number of mandatory recalls of firm i in quarter q of year y. XM includes covariates for mandatory recalls (number of consumer complaints, reported deaths, number of states where the complaints were registered, quality rating), and several time-invariant factors (firm, year, and quarter fixed effects). As stated above, Z_{iyq} is the instrument and it must not correlate with the error term ($E(Z_{\text{iyq}} * u_{\text{iyq}}) = 0$), to meet the exclusion restriction condition.

Simultaneous-Equation System

With previous model, we estimate the relationship between lobbying and recalls while addressing econometric issues such as endogeneity. We reinforce this analysis by incorporating two further considerations in the model specification.

Correlation between Decision Makers. The previous models assume that the recall decision-making process of each entity, firm and regulator, is independent (conditional on observed covariates and time-invariant factors), with no correlation between errors. When we relax this assumption, we consider whether exogenous factors not included in the model might shock both model specifications simultaneously. For example, more media coverage after consumer complaints might influence the decision making of both firms and the regulator. We thus allow for correlation between the error terms in Equations 2b and 2d, then perform an estimate with a simultaneous equation model, to gain an asymptotic efficiency advantage over 2SLS (Zellner and Theil 1962). This specification estimates the firm and regulator models simultaneously, correlating their errors, while correcting for the endogenous nature of the lobbying variable with 2SLS. The resulting specifications for the firm and the regulator are:

$$\text{Vol\_recall}_{\text{iyq}} = \beta_0 + \beta_1 \text{Lobbying}_{\text{iyq}} + \beta_2 \text{XV}_{\text{iyq}} + \vartheta_{\text{iyq}} \text{, and} \tag{3a}$$

$$\text{Mand\_recall}_{iyq} = \alpha_0 + \alpha_1 \text{Lobbying}_{iyq} + \alpha_2 \text{XM}_{iyq} + u_{iyq}, \qquad (3b)$$

where $(\vartheta, u) \sim N(0, \Sigma)$, and the other variables are as previously defined. At an aggregated level, this model is identified, as long as we have at least one exogenous variable that appears in one equation but not the other. Similar to the IV model, XV and XM contain different covariates. Therefore, this condition is satisfied, and we consider our model as being identified.

Beliefs. In the recall process, both firm and regulator have authority to initiate a recall. Before any decision, the firm likely develops a rational expectation of the regulator's probable action (recall/no recall), which it incorporates into its own decision making. In addition to the previously noted correlational link between entities, this effect may create a structural link in the model. Incorporating the belief is consistent with the simultaneous process in Figure 2.1. To denote this expectation, we need a variable equal to the number of mandatory recalls in the firm specification. According to a rational expectation assumption, the regulator's recall outcomes should not differ systematically from what the firm would expect (Muth 1961). That is, an outcome prediction by a rational entity does not differ systematically from the resulting market equilibrium. We also incorporate the number of voluntary recalls as a covariate for the regulator's specification, to reflect the regulator's rational expectation of a firm's possible action. This belief may help the regulator allocate its scarce resources more efficiently. Therefore, the revised specifications are:

$$\text{Vol\_recall}_{iyq} = \beta_0 + \beta_1 \text{Lobbying}_{iyq} + \beta_2 \text{XV}_{iyq} + \beta_3 \text{Mand\_recall}_{iyq} + \vartheta_{iyq}, \text{ and} \qquad (4a)$$

$$\text{Mand\_recall}_{iyq} = \alpha_0 + \alpha_1 \text{Lobbying}_{iyq} + \alpha_2 \text{XM}_{iyq} + \alpha_3 \text{Vol\_recall}_{iyq} + u_{iyq} \qquad (4b)$$

where $(\vartheta, u) \sim N(0, \Sigma)$, and the other variables are as previously defined.

Empirical Results

Table 2.5 contains the results for IV 2SLS model, with the number of recalls (voluntary and mandatory) as the dependent variable. We have predicted that automotive firms with more lobbying expenditures are less likely to initiate voluntary recalls. In Panel 1, we provide the second-stage results for the IV model. In the voluntary recall equation, the coefficient for the predicted value of lobbying expenditures is negative and significant ($\beta_{Lobbying} = -2.398$, $p < .05$). The firm, year, and quarter fixed effects control for unobserved heterogeneity. Furthermore, the severity variable (number of death reports) has a significant and positive coefficient ($\beta_{Deaths} = .072$, $p < .05$), indicating that more reported deaths due to defective vehicles increase the number of voluntary recalls. The complaints variable (number of consumer complaints) has a positive coefficient. In the mandatory recall specification (Panel 2), the coefficient of the lobbying variable is significant and negative ($\beta_{Lobbying} = -.644$, $p < .05$) indicating that firms with higher lobbying are less likely to experience mandatory recalls. The magnitude of this effect is smaller than the voluntary recall equation. The coefficient on severity variable (complaints) is positive and significant ($\beta_{Complaints} = .0005$, $p < .05$); logically, more complaints trigger mandatory recalls.

(Please see Table 2.5 and Table 2.6)

Next, we move to examine the simultaneous equation system in Table 2.6. We consider the correlation of the model errors for the firm and the regulator, while also correcting for endogeneity. Wooldridge (2010, sec. 9.6) recommends the GMM 3SLS estimator, which extends a traditional 3SLS estimator by allowing for heteroskedasticity and autocorrelation-consistent standard errors. With a generalized method of moments (GMM) estimator, we obtain parameter estimates based on the initial weight matrix, compute a new weight matrix based on them, and then reestimate the parameters using the new weight matrix. We select a heteroskedasticity- and autocorrelation-consistent weight matrix with a Bartlett (Newey-West) kernel. Panel 1 of Table

2.6 includes these results (Equations 3a and 3b). The voluntary recall results are consistent with the IV model results ($\beta_{Lobbying} = -2.637$, $p < .05$), and the magnitude of the coefficient is similar. Thus, a firm's lobbying and voluntary recalls are negatively associated. Lobbying investments appear to influence and diminish a firm's tendency to initiate voluntary recalls. Severity indicator (complaints) is positive and significant ($\beta_{Complaints} = .002$, $p < .05$); the extent and severity of the defect positively influences the number of voluntary recalls. Capital expenditures variable displays significant and negative relationship with voluntary recalls. The mandatory recall results are also consistent with the IV model results ($\beta_{Lobbying} = -.668$, $p < .05$). Recall severity (complaints) has a positive effect on the number of mandatory recalls ($\beta_{Complaints} =. 0006$, $p < .05$). Panel 2 of Table 2.6 presents the results from 3SLS model (Equations 4a and 4b), which adds beliefs into the specifications. The main results (voluntary $\beta_{Lobbying} = -3.468$, $p < .05$; mandatory $\beta_{Lobbying} = -1.215$, $p < .05$) are consistent with Panel 1 and the IV model results. All these models control for unobserved heterogeneity with time-invariant fixed effects.

Robustness Assessment

The empirical results highlight that firms' lobbying is significantly associated with the likelihood of their voluntary and mandatory recalls. We examine the robustness of these results with various alternative models.

Nonlinear Specification

As a robustness check, we run an ordered Probit model to take into account the discrete and ordered nature of our outcome variable. Number of recalls is likely to go up as the value of key variables such as complaints and deaths would cross a specific threshold. Thus, we define this outcome variable as an ordered categorical variable representing specific recall decisions for firm *i* in period *t* (i.e., $Recall_{it} = 0$ if there is no recall, $Recall_{it} = 1$ if there is one recall, $Recall_{it} = 2$ if there are two recalls, and so on). Probability of an outcome variable falling in one of the categories is then a linear function of key covariates and error. Based on the frequency distribution of voluntary recalls (panel A of Figure 2.3), we categorize quarterly voluntary recall observations into six groups. Group 1 – 6 correspond to number of recalls varying from 0 to 5 (0, 1, 2, 3, 4, 5 consecutively). These six groups comprise 98.21% values of the outcome variable. Percentage share of remaining observations (with recall frequency greater than 5) is only 1.79%, and thus, we collapse these observations into group 6. Similarly, we create three groups for mandatory recall variable based on its frequency distribution (panel B of Figure 2.3). Mandatory recall observations with values 0 and 1 belong to in group 1 and 2, respectively. Percentage share of remaining observations (with recall frequency equal or greater than 2) is only 2.58%, and therefore, we collapse these observations into group 3. An additional model (linear) for the endogenous variable (lobbying) also accompanies each model. Such a specification is similar to the first-stage of 2SLS, which consists of regressing lobbying variable on instrumental variables and other covariates.

We use a maximum likelihood estimator, named as conditional mixed-process (CMP), to analyze each ordered Probit model. CMP model uses simulated maximum likelihood algorithm (Geweke 1989; Hajivassiliou and McFadden 1998) to jointly estimate two or more equations with linkages among their errors. Joint estimation of two equations using maximum likelihood approach provides potential efficiency gains relative to the more traditional two-stage least squares estimation. CMP, developed by (Roodman 2009), is widely used in marketing (e.g., Kashyap, Antia, and Frazier 2012) and economics studies (e.g., Ferreira et al. 2012). Table 2.7 shows the results, which are consistent with our key findings (voluntary $\beta_{\text{Lobbying}} = -1.323$, $p < .05$; mandatory $\beta_{\text{Lobbying}} = -.1.55$, $p < .05$).[19]

---

[19] We could formulate our decision problem as whether there is one or more voluntary/mandatory recall in a quarter or not. Such a formulation would lead to a binary Probit model specification for voluntary and mandatory recalls

(Please see Table 2.7 and Table 2.8)

Log Specification

In a linear model, we include the natural log transformations of the dependent variable (number of recalls). A log transformation can handle situations in which variables have nonlinear relationships. It transforms skewed data into approximately normal data, so we can run a linear model. Panel 1 in Table 2.8 presents 2SLS results using transformed dependent variable; they are consistent with our previously reported findings (voluntary $\beta_{Lobbying} = -.785$, $p < .05$; mandatory $\beta_{Lobbying} = -.407$, $p < .05$).

Campaign Contributions

We also control for firm's campaign contributions as another potential channel of influence. As discussed earlier, role of firms' campaign contributions is generally limited to the election seasons. In addition, estimated money spent on campaign contributions is significantly smaller than money spent on lobbying. Despite these key differences, we run another robustness check to ensure that our results are not sensitive to the presence of this potential channel.

We collect firms' campaign contributions data from Center for Responsive Politics (CRP) [20] and add this as an additional covariate in the analysis. The CRP website contains the Federal Election Commission data, and has been extensively used in the literature (e.g., Adelino and Dinc 2014; Fremeth, Richter, and Schaufele 2013). This public online database enables us to search individual firms' contribution records. As this contributions value appears at the annual level, we divide this by four to obtain the quarterly value. This variable is significantly correlated with the firm's lobbying expenditures ($\rho = .44, p < .05$). In order to avoid collinearity, we first

(0/1; 0 when there is no quarterly recall otherwise 1). We present results from such a specification in Table WB 2.4 (Appendix), and these results are consistent with others in terms of statistical inference.

[20] See https://www.opensecrets.org/, accessed June 2020.

regress this variable on lobbying amount, firm dummies, and time dummies. We retain the residual of this regression and use it as an additional variable in the 2SLS second-stage equation. Results of this analysis (see panel 2 of Table 2.8) support our key findings (voluntary $\beta_{Lobbying} = -2.025$, $p < .05$; mandatory $\beta_{Lobbying} = -.583$, $p < .05$).

Concluding Remarks

Each year, the automobile industry incurs millions of dollars of costs due to recalls (Jibrell 2018). Studies have explored various recall-related topics, but most of them focus on post-recall elements (e.g., impact on financial performance) rather than the pre-recall phase (Eilert et al. 2017). We study the role of corporate lobbying in this context. Firms use lobbying to build political connections and further their business interests (e.g., Bertrand et al. 2014); we propose that it may have direct, meaningful implications for automotive recalls too. Therefore, our study combines both research streams to uncover an interesting underlying mechanism related to a product recall.

Allegations of lobbying's influence in the recall decision-making to obtain favors from the NHTSA exist, but there is no systematic research on this allegation. Thus, our study investigates whether firms with higher lobbying expenditures have a lower number of recalls. The inspiration for our research began with a congressional report, which highlighted lawmakers' concerns about lobbying influences on recalls (Kirchhoff and Peterman 2010). Product defects have severe societal impacts (e.g., economic loss, loss of lives), so any element that might bias potential actions to correct these defects needs scrutiny. With an empirical investigation, we reveal that automotive firms that engage in lobbying are less likely to initiate a recall voluntarily. They appear to extract benefits from lax regulatory supervision, potentially resulting from their political influence. In particular, approximately $417,014 more in lobbying expenditures is associated with one fewer voluntary recall, on average. A back-of-the-envelope calculation indicates potential benefits to the firm: An average recall in our data involves 247,305 vehicle units. If we assume an average conservative cost of $50 per vehicle (e.g., repair or replacement, loss of revenue), one fewer recall implies approximately $12 million in savings.

Results also suggest that political influence might bias the regulatory agency's recall decisions. Firms with higher lobbying are likely to face fewer mandatory recalls; approximately $1.55 million more in lobbying expenditures is associated with one less mandatory recall. These results validate the concerns raised in the congressional report about lobbying influence on recalls (Kirchhoff and Peterman 2010). Firms' political capital could provide justification for a lower number of agency's corrective actions (mandatory recalls). Lobbying creates political capital (e.g., connections with bureaucrats or politicians), and this capital could result in increased influence on the agency, leading to fewer corrective actions. In a nutshell, this study captures a bias in the recall decision-making processes of firms and the regulatory agency.

This research has implications for policymakers, managers, and academics. From a policy perspective, these findings are relevant for the supervisory framework regarding automotive recalls in the US. The design and implementation of an effective public policy require a deeper understanding of various stakeholders' (e.g., firms, regulatory agencies) behavior and responses. Consistent with the previous studies (e.g., Peltzman 1976; Stigler 1971), our findings suggest that the recall decision process is susceptible to political influence. Importantly, these findings should not be interpreted as evidence for supporting or banning lobbying activities. However, these findings highlight the need for stricter rules and more transparency regarding the lobbying influence in recall decisions. Policymakers should be mindful of the potential dominance of the automotive industry and their lobbyists in recall decisions. Findings also advocate for greater transparency with checks and balances in the recall decision-making process. Given that regulations are intended to protect consumers from harmful product exposure, more may need to be done to ensure that the regulatory enforcement takes place without any bias. This research also highlights a future research opportunity to understand the role of the revolving door phenomenon in regulatory decision-making processes. As discussed earlier, personal incentives of regulatory officials (e.g., seeking corporate careers after leaving the regulatory agency) may drive preferential treatment of regulated firms (Laffont and Tirole 1991). Therefore, due to the possibility of maximizing future career prospects (part of the revolving door), officials may act according to the industry's interests. Our study advocates for greater checks and balances, which could diminish the possibility of any such bias in the decision-making process.

For academia, this research adds to our understanding of links among marketing, politics, and recalls. By highlighting an unexplored channel of influence, we contribute to efforts in understanding why specific recall decisions are taken. As stated earlier, since most studies in the recall literature investigate post-recall elements (e.g., financial performance), our study adds to the handful of studies (e.g., Eilert et al. 2017) that focus on elements associated with the pre-recall phase (i.e., recall decision-making). The study highlights the complexities involved in recall decisions due to a channel beyond typical marketing and financial indicators. Importantly, given that many executives already consider regulatory oversight as one of the powerful factors that impact business (KPMG 2015), this study should encourage other researchers to explore the role of politics in several other marketing contexts. This study also contributes to the research stream within the political science literature that focuses on the returns to lobbying influence.

From the automotive industry perspective, our research furthers understanding of the industry's lobbying effect. We explore an instrument used by the firms to manage their regulatory environment. As stated earlier, findings do not suggest that firms should spend more or less money on lobbying to reduce recalls. However, managers should also be aware of the potential consumer welfare losses ascribed to decision-making distortion. Not initiating a recall could lead to short-term benefits (e.g., avoiding recall costs), but it could create long-term costs in terms of reputational damage and consumer lawsuits for the firm. Most importantly, delaying or refusing to undertake necessary recall actions could lead to more personnel harm (e.g., accidents, injuries, or deaths) for the consumers.

Managers should recognize the effect of lobbying as a barrier to equity in the regulatory environment. A preferential treatment due to lobbying hinders the rightful voice of other stakeholders, such as common citizens who are calling for a recall, in the decision process. Such preferential treatment could also motivate smaller non-lobbying firms to engage in lobbying practices and prompt them to move their limited resources away from activities such as research and innovation. As discussed in the conceptual framework, one of the positives of firms' lobbying channel is to share information with policymakers and regulators regarding its stand. Therefore, our study emphasizes on taking a balanced approach to its lobbying presence while ensuring that such presence does not lead to any bias in the decision-making process, if any.

Indeed, future research may identify and measure the role of other less visible channels in the recall context. Future research may also address some of our study limitations. Notably, we do not observe individual firms' indirect lobbying efforts. Industrial organizations may lobby on firms' behalf but generally do not disclose the source of their funding. Collecting information on indirect lobbying spending remains challenging; we acknowledge that we may have underestimated some firms' actual lobbying intensity. Any method or data set that might provide such information would be useful. We also do not observe make-level lobbying expenditures. Changes in US lobbying data policies in this regard could open the door to many additional research efforts. It is critical for researchers, policymakers, and consumers to understand the regulatory implications and determinants of product recalls. Further research could help establish an even more comprehensive understanding of how political mechanisms interact with firms' marketing and financial objectives during a product-harm crisis.

Currently, the focus of the study is limited to the automotive industry. These results could be extended to the pharmaceutical context as well. The automotive industry and the pharmaceutical industry carry certain similar institutional features regarding lobbying and recall dimensions. For example, pharmaceutical companies also actively engage in lobbying activities. In 2018, the pharmaceutical companies (including Pfizer and Amgen) spent about $27.5 million on lobbying activities amid pressure to lower drug prices[21]. Such lobbying presence could allow pharmaceutical companies to obtain political influence and get special treatment during regulatory processes such as faster product approval by the agency (Mundy 2009)[22]. Such preferential regulatory treatment is similar to what we have discussed in the automobile industry context. Similarly, both industries also carry few similar institutional features regarding recall process. Like the NHTSA process, the FDA has discretion along the supervisory process (e.g., determining the severity, the decision to initiate a recall). Regulatory agencies' deliberations are also confidential by nature. Due to such discretion, firms could potentially exert influence on the regulatory agency to extract undue benefits. Hence, this empirical context could be studied on the pharmaceutical industry in future research.

[21] See https://www.cnn.com/2019/01/23/health/phrma-lobbying-costs-bn/index.html, accessed July 2021.

[22] See https://www.wsj.com/articles/SB123629954783946701, accessed July 2021.

REFERENCES

Adams, Gordon (1981), *The Politics of Defense Contracting*. Council on Economic Priorities.

Adelino, Manuel and I. Serder Dinc (2014), "Corporate Distress and Lobbying: Evidence from the Stimulus Act," *Journal of Financial Economics*, 114 (2), 256–272.

Agrawal, Anup and Charles R. Knoeber (2001), "Do Some Outside Directors Play a Political Role?" *Journal of Law and Economics*, 44 (1), 179–198.

Alexander, Raquel M., Stephen W. Mazza, and Susan Scholz (2009), "Measuring Rates of Return for Lobbying Expenditures: An Empirical Case Study of Tax Breaks for Multinational Corporations," *Journal of Law and Politics*, 25 (4), 401–457.

Ansolabehere, Stephen, John M. De Figueiredo, and James M. Snyder Jr. (2003), "Why Is There so Little Money in US Politics?" *Journal of Economic Perspectives,* 17 (1), 105–130.

Ater, Itai and Nir Yosef (2018), "The Impact of Product Recalls on the Secondary Market: Evidence from Dieselgate," working Paper, Tel Aviv University.

Bala, Ram, Pradeep Bhardwaj, and Pradeep K. Chintagunta (2017), "Pharmaceutical Product Recalls: Category Effects and Competitor Response," *Marketing Science*, 36 (6), 931–943.

Bertrand, Marianne, Matilde Bombardini, and Francesco Trebbi (2014), "Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process," *American Economic Review*, 104 (12), 3885–3920.

Blanes i Vidal, Jordi, Mirko Draca, and Christian Fons-Rosen (2012), "Revolving Door Lobbyists," *American Economic Review*, 102 (7), 3731–48.

Borah, Abhishek and Gerard J. Tellis (2016), "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research*, 53 (2), 143–160.

Borghesi, Richard and Kiyoung Chang (2015), "The Determinants of Effective Corporate Lobbying," *Journal of Economics and Finance*, 39 (3), 606–624.

Borisov, Alexander, Eitan Goldman, and Nandini Gupta (2016), "The Corporate Value of (Corrupt) Lobbying," *Review of Financial Studies*, 29 (4), 1039–1071.

Bray, Robert L., Juan C. Serpa, and Ahmet Colak (2019), "Supply Chain Proximity and Product Quality," *Management Science*, 65 (9), 4079–4099.

Chang, Alisa (2013), “When Lobbyists Literally Write the Bill,” *National Public Radio*, (November 11), (accessed June 17, 2020), [available at https://www.npr.org/sections/itsallpolitics/2013/11/11/243973620/when-lobbyists-literally-write-the-bill].

Cheah, Eng T., Wen L. Chan, and Corinne L.L. Chieng (2007), “The Corporate Social Responsibility of Pharmaceutical Product Recalls: An Empirical Examination of U.S. and U.K. Markets,” *Journal of Business Ethics*, 76 (4), 427–449.

Chen, Hui, David Parsley, and Ya-Wen Yang (2015), “Corporate Lobbying and Firm Performance,” *Journal of Business Finance and Accounting*, 42 (3/4), 444–481.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), “Does a Firm’s Product Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises,” *Journal of Marketing*, 73 (6), 214–226.

Chon, Gina (2016), “Rising Drug Prices Put Big Pharma’s Lobbying to the Test,” *The New York Times*, (September 1), (accessed June 17, 2020), [available at https://www.nytimes.com/2016/09/02/business/dealbook/rising-drug-prices-put-big-pharmas-lobbying-to-the-test.html].

Chu, Ting-Heng, Che-Chun Lin, and Larry J. Prather (2005), “An Extension of Security Price Reactions Around Product Recall Announcements,” *Quarterly Journal of Business and Economics*, 44 (3/4), 33–48.

Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), “Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises,” *Journal of Marketing*, 77 (2), 58–77.

Cleeren, Kathleen, Marnik G. Dekimpe, and Kristiaan Helsen (2008), “Weathering Product-Harm Crises,” *Journal of the Academy of Marketing Science*, 36 (2), 262–270.

Correia, Maria M. (2014), “Political Connections and SEC Enforcement,” *Journal of Accounting and Economics*, 57 (2), 241–262.

Dannemiller, Doug, Lynette DeWitt, and Ankur Gajjaria (2017), “Building regulatory-ready organizations,” *Deloitte*, (accessed June 17, 2020), [available at https://www2.deloitte.com/ content/dam/insights/us/articles/3447_Building-regulatory-ready-organizations/DUP_Building-regulatory-ready-organizations.pdf].

Davenport, Christian (2019), “SpaceX is Suing the Government Once Again, but the Reason is a Secret,” *The Washington Post*, (May 18), (accessed June 17, 2020), [available at https://www.washingtonpost.com/technology/2019/05/18/spacex-is-suing-government-once-again-reason-is-secret/].

Dawar, Niraj and Madan M. Pillutla (2000), “Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Customer Expectations,” *Journal of Marketing Research*, 37 (2), 215–226.

De Figueiredo, John M. and Brian K. Richter (2014), “Advancing the Empirical Research on Lobbying,” *Annual Review of Political Science*,” 17 (May), 163–185.

De Figueiredo, John M. and Brian S. Silverman (2006), “Academic Earmarks and the Returns to Lobbying,” *Journal of Law and Economics*, 49 (2), 597–625.

De Vault, James M. (2002), “Congressional Dominance and the International Trade Commission,” *Public Choice*, 110, 1–22.

Doukas, John A., Chansog Kim, and Christos Pantzalis (2000), “Security Analysis, Agency Costs, and Company Characteristics,” *Financial Analysts Journal*, 56 (6), 54–63.

Dranove, David and Chris Olsen (1994), “The Economic Side Effects of Dangerous Drug Announcements,” *Journal of Law and Economics*, 37 (2), 323–348.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), “Does It Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry,” *Journal of Marketing*, 81 (3), 111–129.

Ernst & Young (2011), “Turn Risks and Opportunities into Results,” (accessed June 17, 2020), [available at https://www.ey.com/Publication/vwLUAssets/The_top_10_risks_and_opportunities_for_global_organizations/$FILE/Business%20Challenge%20main%20report-%20SCORED.pdf].

Farnam, T.W. (2011), “Study Shows Revolving Door of Employment between Congress, Lobbying Firms,” *The Washington Post*, (September 13), (accessed June 17, 2020), [available at https://www.washingtonpost.com/study-shows-revolving-door-of-employment-between-congress-lobbying-firms/2011/09/12/gIQAxPYROK_story.html].

Ferreira, Fernando, Joseph Gyourko, and Joseph Tracy (2012), “Housing Busts and Household Mobility: An update,” *Economic Policy Review,* 18 (3), 1–15.

Fidrmuc, Jana P., Peter Roosenboom, and Eden Q. Zhang (2018), "Antitrust Merger Review Costs and Acquirer Lobbying," *Journal of Corporate Finance*, 51 (August), 72–97.

Freedman, Seth, Melissa Kearney, and Mara Lederman (2012), "Product Recalls, Imperfect Information, and Spillover Effects: Lessons from the Consumer Response to the 2007 Toy Recalls," *Review of Economics and Statistics*, 94 (2), 499–516.

Freeman, J.L. (1965), *The Political Process*, New York, NY: Random House.

Fremeth, Adam, Brian K. Richter, and Brandon Schaufele (2013), "Campaign Contributions over CEOs' Careers," *American Economic Journal: Applied Economics*, 5 (3), 170–88.

Gao, Meng and Jiekun Huang (2016), "Capitalizing on Capitol Hill: Informed Trading by Hedge Fund Managers," *Journal of Financial Economics*, 121 (3), 521–545.

Geweke, John (1989), "Bayesian Inference in Econometric Models Using Monte Carlo Integration," *Econometrica*, 57 (6), 1317–1339.Hajivassiliou, Vassilis A. and Daniel L. McFadden (1998), "The Method of Simulated Scores for the Estimation of LDV Models," *Econometrica*, 66 (4), 863–896.

Han, Kyuhong, Jihye Jung, Vikas Mittal, Jinhing Zyung, and Hajo Adam (2019), "Political Identity and Financial Risk Taking: Insights from Social Dominance Orientation," *Journal of Marketing Research*, 56 (4), 581–601.

Hartman, Raymond S. (1987), "Product Quality and Market Efficiency: The Effect of Product Recalls on Resale Prices and Firm Valuation," *Review of Economics and Statistics*, 69 (2), 367–372.

Haunschild, Pamela R. and Mooweon Rhee (2004), "The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls," *Management Science*, 50 (11), 1545–1560.

Hill, Matthew, G. Wayne Kelly, G. Brandon Lockhart, and Robert A. Van Ness (2013), "Determinants and Effects of Corporate Lobbying," *Financial Management*, 42 (4), 931–957.

Hoffer, George E., Stephen W. Pruitt, and Robert J. Reilly (1988), "The Impact of Product Recalls on the Wealth of Sellers: A Reexamination," *Journal of Political Economy*, 96 (3), 663–670.

Igan, Deniz, Prachi Mishra, and Thierry Tressel (2012), "A Fistful of Dollars: Lobbying and the Financial Crisis," *NBER Macroeconomics Annual*, 26 (1), 195–230.

Jarrell, Gregg and Sam Peltzman (1985), "The Impact of Product Recalls on the Wealth of Sellers," *Journal of Political Economy*, 93 (3), 512–536.

Jensen, Michael C. (1986), "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *The American Economic Review*, 76 (2), 323–329.

Jensen, Michael C. and William H. Meckling (1976), "Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure," *Journal of Financial Economics*, 3 (4), 305–360.

Jibrell, Anisa (2018), "Auto Recall Bill Grew 26% to $22 Billion in 2016, Study Says," *Automotive News*, (January 30), (accessed June 17, 2020), [available at https://www.autonews.com/article/ 20180130/RETAIL05/180139974/auto-recall-bill-grew-26-to-22-billion-in-2016-study-says].

Johnson, Garrett A., Randall A. Lewis, and David H. Reiley (2017), "When Less Is More: Data and Power in Advertising Experiments," *Marketing Science*, 36 (1), 43–53.

Jung, Jihye and Vikas Mittal (2020), "Political Identity and the Consumer Journey: A Research Review," *Journal of Retailing*, 96 (1), 55–73.

Kashyap, Vishal, Kersi D. Antia, and Gary L. Frazier (2012), "Contracts, Extracontractual Incentives, and *Ex Post* Behavior in Franchise Channel Relationships," *Journal of Marketing Research*, 49 (2), 260–276.

Kerr, William R., William F. Lincoln, and Prachi Mishra (2014), "The Dynamics of Firm Lobbying," *American Economic Journal: Economic Policy*, 6 (4), 343–379.

Kini, Omesh, Jaideep Shenoy, and Venkat Subramaniam (2017), "Impact of Financial Leverage on the Incidence and Severity of Product Failures: Evidence from Product Recalls," *Review of Financial Studies*, 30 (5), 1790–1829.

Kirchhoff, Suzanne M. and David R. Peterman (2010), "Unintended Acceleration in Passenger Vehicles," *Congressional Research Service*, (April 26), (accessed July 16, 2021), [available at https://fas.org/sgp/crs/misc/R41205.pdf].

KPMG (2015), "Setting the Course for Growth: CEO Perspectives," (accessed July 16, 2021), [available at https://images.forbes.com/forbesinsights/StudyPDFs/KPMG_CEO_Survey_STUDY.pdf]

Krumholz, Sheila and Dave Levinthal (2010), "Toyota Mess Rife with Potential Conflicts," CNN, (March 2), (accessed June 17, 2020), [available at https://www.cnn.com/2010/OPINION/02/26/toyota.conflicts.congress/index.html].

Lehn, Kenneth and Annette Poulsen (1989), "Free Cash Flow and Stockholder Gains in Going Private Transactions," *Journal of Finance*, 44 (3), 771–787.

Liu, Angela X., Yong Liu, and Ting Luo (2016), "What Drives a Firm's Choice of Product Recall Remedy? The Impact of Remedy Cost, Product Hazard, and the CEO," *Journal of Marketing*, 80 (3), 79–95.

Liu, Yan and Venkatesh Shankar (2015), "The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry," *Management Science*, 61 (10), 2514–2535.

Marsh, Thomas L., Ted C. Schroeder, and James Mintert (2004), "Impacts of Meat Product Recalls on Consumer Demand in the USA," *Applied Economics*, 36 (9), 897–909.

Martin, Kelly D., Brett W. Josephson, Gautham G. Vadakkepatt, and Jean L. Johnson (2018), "Political Management, Research and Development, and Advertising Capital in the Pharmaceutical Industry: A Good Prognosis?" *Journal of Marketing*, 82 (3), 87–107.

Milyo, Jeffrey, David Primo, and Timothy Groseclose (2000), "Corporate PAC Campaign Contributions in Perspective," *Business and Politics*, 2 (1), 75–88.

Mullins, Brody and Kara Scannell (2006), "Hedge Funds Hire Lobbyists To Gather Tips in Washington," *The Wall Street Journal*, (December 8), (accessed June 17, 2020), [available at https://www.wsj.com/articles/SB116554698892944296].

Muoio, Danielle (2019), "Tesla Renews Lobbying Efforts to Open More Retail Stores in New Jersey," *POLITICO*, (January 17), (accessed June 17, 2020), [available at https://www.politico.com/states/california/story/2019/01/17/tesla-renews-lobbying-efforts-to-open-more-retail-stores-in-new-jersey-781511].

Muth, John F. (1961), "Rational Expectations and the Theory of Price Movements," *Econometrica*, 29 (3), 315–335.

Ni, John Z., Barbara B. Flynn, and F. Robert Jacobs (2014), "Impact of Product Recall Announcements on Retailers' Financial Value," *International Journal of Production Economics*, 153 (July), 309–322.

Pattabhiramaiah, Adithya, S. Sriram, and Shrihari Sridhar (2018), "Rising Prices Under Declining Preferences: The Case of the U.S. Print Newspaper Industry," *Marketing Science*, 37 (1), 97–122.

Powell, Lynda W. (2012), *The Influence of Campaign Contributions in State Legislatures*. Ann Arbor: University of Michigan Press.

Rayfield, Blake and Omer Unsal (2019), "Product Recalls, Lobbying, and Firm Value", *Management Decision*, 57 (3), 724–740.

Richter, Brian K., Krislert Samphantharak, and Jeffrey F. Timmons (2009), "Lobbying and Taxes," *American Journal of Political Science*, 53 (4), 893–909.

Ridge, Jason W., Amy Ingram, and Aaron D. Hill (2017), "Beyond Lobbying Expenditures: How Lobbying Breadth and Political Connectedness Affect Firm Outcomes," *Academy of Management Journal*, 60 (3), 1138–1163.

Roodman, David (2009), "Estimating Fully Observed Recursive Mixed-Process Models with CMP," Center for Global Development Working Paper 168, (accessed June 17, 2020), [available at https://www.cgdev.org/publication/estimating-fully-observed-recursive-mixed-process-models-cmp-working-paper-168].

Ross, Alasdair (2005), "Regulatory risk Trends and strategies for the CRO," *Economist Intelligence Unit*, (accessed June 17,2020), [available at http://graphics.eiu.com/files/ad_pdfs/ eiu_CRO_RISK_WP.pdf].

Salin, Victoria and Neal H. Hooker (2001), "Stock Market Reaction to Food Recalls," *Review of Agricultural Economics*, 23 (1), 33–46.

Shapiro, Bradley T. (2018), "Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants," *Journal of Political Economy*, 126 (1), 381–437.

Souiden, Nizar and Frank Pons (2009), "Product Recall Crisis Management: The Impact on Manufacturer's Image, Consumer Loyalty and Purchase Intention," *Journal of Product & Brand Management*, 18 (2), 106–114.

Steven, Adams B., Yan Dong, and Thomas Corsi (2014), "Global Sourcing and Quality Recalls: An Empirical Study of Outsourcing-Supplier Concentration-Product Recalls Linkages," *Journal of Operations Management*, 32 (5), 241–253.

Strittmatter, Anthony and Michael Lechner (2020), "Sorting in the Used-Car Market After the Volkswagen Emission Scandal," *Journal of Environmental Economics and Management*, 101, 102305.

Tau, Byron (2014), "GM Lobbying Pushback Takes Shape," *POLITICO*, (June 4), (accessed March 8, 2020), [available at https://www.politico.com/tipsheets/politico-influence/2014/06/gm-lobbying-pushback-takes-shape-mayer-brown-signs-russian-metal-lobby-barnes-thornburg-hires-spooner-commercial-fisheries-form-association-212543].

Thirumalai, Sriram and Kingshuk K. Sinha (2011), "Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences," *Management Science*, 57 (2), 376–392.

Thomsen, Michael R. and Andrew M. McKenzie (2001), "Market Incentives for Safe Foods: An Examination of Shareholder Losses from Meat and Poultry Recalls," *American Journal of Agricultural Economics*, 83 (3), 526–538.

Tracy, Ryan (2019), "Tech Firms Ramp Up Lobbying as Antitrust Scrutiny Grows," *The Wall Street Journal*, (October 28), (accessed June 17, 2020), [available at https://www.wsj.com/articles/tech-firms-ramp-up-lobbying-as-antitrust-scrutiny-grows-11572255000].

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230–245.

Weingast, Barry R. (1984), "The Congressional-Bureaucratic System: A Principal Agent Perspective (with Applications to the SEC)," *Public Choice*, 44 (1), 147–191.

Weingast, Barry R. and Mark J. Moran (1983), "Bureaucratic Discretion or Congressional Control? Regulatory Policymaking by the Federal Trade Commission," *Journal of Political Economy*, 91 (5), 765–800.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Sections and Panel Data*. Cambridge, MA: MIT Press.

Wooldridge, Jeffrey M. (2010), *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wooldridge, Jeffrey M. (2012), Introductory Econometrics: A Modern Approach, 5th ed. Mason, Ohio: South-Western Cengage Learning.

Yu, Frank and Xiaoyun Yu (2011), "Corporate Lobbying and Fraud Detection," The Journal of Financial and Quantitative Analysis, 46 (6), 1865–1891.

Zellner, Arnold and H. Theil (1962), "Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations," *Econometrica*, 30 (1), 54–78.

Zhao, Yi, Ying Zhao, and Kristiaan Helsen (2011), "Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics after a Product-Harm Crisis," *Journal of Marketing Research*, 48 (2), 255–267.

Table 2.1: Examples of Lobbying Influences across Industries

Industry	Context	Source
Pharmaceutical	To avoid legislative proposals to curb rising prescription prices, drug makers spent up to $2.3 billion lobbying over a decade. During the debate, big pharmaceutical companies spent $27.5 million in 2018.	Chon (2016)
Chemical	In mergers, lobbying before deal announcements is associated with favorable review outcomes. In 2016, Bayer AG announced a deal to buy Monsanto for a mere $66 billion. Bayer then started lobbying on various issues related to this proposed corporate acquisition.	Fidrmuc et al. (2018)
Space	With their lobbying power, Lockheed Martin and Boeing (in the joint venture ULA) maintain a monopoly over military launch contracts. In 2014, SpaceX sued the Air Force, in order to compete against ULA for contracts.	Davenport (2019)
Automotive	Tesla invested in lobbying to open new retail stores in New Jersey. Finally, a 2015 law allowed Tesla to operate four direct-sale stores.	Muoio (2019)

Table 2.2: Overview of Recall Literature

Research Stream	Study	Key Variable	Key Points
Firm performance (depicts different tangible and intangible outcomes)	Jarrell and Peltzman (1985)	Firm value	Product recalls affect shareholders' wealth negatively. Such costs are higher than the costs of the recall itself.
	Dawar and Pillutla (2000)	Brand equity	Consumers interpret firms' responses to recalls using their prior expectations. Existing consumers and potential future consumers expect different assurances from the recalling firm.
	Freedman et al. (2012)	Sales	For firms with recalls, unit sales of the types of toys involved in the recall fall relative to sales of toys in other categories. No evidence of within-manufacturer spillover to dissimilar toys.
	Haunschild and Rhee (2004)	Learning	Learning takes place within firms due to recalls. Greater learning takes place for firms that recall voluntarily rather than mandatorily.
	Cheah, Chan, and Chieng (2007)	Corporate social responsibility	The impact of CSR practices on a firm's financial value indicate that U.S. investors punished non-CSR firms during a recall, but U.K. investors rewarded such non-CSR firms.
	Van Heerde, Helsen, and Dekimpe (2007)	Revenue	Severe product recalls can cause a significant loss in brand revenues in the periods after the crisis.
	Strittmatter and Lechner (2020)	Brand share; Price	Supply of used Volkswagen diesel vehicles increased after the emission scandal. The positive supply-side effects increase with the probability of manipulation.
Marketing instrument (highlights role of marketing-mix variables)	Cleeren, van Heerde, and Dekimpe (2013)	Advertising; Brand share	Post-recall advertisements and price changes affect the product's brand share and category purchase, moderated by the extent of negative publicity surrounding the recall and the brand's public acknowledgement of it.
	Liu and Shankar (2015)	Advertisement; Brand	When recalls are associated with greater media attention and severe consequences, consumers' responses are more negative. Parent brand advertising and sub-brand advertising effectiveness declines due to recalls; the decline is greater for the latter.
Firm decision (includes different types of firm-level decisions)	Chen, Ganesan, and Liu (2009)	Recall strategy	A comparison of the impact of proactive and passive recall strategies shows that the proactive strategy has a stronger negative effect on firm value.
	Liu, Liu, and Luo (2016)	Recall remedy	Companies are more likely to provide full remedy for more severe product hazards. The CEO's personal interests interfere with remedy decisions; full remedy is less likely when the CEO receives greater cash compensation.
	Eilert et al. (2017)	Recall timing	Authors find that markets punish recall delays. Severity increases time to recall, but the relationship is weaker when the brand has a strong reputation for reliability and has experienced severe recalls in past.
	This study	Political influence	Corporate lobbying influences the recall behavior of the firm and the regulator such that as lobbing expenditures increase firms initiate fewer voluntary recalls and the regulator asks for fewer mandatory recalls.

Table 2.3: Definition of Variables

Variable	Operationalization (measured quarterly at the firm level)	Data Sources
Voluntary recalls	Number of recalls initiated by the firm	NHTSA
Mandatory recalls	Number of recalls initiated by the regulator	NHTSA
Lobbying amount	Spending by firms in lobbying activities	USA Senate
Complaints	Number of complaints associated with firm's vehicles	NHTSA
Deaths	Number of deaths associated with firm's vehicles	NHTSA
States	Number of states where consumer complaints were registered	NHTSA
Contributions	Contributions made by individuals in a given county	FEC
Sales	Accumulative sales of the firm's vehicles	Automotive News
Liabilities_std	Liabilities / Sales	Compustat
Capex_std	CAPEX / Sales	Compustat
Agency costs	(Free Cash Flow/Total Assets) × Growth indicator, where Growth indicator = 1 when Tobin's q < 1	Compustat
Rating	Quality rating of the vehicles	Consumer Reports

Table 2.4: Descriptive Statistics

	Panel A - Descriptive Statistics						Panel B - Correlation Table										
	Variables	Min	Max	Median	Mean	Stdev	1	2	3	4	5	6	7	8	9	10	11
1	Lobbying amount	0	7.86	.25	.67	.91	1										
2	Voluntary recalls	0	15	1	1.1	1.59	**0.29**	1									
3	Mandatory recalls	0	5	0	0.16	.49	**0.21**	**0.24**	1								
4	Complaints	0	4078	176	437.42	585.43	**0.78**	**0.49**	**0.29**	1							
5	Deaths	0	19	0	.47	1.77	**0.34**	**0.39**	**0.22**	**0.56**	1						
6	Rating	1.7	5	2.65	2.90	.9	**-0.23**	**-0.22**	**-0.13**	**-0.23**	-0.06	1					
7	Sales	0	.83	.08	.15	.17	**0.76**	**0.2**	**0.25**	**0.72**	**0.24**	**-0.25**	1				
8	States	6	57	43.5	38.81	14.4	**0.57**	**0.34**	**0.22**	**0.62**	**0.21**	**-0.6**	**0.68**	1			
9	Liabilities_std	0	110.97	1	3.15	13.57	-0.11	-0.1	-0.05	-0.11	-0.04	**0.34**	**-0.14**	**-0.27**	1		
10	Capex_std	0	2143.8	.06	27.05	208.16	-0.09	-0.05	-0.04	-0.1	-0.01	**0.29**	-0.11	**-0.21**	**0.32**	1	
11	Agency costs	-1.51	.14	.05	.03	.15	0.09	0.1	0.05	0.11	0.02	**-0.34**	**0.14**	**0.37**	**-0.11**	-0.04	1

Notes: Liabilities_std and Capex_std refer to the ratios of the firm's liabilities and CAPEX to its sales. Lobbying amount is in millions of USDs. Sales is in millions of USDs. In correlation table, *p-value <.01* is in bold.

Table 2.5: Two Stage Least Squares Regression Results

IV 2SLS Model	Panel 1 - Voluntary Recall				Panel 2 - Mandatory Recall			
	First-stage		Second-stage		First-stage		Second-stage	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Intercept	.243	(.625)	2.574*	(1.293)	.268	(.619)	.245	(.555)
Contribution_hq	-.001	(.003)			-.001	(.003)		
Contribution_plant	-.017**	(.005)			-.017**	(.005)		
Lobbying			-2.398**	(.780)			-.644*	(.292)
Complaints	.00001	(.0001)	.002	(.001)	$3.9\text{x}10^{-6}$	(.0001)	.0005**	(.0002)
Deaths	-.007	(.015)	.072**	(.025)	-.007	(.015)	.006	(.009)
States	.003	(.013)	.018	(.031)	.662*	(.322)	.009	(.010)
Rating	-.107	(.142)	-0.895	(.600)	.003	(.013)	-.157	(.208)
Liabilities_std	.0004	(.002)	.001	(.002)				
Capex_std	-.00003	(.0001)	-.0002	(.0001)				
Agency costs	.076	(.160)	-.113	(.255)				
Sales	.669*	(.326)	-.376	(3.757)				
Firm	Yes		Yes		Yes		Yes	
Year	Yes		Yes		Yes		Yes	
Quarter	Yes		Yes		Yes		Yes	
Observations	504		504		504		504	
R^2	.79		.43		.79		.16	
F-statistic	51.95*** (df = 34; 469)		-		57.29*** (df = 31; 472)		-	

Notes: Lobbying amount is the dependent variable in the first-stage equation. Lobbying amount is in millions of USD. Contribution_hq and Contribution_plant are instrumental variables and represent aggregated individual contributions at the firm's headquarters and plant locations, respectively. We cluster second-stage errors at the firm level, and all standard errors appear in parenthesis.
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.6: Simultaneous Equation System Results

	Panel 1 - Correlating Errors				Panel 2 - Incorporating Beliefs			
	Voluntary Recall		Mandatory Recall		Voluntary Recall		Mandatory Recall	
Constant	2.212	(1.191)	-.050	(.457)	2.20	(1.351)	.598	(.884)
Lobbying	-2.637***	(.716)	-.668*	(.267)	-3.468*	(1.455)	-1.215*	(.559)
Complaints	.002*	(.001)	.0006***	(.0001)	.002*	(.001)	.0009**	(.0003)
Deaths	.066	(.037)	.0084	(.009)	.096*	(.047)	.032	(.025)
States	.023	(.026)	.014	(.008)	.0361	(.039)	.0181	(.011)
Rating	-.827	(.553)	-.121	(.196)	-.872	(.717)	-.299	(.337)
Liabilities_std	.002	(.002)			.002	(.002)		
Capex_std	-.0003*	(.0001)			-.0002	(.0001)		
Agency costs	-.014	(.251)			-.015	(.162)		
Sales	.591	(3.34)			.989	(4.033)		
Mand_unique					-2.043	(1.664)		
Vol_unique							-.348	(.193)
Firm	Yes		Yes		Yes		Yes	
Year	Yes		Yes		Yes		Yes	
Quarter	Yes		Yes		Yes		Yes	
Observations	504		504		504		504	

Notes: Lobbying amount is in millions of USD. Mand_unique and Vol_unique represent the number of unique mandatory and voluntary recalls, respectively. Heteroskedastic and autocorrelation consistent standard errors are in parenthesis.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.7: Non-linear Estimates

Recall equation	Voluntary recall		Mandatory recall	
Lobbying	-1.323***	(.250)	-1.55***	(.315)
Complaints	.001	(.0004)	.001	(.0004)
Deaths	-.030	(.028)	-.051	(.035)
States	.038	(.030)	.031	(.030)
Rating	-.766*	(.361)	-.014	(.471)
Sales	.008	(1.894)		
Liabilities_std	-.016***	(.002)		
Capex_std	.0001	(.0001)		
Agency_costs	-.267	(.456)		
Fixed effects	Yes		Yes	
Endogenous variable equation				
Contribution_hq	-.0002	(.003)	-.0008	(.002)
Contribution_plant	-.017***	(.003)	-.017***	(.003)
Complaints	8.1×10^{-6}	(.0003)	-.00001	(.0003)
Deaths	-.007	(.018)	-.010	(.023)
States	.003	(.005)	.005	(.008)
Rating	-.107	(.211)	-.191	(.148)
Sales	.667	(.995)		
Liabilities_std	.0004	(.0004)		
Capex_std	-.00003	(.00003)		
Agency_costs	.076	(.089)		
Fixed effects	Yes		Yes	

Notes: Lobbying amount is in millions of USDs. Number of voluntary and mandatory recalls are dependent variables. Fixed effects include firm, year, and quarter level effects. Errors are clustered at the firm level and shown in parenthesis.
**p* < .05, ***p* < .01, ****p* < .001.

Table 2.8: Robustness Assessment

	Panel 1 - Log transformation				Panel 2 – Campaign contribution			
	Voluntary Recall		Mandatory Recall		Voluntary Recall		Mandatory Recall	
Intercept	1.014	(.563)	.129	(.321)	2.489*	(1.244)	.223	(.530)
Lobbying	-.785***	(.145)	-.407**	(.132)	-2.025***	(.298)	-.583**	(.183)
Complaints	.0004	(.0003)	.0002*	(.0001)	.002	(.001)	.0005**	(.0001)
Deaths	-.011	(.017)	-.009	(.006)	.075***	(.015)	.006	(.010)
States	.014	(.013)	.006	(.007)	.016	(.030)	.009	(.010)
Rating	-.381*	(.182)	-.087	(.123)	-.848	(.602)	-.146	(.194)
Liabilities_std	-.001	(.001)			.001	(.002)		
Capex_std	-.0001	(.000)			-.0002	(.0001)		
Agency costs	-.08	(.099)			-.162	(.194)		
Sales	-.113	(1.101)			-.547	(3.187)		
Campaign					.001	(.001)	.0001	(.0002)
Firm	Yes		Yes		Yes		Yes	
Year	Yes		Yes		Yes		Yes	
Quarter	Yes		Yes		Yes		Yes	
Observations	504		504		504		504	

Notes: Results are from the second stage of 2SLS regressions. Lobbying amount is in millions of USD. In panel 1, dependent variable is Log (number of recalls + 1). Panel 2 includes firm's campaign contributions as an additional covariate. We cluster errors at the firm level, and these errors appear in parenthesis.
$*p < .05$, $**p < .01$, $***p < .001$.

Figure 2.1: Recall Process

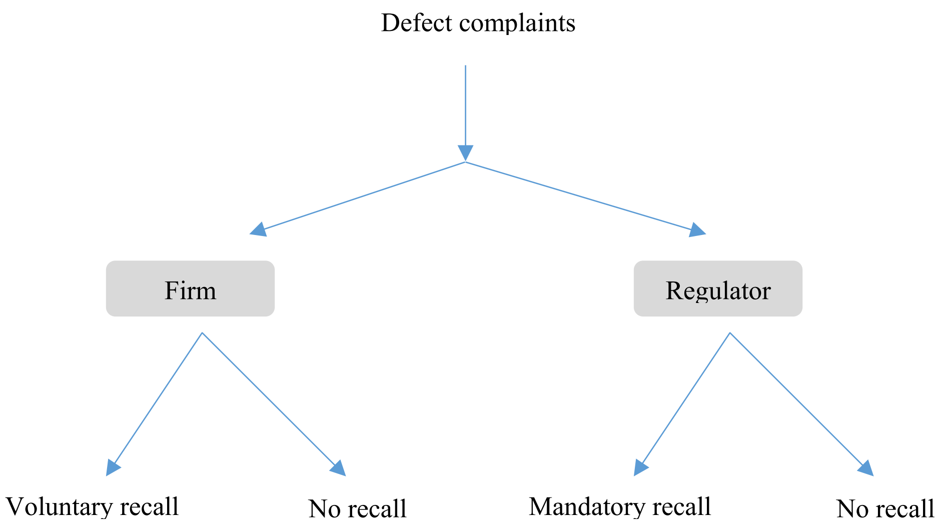


Figure 2.2: Congressional Committee of Jurisdiction

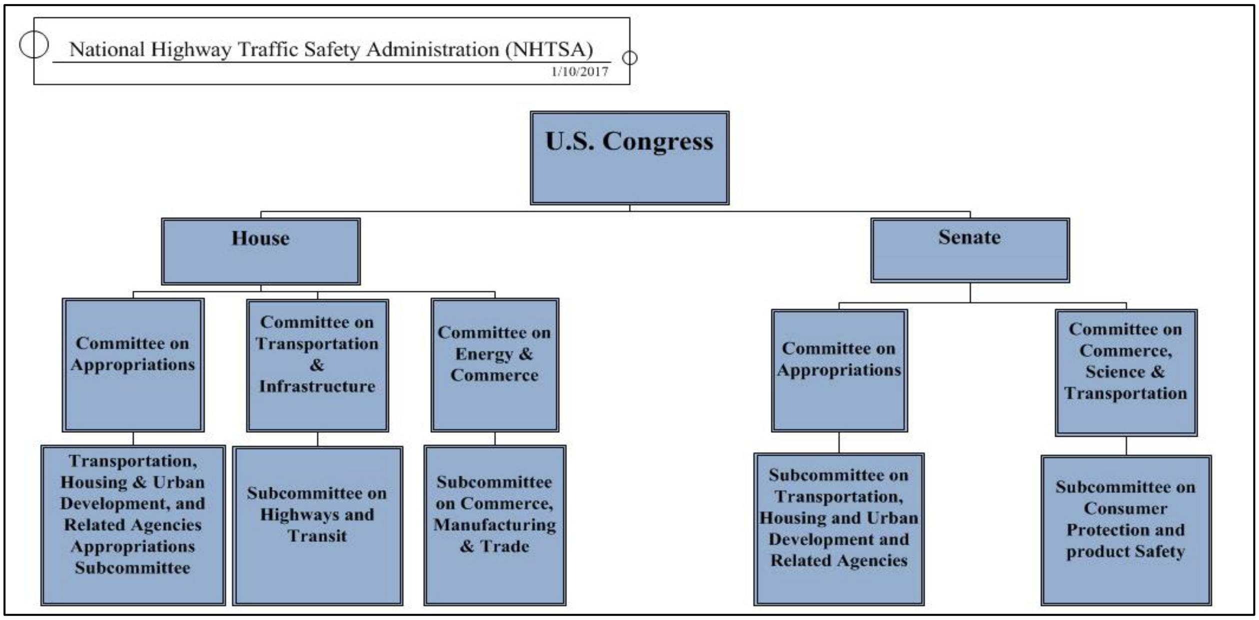
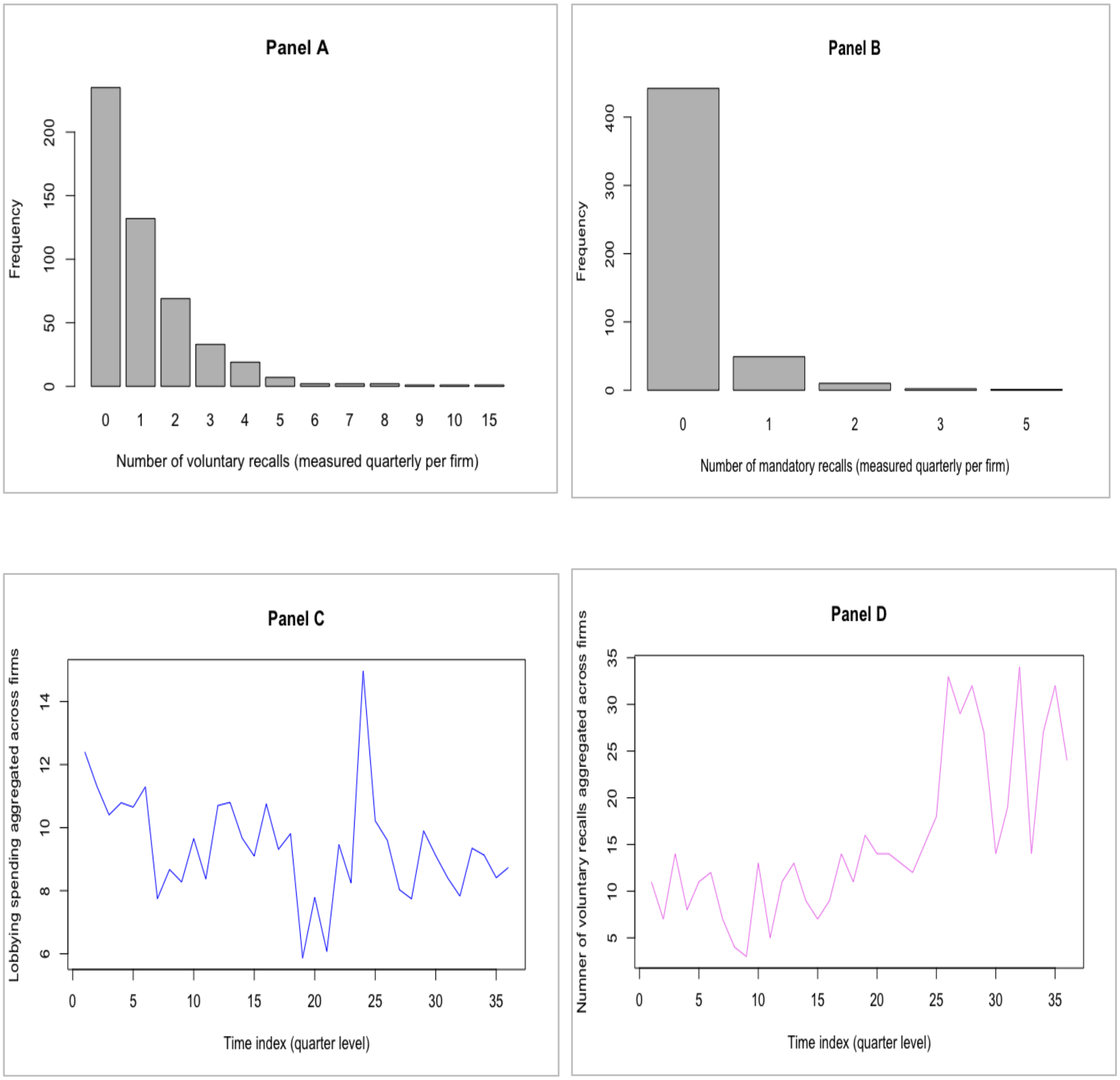


Figure 2.3: Distributions of Key Variables



Notes: Panel A shows the frequency distribution of voluntary recalls (quarterly observation per firm) in the data. Panel B represents the frequency distribution of mandatory recalls (quarterly observation per firm) in the data. Panel C shows variation in the quarterly lobbying expenditures (million USD) variable (aggregated across firms) for our nine-year study period. Panel D indicates variation in the total number of voluntary recalls (aggregated across firms) at the quarter level for the nine-year study period.

CHAPTER 3: PRODUCT RECALL AND STRATEGIC INTERACTIONS BETWEEN FIRM AND REGULATOR: A DISCRETE GAME MODEL

Introduction

Product recalls are inevitable events across many industries, such as automobiles, medical equipment, and consumer products. Examples of some of the biggest recalls include Johnson & Johnson's Tylenol recall, Volkswagen Emissions recall, and Pfizer's Bextra recall. The number of product recalls has been increasing over the past two decades and is likely to rise in the future (Borah and Tellis 2016). Notably, recalls are so pervasive in the automobile industry that all major firms encounter recalls frequently. In 2016, vehicle recalls affected 50.5 million vehicles and cost firms almost $22.1 billion (Jibrell 2018). Due to their economic significance, product recall events are of considerable interest to academics, practitioners, and policymakers (Cleeren, Dekimpe, and Heerde 2017). Extant empirical research, however, has primarily focused on the impact of recalls on the firm's financial and non-financial performance (e.g., Jarrell and Peltzman 1985; Thirumalai and Sinha 2011); it is mostly silent on the automaker's strategic decision-making to initiate a recall. For example, underlying mechanisms (e.g., complaints negativity) determine the tradeoff associated with every recall decision (recall/no recall) a firm may take after receiving consumer complaints. However, systematic empirical research of these mechanisms has received scant attention in the recall literature. In particular, the tradeoff would decide whether firms should opt for a voluntary recall (which firm initiates) or a mandatory recall (which the regulator initiates). This decision is not straightforward because every decision may lead to both positive and negative outcomes.

On the one hand, a voluntary recall would indicate a proactive action by the firm. It would enable consumers to take necessary steps to prevent further potential harmful exposure to defective products. Literature finds that voluntary recalls allow stakeholders to retain a positive impression of the firm (Souiden and Pons 2009). Failing to act quickly could also lead to a higher number of injuries/deaths in the future. On the other hand, substantial recall costs (e.g., defect repair and replacement, loss of revenue) may prompt firms to avoid a voluntary recall. A hasty recall might lend credibility to an unsubstantiated defect claim. Alternatively, if the firm decides to take no action, the regulatory agency National Highway Traffic Safety Administration (NHTSA) may step in and recommend a recall if required. The regulator, which is also authorized to initiate a recall (defined as a mandatory recall) if the firm does not take any action, brings additional complexity to the tradeoff in a firm's decision-making process. On the one hand, the absence of any voluntary recall action could lead to a defect investigation and a mandatory recall by the regulator if the regulator's analysis also finds a defect. A mandatory recall may lead to potentially more significant economic and reputation damage, such as penalties and potential lawsuits for firms (relative to the voluntary recall). On the other hand, NHTSA's investigation may find products to be safe and thus require no recall actions. Such possible outcomes would prompt firms to incorporate a belief of the regulator's expected action in its decision. Figure 3.1 depicts this decision-making process. In other terms, the firm's equilibrium choice would be conditional on its belief of NHTSA's expected decision. Such dependence would create a strategic interaction between the regulator and the firm's recall decision-making.

NHTSA's decision-making process also involves complications. The regulatory agency would like to keep consumers safe and recommend a mandatory recall if required. However, before any recall recommendation, NHTSA needs to complete a thorough defect analysis, which is costly and requires resources. Resource constraints affect public agencies' functional capabilities (Kedia and Rajgopal 2011). Limited resources and budget constraints may also influence NHTSA's actions. An audit by the Office of Inspector General (2015) reveals that the agency ignores 90% of consumer complaints to prioritize specific incident types. During a 2015 interview, Mark Rosekind (former NHTSA Administrator) admitted that the agency only had seven to nine people to look through 77,000 safety complaints (Consumer Reports 2015). Thus, resource constraints may prevent NHTSA from investigating vehicle defects and drive the regulator to rely on a firm's voluntary actions. Therefore, the regulator's decision-making would be a function of the firm's expected decision. Such strategic interaction between a firm and its supervising agency is of substantial importance and needs comprehensive scrutiny.

Considering these arguments, one could infer that decision to initiate a recall is not a straightforward process. Consumers' defect complaints may prompt entities (firm and the regulator) to go through this decision-making process and choose the best possible option (i.e., maximizing their corresponding utility). Lack of insights on this decision-making process raises relevant policy-oriented questions: Therefore, we research the following questions: Does the presence of a regulatory agency affect a firm's recall decisions? Does the firm's expected voluntary action affect the regulatory agency's possible decision? Which other key determinants (e.g., defect and product-level characteristics) could also affect these recall decisions? We develop a discrete game model that we calibrate with automotive recalls and consumer complaints data set over 14 years (2003–2016) to investigate these questions. We also account for the potential correlation in recall decisions by allowing for common information in the model created through information exchange. Players (automakers and the regulator) may communicate with each other and provide relevant information (e.g., complaints analysis, vehicle test results). We estimate each entity's choice of recall strategy as a discrete game of incomplete information, thus capturing the strategic interaction and its impact on recall decisions.

Related Literature

Product Recalls

Marketing studies of product recalls span several areas. Some studies focus on tangible performance aspects, revealing that recalls negatively affect a firm's value and performance indicators, such as sales and profits (e.g., Chu, Lin, and Prather 2005; Salin and Hooker 2001). Another set of studies explores strategic aspects, such as the effectiveness of advertising and other marketing mix variables following a recall (e.g., Van Heerde, Helsen, and Dekimpe 2007; Zhao, Zhao, and Helsen 2011). For example, in comparing proactive and passive recall response strategies, Chen, Ganesan, and Liu (2009) determine that the stock market responds negatively if a firm initiates a recall before receiving any reports of injuries. Studies also investigate intangible outcomes (e.g., loyalty, image, reputation) of a product recall. Cleeren, Dekimpe, and Helsen (2008) argue that brand advertising can counter the adverse effects of a recall and enhance consumers' first post-recall purchase decisions. According to Souiden and Pons (2009), if manufacturers contest recalls, it negatively affects their image and consumer loyalty. Product recalls help firms learn, though, and a greater recall magnitude can diminish the number of future recalls or and injuries (Haunschild and Rhee 2004).

Secondary markets could also face adverse outcomes due to product recalls. Hartman (1987) finds that General Motors' safety recalls diminished the resale value of its recalled products but did not affect the value of other GM products. Ater and Yosef (2018) and Strittmatter and Lechner (2020) study the supply-side implications of recalls in secondary markets, using the Volkswagen emission scandal. Some studies (e.g., Bala et al. 2017; Cleeren et al. 2013; Marsh et al. 2004) find spillover effects on products produced by the same manufacturer, competitors in the category, and the industry. Similarly, Borah and Tellis (2016) observe that negative online chatter about a recalled car model increases negative chatter for others with the same brand.

We contribute to this literature on the following fronts. Extant recall literature has primarily focused on the post-recall elements (e.g., consequences of recall on financial performance and marketing mix elements). In contrast, our research focuses on the pre-recall phase (decision to initiate a recall). Firm's strategic decision-making before starting a recall is crucially important, and only a few studies have looked into it (Colak and Bray 2016; Eilert et al. 2017). Eilert et al. (2017), with a reduced model approach, focus on the timing of product recalls and its effect on stock markets. Authors find that problem severity increases time to recall, and brand characteristics moderate this relationship. A working paper by Colak and Bray (2016), who study why do automotive firms initiate recalls, displays resemblance to our study. We note that few dimensions differentiate our study. The first dimension is a key institutional feature. We distinguish between original equipment manufacturer (OEM) and non-OEM parts recall. This differentiation is extremely important because it highlights the recall's key decision-maker, who is the primary player in the study. Each third-party–supplied part (i.e., non-OEM group) could be present in several cars makes, so a defect in a non-OEM part is likely to trigger recalls for multiple firms. One such example is Takata airbag recall, which affected 19 different automakers.[23] Non-OEM part recall creates an indirect dependency among multiple firms. In such cases, recall decision-making takes place outside the firm, therefore examining the decision choice of such recalls with two players discrete game might not reflect a correct estimation

[23] See https://www.consumerreports.org/car-recalls-defects/takata-airbag-recall-everything-you-need-to-know/, accessed July 2020.

approach. Between 2003-2016, 66% of recalls were non-OEM recalls, so any assumption regarding considering both OEM and non-OEM recalls similar is very strong. Our study acknowledges this key feature and aims to address this co-dependency issue accordingly.[24] Second, we consider the possibility that automakers and the regulator might exchange relevant information, which could affect recall decisions, with each other. This common information would be known to both players but not observed by the researcher. Such information, when not considered, may bias the estimates. The model also incorporates researcher uncertainty arising from make-level common information. This feature allows for potential correlation among players' recall decisions by incorporating unobserved common factors that could affect both automakers and the regulator's recall decisions. We rely on various institutional features to identify the interaction parameters. Table 3.1 presents a brief overview of the previous research on product recalls. It also highlights that the topic of a firm's strategic decision-making during product harm-crisis remains largely unexplored.

(Please see Table 3.1)

Discrete Games

Literature has studied a wide range of settings (e.g., pricing formats, firm's entry, product quality, and store format) with the discrete game framework. Bresnahan and Reiss (1991) were the first to represent the econometric analysis of such discrete games and model the relationship between the number of firms in a market, market size, and competition with a simultaneous-move game with a linear system of endogenous variables. Berry (1992), another early paper on firm entry, analyzed entry of airlines into specific city-pair markets. Other discrete game studies such as Mazzeo (2002), Seim (2006), Aguirregabiria and Mira (2007), Ellickson and Misra

[24] We intend to build on this and consider a three-player model study to address co-dependency issue.

(2008), Bajari et al. (2010) tackle a wide range of issues. For example, Mazzeo (2002) investigates the relationship between prices and market structure in the motel industry, shedding light on why the number of firms in a market affects entry threshold. Ellickson and Misra (2008) focus on pricing as the primary decision variable in the context of discrete games. With supermarkets data, the authors investigate the choice of pricing strategy (EDLP vs. HiLo) under a static discrete game setting. Zhu et al. (2009) examine the store presence and format decisions of Wal-Mart, Kmart, and Target in local markets as a function of competitors' decisions and market characteristics. Bajari et al. (2010) apply a discrete game setting to investigate the factors that govern the assignment of stock recommendations by equity analysts. Aguirregabiria and Ho (2012) study the role of demand, costs, and strategic factors to the adoption of hub-and-spoke networks in the US airline industry. Vitorino (2012) examines a strategic model of entry that allows for positive and negative spillovers among firms. We seek to build on this discrete game foundation by studying the effect of strategic interaction in the context of product-harm crises.

Theoretical Framework

This study consists of two players, automaker[25] and the regulator (NHTSA) and models the behavior displayed by these two players under a discrete game setting. Game theory models investigate a broad range of economic problems (e.g., entry decision, pricing format, store location). However, the estimation could be involved. The computational burden of estimating a structural model is one big hurdle in the estimation. For example, nested fixed-point algorithm (Rust 1987) used for estimating games, is computationally demanding because it repeatedly takes a guess for structural parameters and then solves the corresponding endogenous economic variables. Furthermore, the presence of many equilibrium points can exacerbate this problem, as

[25] We consider MAKE (e.g., Acura, Honda, Lexus) as the decision maker. Therefore, we use the term "automaker".

a researcher should find all of the equilibria for each vector of parameters to calculate the corresponding likelihood value. Such computational burden of implementing the estimation algorithm has led to the development of computationally light estimators.

Estimator

The two-step estimators (e.g., Bajari et al. 2010) can help us stay clear from the computational burden. The first step of the two-step estimator uses a flexible method to estimate the reduced form to the game. The reduced form is an econometric model of how an agent's choice depends on exogenous or predetermined variables. The second step recovers the model's structural parameters; how payoffs depend on actions and control variables. This approach allows us to build the game's specification in the data rather than on our prior beliefs. Additionally, two-step estimators do not require researchers to solve the fixed-point problem when evaluating the corresponding likelihood function (Bajari et al. 2010). This can help avoid multiple equilibria. Two-step estimators assume that there is only one equilibrium in the data (e.g., Aguirregabiria and Mira 2007, Bajari et al. 2010). These estimators rely on the data for the payoffs that best explain the observed behavior. It assumes that the observed data originates from the plays of a game and covariates that influence payoffs. We can then specify payoffs as a parametric or non-parametric function of other players' actions and payoff relevant covariates.

Formulation of a discrete game requires specifying each player's information set, meaning what a player can observe about other players. There are two approaches in reference to the players' information sets: complete information (Bresnahan and Reiss 1991) and incomplete information (Ellickson and Misra 2011). The information structure is an essential guide for econometric analysis. Under the complete information setting, the researcher assumes that every player can observe everything about others' payoffs. This enables us to infer that players do not face any uncertainty regarding the payoffs of their rivals. In contrast, under incomplete information setting, the researcher assumes that the players do not observe everything about others' payoffs, which leads to uncertainty about other players' actions. Such unobservables could be incorporated as private information in the discrete game framework.

We consider incomplete information as a reasonable approach for our setting, as players may not have full information about other players' payoffs. Ellickson and Misra (2012) state that the incomplete information assumption also enables breaking a system of equations into a collection of single-agent problems in which selection can be addressed directly. Players form expectations about others' actions and thus decide their own actions to maximize the payoffs. This private information is assumed independent across players; therefore, we do not need to estimate the joint probability of actions of all players. Estimating the choice probability for each player one at a time is sufficient to provide consistent estimates in the second stage. We model private information in the form of ε, an additive separable component of payoffs, which is unobserved to the researcher. Player f has information about its payoff and ε_{fmt} , however, only knows the distribution of other players ε_{rmt}. Every player can now calculate its payoff after including expectation of its rivals' actions and then choose the option with the maximum payoff.

$$Y_{fmt} = 1[\beta_{fmt}X_{fmt} + \gamma_1\hat{\rho}_{rmt} + \varepsilon_{fmt} \geq 0] \qquad Y_{rmt} = 1[\beta_{rmt}X_{rmt} + \gamma_2\hat{\rho}_{fmt} + \varepsilon_{rmt} \geq 0]$$

Where, f represents the automaker and r represents the regulator. X represent the covariates influencing the player's payoffs and β are corresponding parameters. Y is an indicator representing the choice of the player (automaker or regulator) at time t. Y equal to one indicates a recall decision by the player. These choices depend on the payoff function written within the parenthesis. Value of the payoff function depends on various exogenous covariates X. Most importantly, each equation contains other player's choice probability. The probability $\hat{\rho}_{-f}$ is player f's beliefs about other players' action.

The two-step approach – based on Hotz and Miller (1993) – captures the strategic interplay in our study. The first-stage estimates of the predicted choice probability enable us to estimate the equilibrium choice beliefs/probabilities, conditional on the covariates. The second step involves estimating the random utility model using these equilibrium beliefs about others' behavior from the first step (Bajari et al. 2010).

Data Description

The empirical context for this study is the U.S. passenger car market. As a regulated industry, the automobile industry has well-maintained data records, which we use for our empirical setting. Most importantly, the regulator's supervision over the recall process provides the right setting for our research questions. This industry has a substantial recall frequency, which provides a good number of observations for analysis. Furthermore, this industry represents considerable economic significance as it contributes almost 3% of the U.S. GDP. No other manufacturing sector generates as many jobs.[26]

We use multiple datasets for our analysis. The first dataset contains information regarding automotive firms' recalls. This dataset important details of each recall such as name of the recalled make and date of the recall. Data also indicates whether it was a voluntary recall or mandatory recall depending on who initiated the recall. The second dataset includes details on consumer complaints regarding their vehicle defects. Following sections describe these datasets in detail. We refer to Compustat for different financial indicators (sales, liability, capex). Automotive News and Ward's Automotive provide firms' dealers network and firms' sales information, respectively.

[26] See http://www.americanautocouncil.org/us-economic-contributions, accessed July 2020.

We source consumer complaints, and vehicle recalls data from the NHTSA website.[27] The recall data set contains details of passenger vehicle recalls with key variables such as the name of the firm, make, brief description of the vehicle defect, and initiator of the recall. This dataset provides our dependent variable (number of voluntary and mandatory recalls). We consider a balanced panel of 14-year data (2003– 2016). It covers a total of 23 makes (e.g., Acura, Audi, BMW, Buick, Cadillac, Chevrolet) and corresponding parent firms (BMW, Daimler, Ford, General, Honda, Hyundai, Kia, Mazda, Mitsubishi, Nissan, Porsche, Subaru, Toyota, Volkswagen, and Volvo). Figure 3.2 highlights the variation in the number of voluntary and mandatory recalls over different quarters (values aggregated over all makes). Figure 3.3 highlights the number of voluntary and mandatory recalls or each make aggregated over the entire period.

(Please see Figure 3.2, Figure 3.3)

Complaint dataset comprises of consumers' complaints received by the NHTSA for vehicle defects. Relevant details in this dataset include the automobile firm's name, make, model, model-year, and a brief description of the complaint. In our dataset, we observe 37 consumer complaints[28] (e.g., airbag, suspension, steering) and the corresponding group. We broadly categorize these complaints into OEM (Original equipment manufacturer) vs non-OEM group and then continue with the OEM group. Automobile industry experts (not associated with this study) were interviewed to help us with this categorization. The key idea behind this step is that a third party supplied part (non-OEM) could be present in several makes from different

[27] See: https://www.nhtsa.gov/recalls#vehicle, accessed September 17, 2020

[28] These categories are: Air bags; Back over prevention; Child seat; Communications; Electrical system; Electronic stability control; Engine; Engine and engine cooling; Equipment; Equipment adaptive; Exterior lighting; Forward collision avoidance; Fuel system diesel; Fuel system gasoline; Fuel system; other; Hybrid propulsion system; Interior lighting; Latches/locks/ linkages; Other; Parking brake; Power train; Seat belts; Seats; Service brakes; Service brakes air; Service brakes electric; Service brakes hydraulic; Steering; Structure; Suspension; Tires; Traction control system; Trailer hitches; Vehicle speed control; Visibility; Visibility/wiper; Wheels.

firms. Thus, a defect in such third party vehicle part would trigger the possibility of recall over multiple firms, and create an indirect correlation among these firms. Focusing on the OEM recalls would allow us to avoid co-dependency of one firm's recall with another firm's recalls. We consider seven OEM complaint categories, each of which represent at least 2% of all OEM recalls (make-level) in our data set (electrical system, fuel system [gasoline], powertrain, engine [engine cooling], suspension, exterior lighting, and structure), and together these seven categories account for 96% of all OEM recalls (Table 3.2).

We observe 891 recall decisions[29] during this period for OEM categories. Table 3.3 highlights the distribution of voluntary and mandatory recalls for chosen seven categories. General Motors faced the highest number of recalls[30](132). Among defect categories, the highest number of voluntary recalls belonged to the "Fuel system (gasoline)" category (192). "Exterior lighting" defect category represented the highest ratio of mandatory recalls over total recalls (22.1%). In contrast, the lowest ratio (11.7%) belonged to the "Power train" defect category, where automakers seem to engage in more voluntary recalls. Chevrolet make received up to 1,251 consumer complaints in one quarter for potential defects in its electrical system. The mean quarterly value of consumer complaints and death reports is 31 and .9 (make-component level). Furthermore, we refer to Ward's automotive data for makes' quarterly sales. Automotive news data provides dealership network information for each firm.

(Please see Table 3.2, Table 3.3)

---

[29] If firms start multiple recalls in a defect category in a given time period (quarter), we consider this as one recall decision. Recalls belonging to the same defect category are more likely to be correlated.

[30] We consider seven complaint categories for recalls, and explain this further in next section.

Determinants of Recall Decisions

Beyond the strategic interaction effect, we note several payoff-relevant elements (complaint characteristics such as number of complaints, number of crashes, and geographical dispersion of complaints), which could also affect recall decisions of automakers and the regulator. The number of complaints and crashes can help determine how severe the issue is. Recall severity has been discussed extensively in the literature. For automobile recalls, studies find that severe recalls attract more negativity from stakeholders and impact sales (e.g., Hoffer, Pruitt and Reilly, 1988; Liu and Shankar, 2015). The number of crashes represents the economic and personal loss of society. Eilert et al. (2017) use information associated with the number of complaints and crashes for analysis. A higher number of complaints could indicate a widespread vehicle defect. Beyond just the sheer number of accumulated complaints, the severity of complaints would also play an important role as more crashes would draw automaker's attention and trigger a product-harm crisis.

Figure 3.4 indicates the variation in number of consumers' complaints over different quarters. In our data, we observe that, on average, one voluntary recall is associated with approximately 24 fewer complaints and .22 less number of crashes (Figure 3.5). Hence, broadly, one could argue that if motivators such as regulatory actions are prompting automakers to initiate more voluntary actions, it could possibly lead to a lower personal and economic loss to society. We also create a Geodispersion variable, which denotes how consumers' complaints are geographically dispersed (denoted by the number of states). In data, we observe the geographical state of each complaint. We use this information to derive how many states did these injury reports belong to. More geographically dispersed complaints (e.g., reported in several different states) are likely to create more negative social buzz and attract more public attention, and affect automaker's reputation. Geographically dispersed complaints are also likely to create more dispersed personal injury/class action lawsuits, which is likely to be costlier for automakers than the scenario when all the lawsuits were filed in the same state. Managing multiple cases would require dealing with multiple state courts and thus could lead to more billable hours for automakers.

Product features that could affect recall decisions could include whether the reported vehicle is a current year model. A recent vehicle model represents more revenue opportunities (also revenue loss) for the automaker. The impact on reputation may also be higher if a new vehicle model contains defects (Rupp 2001). Hence, an automaker might be more likely to take corrective action for the current year model. We create this variable by capturing the model-year value for the defective vehicles in the complaints dataset. Component specific characteristics, such as the complexity level of the vehicle component, which contains the potential defect, could also affect the recall decisions. For example, powertrain as a component is likely to be more complex than an external lighting component. Such complexity generally is expected to be associated with higher repair and maintenance costs if a recall is initiated. Complex components (e.g., engine) also tend to be more critical for the vehicle. Hence, firms may display different responses as per the component involved in defects. We refer to the NHTSA website to capture average complexity level of the recalled vehicle components. We also take into account the make reliability rating in the analysis. We obtain the reliability rating from consumer reports data. Consumer Reports - a nonprofit organization - collects survey information regarding consumers' issues with a particular vehicle model and then aggregates this information into problem rates. Reliability is measured using a 5-point scale of problem rates. Higher scores reflect higher reliability for the models (Eilert et al. 2017). In line with prior research, we aggregate model level reliability information to the make-level.

The automaker's resource capability of handing recalls could also affect their actions. An automaker, which is not well-equipped to handle a recall process, may be hesitant to initiate a recall. We incorporate this capability by incorporating automaker's dealership information. A bigger dealership network would enable the automaker to handle the recall process, which includes repair and maintenance of vehicles, more effectively. Similarly, resource constraints could also play a role in the regulator's decision-making. The process to determine whether a mandatory recall is required is costly as the regulator has to conduct a robust defect-analysis before recommending a mandatory recall action. Furthermore, the regulator already faces resource constraints, which have been discussed in government documents (Office of Inspector General 2015). Hence, the regulator's resource constraint could play a role in its recall decision-making. We consider regulator's administrative expenses to indicate this constraint. Higher administrative expenses would indicate a lower level of financial resources available for the recall process. Such constraints could affect the number of complaints reviewed by the regulator to detect potential recalls (Office of Inspector General 2015), which could affect the number of mandatory recalls initiated by the regulator. Table 3.4 highlights payoff relevant covariates.

Role of Information Exchange

Common Information: Before taking any recall decision, the automaker and the regulator might communicate with each other and exchange relevant information (e.g., vehicle test results, complaints analysis). Such information, which is common in information sets of these two players, could potentially affect recall decisions. For example, both automaker and regulator might conduct their complaints tests. Let's assume that the automaker's analysis does not lead to a certain conclusion regarding recall decisions. After information exchange, the regulator might provide some new information (e.g., vehicle tests), which may reduce the automaker's uncertainty regarding vehicle defects. Lower uncertainty could lead to a voluntary recall. This common information, created through information exchange and often not observed by the researcher, can affect recall decisions. Such unobserved information can lead to biases in strategic recall decisions if not considered in the model.

This two-way information exchange may also affect the belief creation process. Every player's payoff function includes belief (variable $\hat{\rho}$) about other player's possible actions. Depending on how effective the information exchange is, a player's belief might change; a better(worse) exchange could lead to a better(worse) belief creation. For example, if this process contains costs, it could hinder the information exchange process and make it less effective. This hindrance would not only affect the level of common information available with both automaker and the regulator but also affect the resulting beliefs of each player.

The researcher may not observe such common information. We use an exogenous variable, the distance between the automaker's headquarter and the regulator's office, to incorporate the extent of this common information (and corresponding potential cost). Geographical distance as a proxy for the information exchange and the ease of monitoring between two entities has been used in several studies (e.g., Lerner 1995; Petersen and Rajan 2002). Research shows that proximity facilitates access to information and monitoring (e.g., Giroud 2013). For example, banks located closer to their borrowers are more likely to lend to informationally difficult borrowers, which are borrowers without any financial records (Petersen and Rajan 2002). In lobbying literature, the distance between a firm's headquarter and Capitol Hill has been used as an instrumental variable to indicate the firm's corporate lobbying costs (Unsal, Hassan, and Zire 2016). Following this literature, we use the geographical distance, an exogenous variable, between an automaker's headquarter and the regulator's office to indicate the cost of information exchange and the extent of this common information between these two players. For example, a greater distance would indicate a higher cost of information exchange. A higher cost could adversely affect the information exchange process (shared common information), which may not help with decision-making uncertainty. We empirically examine whether such variation in common information through information exchange could play any significant role in recall decision-making process.

(Please see Table 3.4, Figure 3.4, Figure 3.5)

Empirical Implementation

We model the decision process of two players, an automaker and the regulator (NHTSA), as a simultaneous move game. We begin this section with the model setup and a brief discussion of different aspects of observed data for the aforementioned model. Then, we describe payoff-relevant variables and players' utility functions. Then, we move to the identification section.

Information Structure

As discussed in section 3.1, we consider an incomplete information approach for our setting, as players may not have full information about other players' payoffs. There are multiple factors which could affect the choice selection and may not be observable to other players. For example, sometimes, firms may recall products with minor defects, to signal consumers that it is paying attention to the quality of their products (Haunschild and Rhee 2004). Such information would not be observable to the external entities. Not knowing an actual cause of the potential defect could be another example. Similarly, NHTSA has severe budget constraints, making it difficult to focus on all complaints in a timely manner. In 2014, the agency only had seven to nine people to look through 77,000 safety complaints (Consumer Reports 2015). Such constraints could lead to the regulator prioritizing some specific types of complaints over other complaints as the regulator does not have sufficient resources to analyze all complaints and complete defect analysis in time for recommending required recalls. Such constraints and subsequent prioritization is the regulatory agency's private information, and outside automakers do not observe this. Given such incomplete information case, players form expectations about others' actions and then choose their actions to maximize the payoffs. Private information is assumed to be independent across players; therefore, we do not need to estimate the joint probability of all players' actions. Estimating the choice probability for each player one at a time is sufficient to provide consistent estimates in the second stage.

Unit of Analysis

Our unit of analysis is the combination of Make and Component. (e.g., Acura-Suspension, Acura-Power Train, BMW-Suspension). Following recall literature (e.g., Haunschild and Rhee 2004), we focus on Make (e.g., Acura, Lexus) as the decision-making entity. In the automobile industry, each vehicle manufacturer typically offers multiple cars makes. For example, as a parent firm, Honda offers different makes (e.g., Honda, Acura). These makes (termed as automakers here) assume responsibility for decisions on the recall process rather than being managed by their parent brand (Haunschild and Rhee 2004). In addition, recall decisions could vary significantly depending on the vehicle component. Hence, this make-component combination allows us to capture the heterogeneity in observed behavior. Players' (automaker and the regulator) decision making is considered independent across different units (make-component). Quarter represents the unit for this analysis.

Model Formulation

Following previous research (e.g., Bajari et al. 2005; Ellickson and Misra 2008; Zhou et el. 2020), we use a two-step conditional choice probability estimator to obtain parameter vectors (β and γ). We begin by stating some key assumptions associated with the model before discussing the model. For example, ideally an automaker's payoff should consist of both revenue and cost. However, it is extremely difficult, if not impossible, to observe information on revenue and costs for each recall/no recall decision by each player (automakers or the regulator). Therefore, following previous research (e.g., Ellickson and Misra 2008; Zhou et el. 2020), we assume that observed recall decisions reflect player's payoffs, which means that a player take the recall decision that results in the highest payoffs. A player (automaker or the regulator) does not observe the recall choices of other players, instead creates a rational expectation about other player's choice. Unobserved factors (e.g., strategic motives to initiate/not initiate a recall) could also influence recall choices. We assume that these unobserved factors follow a known distribution (e.g., extreme value). Hence, the choice probability of recall decisions is computed by integrating over the unobserved error.

An automaker f takes a decision for a unit m in each time period t = 1, 2, …T. As stated before, make-component combination (e.g., Acura-Suspension, Acura-Power Train) represents a unit for the analysis. Similarly, the regulator (NHTSA), indicated by *r* also takes decision for each unit separately. Every player chooses among two decisions: recall or no recall. For every unit m and time t, an automaker's state vector is denoted s_{fmt}. The state vector s_{fmt} is observed by other players and the researcher. It includes different payoff-relevant covariates (e.g., complaint characteristics), which we assume to be exogenous. For each automaker f and regulator, unobserved state variables are modeled as private information for each automaker. These unobserved state variables are ε_{fmt} and ε_{rmt}represent player-specific shocks to the payoffs associated with each choice. Unobserved state variables are drawn from a distribution that is known to the researcher and all the players. Due to private information assumption, simultaneous decision represents an incomplete information, with a Bayesian Nash equilibrium.

Payoff specification for an automaker f in time t is as follows:

$$U_{fmt} = f(s_{fmt}, a_{fmt}, a_{-fmt}) + \varepsilon_{fmt}, \quad (1)$$

where f is a known and deterministic function of state variables and actions (automaker and the regulator) and error term ε_{fmt} represents the private information available to the automaker f for unit m in time t. s_{fmt} represents the state variable vector, which corresponds to automaker f for unit m at time t. Each entity's decision would only depend on its own private information and other player's private information would not be a part of this. The following expression gives us a probability of an automaker choosing action k conditional on the state vector and private information:

$$\rho(a_{fmt} = k) = \int 1\left\{ d_{fmt}(s_{fmt}, \varepsilon_{fmt}) = k \right\} g(\varepsilon) d\varepsilon_{fmt}, \tag{2}$$

where $1\left\{ d_{fmt}(s_{fmt}, \varepsilon_{fmt}) = k \right\}$ is an indicator equal to 1 if player f chooses action k and 0 otherwise at time t for unit m. These probabilities represent the expected action of a given player choosing a certain action from the perspective of other players. ρ_f is defined as the set of these probabilities for an automaker f. As stated earlier, since the automaker does not observe regulator's actions prior to choosing its own action, the automaker takes decision based on its expectation of regulator's possible action. Hence, the expected payoff for a player f from choosing an action a_{fmt} at time t is then:

$$\widehat{U}_{fmt}(a_{fmt}, s_{fmt}, \varepsilon_{fmt}, \rho_f) = \sum_{a_{fmt}} f(s_{fmt}, a_{fmt}, a_{-fmt})\, \rho_{-fmt} + \varepsilon_{fmt}, \tag{3}$$

where $\rho_{-fmt} = \prod_{j \neq f} \rho_{jmt}\left(a_{jmt} \,|\, s_{jmt}\right)$.

Given these expected payoffs, the optimal action for a player is:

$$\psi_{a,fmt} = \Pr\left\{ \widehat{U}_{fmt}(a_{fmt}, s_{fmt}) + \varepsilon_{fmt}(a_{fmt}) > \widehat{U}_{fmt}(b_{fmt}, s_{fmt}) + \varepsilon_{fmt}(b_{fmt})\ \forall\, b_{fmt} \neq a_{fmt} \right\} \tag{4}$$

With errors ε following a type1 extreme, the underlined Bayesian Nash equation would follow a system of logit equations. Payoffs are assumed to be a linear function of the state variables s_{fmt} and expected belief of other players:

$$\widehat{U}_{fmt}\,(a_{fmt} = k, s_{fmt}, \varepsilon_{fmt}, \rho_f) = \beta\, s_{fmt} + \gamma\, \rho_{-fmt} + \varepsilon_{fmt}(k), \tag{5}$$

where ρ_{-fmt} represents the regulator's choice probability of taking mandatory recall decision for unit m at time t. Other variables are defined as before. With this specification, the optimal choice probabilities for the automaker f:

$$\psi_{fmt}(a_{fmt} = k|\rho_{mt}, s_{fmt}, \varepsilon_{fmt}, \beta, \gamma) = \frac{\exp(\beta\, s_{fmt} + \gamma\, \rho_{-fmt})}{\sum_{k' \epsilon \{\text{recall, no recall}\}} \exp\left(\beta\, s_{fmt} + \gamma\, \rho_{-fmt,k'}\right)} \tag{6}$$

Similar equation could be written for the regulator r for unit m at time t. Using choice probabilities of both automaker and the regulator, likelihood can be constructed as:

$$\left\{ \prod_t \prod_m \prod_{i \epsilon \{f,r\}} \left(\psi_{imt}(a_{imt} = k|\rho_{mt}, s_{imt}, \varepsilon_{imt}, \beta, \gamma)\right)^{\delta_{imt}(k)} \right\} \tag{7}$$

such that $\psi_{mt} = \rho_{mt}$

We first obtain estimates of ρ_{mt} (choice probabilities that are implicitly included in equation 6). Using these probabilities and and state variables, equation 6 provides the beliefs ψ_{mt} of players (automaker and regulator) taking recall decisions. These ψ_{mt} are then used in the likelihood function. Second stage of the estimation involves maximization of this likelihood function to provide parameters β and γ. Using these parameters, we update players' beliefs about other players' recall probabilities and perform the maximum likelihood estimation with these updated beliefs. We update parameters and beliefs iteratively until we achieve convergence and consistent parameter estimates. Likelihood formulation includes a system of discrete choice equations that must satisfy a fixed-point constraint $\rho_{mt} = \psi_{mt}$. We use bootstrap approach to obtain standard errors for the parameters.

Identification

We briefly discuss a set of assumptions that helps identify discrete games with incomplete information. Identification requires that different values of the primitives generate different choice probabilities; violation of this condition would not allow recovery of unique structural parameters. First, private information is assumed to be independently distributed across actions and players (Bajari et al. 2010). We also normalize the payoffs and only determine payoffs relative to the payoff under no recall decision (Vitorino 2012). Another important assumption is the exclusion restriction. Identification of the structural payoff parameters depends on the covariation between the explanatory variables and the revealed choice data (Ellickson and Misra 2012). In this model, we observe that the player's beliefs and corresponding payoff are both a function of X variables, leading to collinearity and the identification issue. Therefore, we need covariates that will directly affect one player's payoff but not the payoff of other players. Such unique covariates would help us identify parameters in the payoff function. For example, Zhu and Singh (2009) and Vitorino (2012) use variations in distances from the market to firms' headquarters and the nearest distribution centers, as exclusion restrictions for model identification. Ellickson and Misra (2008) fulfill the exclusion restriction condition using private information, which influences firm's own payoff, but would not influence other firms' payoffs. In the current recall setting, the automaker's dealership information and the regulator's administrative expenses help with the exclusion restriction condition. The dealership network, which denotes the automaker's potential capability of handling recalls, is specific to the automaker and only appears in the automaker's payoff specification. Similarly, the regulator's administrative expenses appear only in the regulator's specification.

Common Information Structure

We enrich the current model by incorporating correlated decisions structure through the inclusion of make specific common information in the decision-making process (Orhun 2013).[31]

[31] This analysis is currently in the process and has not been included in this draft.

Since the model considers the component level analysis, we observe seven make-component combinations (e.g., Acura-electrical system, Acura-fuel system, Acura-powertrain, Acura-engine, Acura-suspension, Acura-lighting, and Acura-structure) for every automaker. Presence of a common factor (e.g., decision-making team) among these combinations could create correlation among these decisions. For example, for every automaker there could be a designated team of decision-makers, who take a recall/no recall decision for every complaint case. Presence of such common designated team could create the possibility of correlation among these seven decisions (e.g., Acura-powertrain, Acura-engine). For example, conditional on an automaker (e.g., Acura) deciding to initiate a recall for a potential defect case (e.g., Acura-powertrain) not likely to be recalled based on observables, our expectations that the automaker also decides to initiate a recall for another potential defect (e.g., Acura-engine) is higher. Similarly, conditional on the automaker not deciding to initiate a recall for a potential defect case that is likely to be chosen based on observables, our expectations that the automaker decides to not initiate a recall for another potential defect is higher. Presence of any such correlation in decisions could bias the parameters if ignored. We define such common information at the make level k. This could be incorporated in the payoff as follows:

Automaker: $U_{fmt} = \theta_1 X_1 + \xi_f + \varepsilon_{fmt}$

Regulator: $U_{rmt} = \theta_2 X_2 + \xi_f + \varepsilon_{rmt}$

ξ_f represents the automaker f's specific unobserved factor, which affects both automaker and regulator recall decisions. X_1 and X_2 consist of automaker and regulator specific payoff relevant variables, respectively. As previously discussed, private information ε is assumed independent across players and units. Hence, we then express the probability of observing a unit outcome a_m conditional on the common information ξ_f across makes:

$$L\,(a, X, \xi; \beta) = \prod_{m=1}^{M}\prod_{t=1}^{T}\prod_{j\in\{f,r\}} P\big(a_{jmt}\big|\, X_{jmt},\, \xi_f; \theta\big)$$

Since the researcher does not observe the common information, the likelihood of an outcome is estimated by integrating out ξ_k.

$$L\,(a, X, \xi; \beta) = \prod_{m=1}^{M}\prod_{t=1}^{T}\prod_{j\in\{f,r\}} \int P\big(a_{jmt}\big|\, X_{jmt},\, \xi_f; \theta\big)\, dG(\xi_f|\sigma)$$

The scalar σ is the distributional parameter indicating the standard error of the make-specific common information ξ. Since, the integration over ξ does not have a closed form, we use the numerical approach to approximate it. We take R draws of ξ from N(0, σ^2) to construct the numerical likelihood of a a recall decision.

$$\int P\big(a_{jmt}\big|\, X_{jmt},\, \xi_f; \theta\big)\, dG\big(\xi_f, \sigma\big) = \frac{1}{R}\sum_{r=1}^{R} P_{jmt}^{r}(a_{jmt})$$

Given R = 400 draws of N(0,1) for unobserved common information, we can use these simulated probabilities of unit decisions to calculate the log-likelihood function.

Text Analysis of Consumer Complaints

We supplement this current set of analysis by examining consumers' defect complaints through text analysis. In our dataset, we can observe the content of consumers' complaints. To the best of my knowledge, no study in the automobile recall literature has examined consumer complaints to extract relevant insights regarding recall decisions.

First, we underline the reasons to conduct complaints' text analysis. Conditional on different covariates (e.g., complaints, crashes, product features, etc.), why would complaints' text characteristics be important in the recall decisions? The underlying rationale for this question links back to the regulator's resource constraints (previously discussed). For example, in 2014, the regulator received almost 77,000 complaints, but the regulator only had 7 to 9 analysts to screen those complaints and decide whether complaints need further analysis (Consumer Reports 2015). Because these analysts screen thousands of complaints, the determination of whether complaints warrant further review (or ignored) is made within a matter of seconds (Office of Inspector General 2015). Since the decision to analyze complaints is taken within a matter of seconds, one could imagine that the way complaints are written could potentially impact whether these complaints are considered for further analysis. Therefore, we would like to know whether certain complaint characteristics (e.g., brevity of complaints) could influence the probability of complaints' analysis (which would subsequently affect recall decisions)? A text analysis would provide some insights into these questions.

Figure 3.6 presents a few examples of customer complaints about the Acura make and power train component. These complaints differ on various text dimensions (e.g., length, content). We use the natural language processing methods to explore the following dimensions in the text. First, we use the average number of words to consider a complaint's size. Length of the text can affect the text's content as the need to generate shorter content could encourage users to focus on the overall gist of their experience (Melumad et al. 2019). The length of the complaints' text could also affect the probability of a complaint being considered for further analysis. If an analyst has to screen an overwhelming number of complaints in a very limited timeframe, the analyst is more likely to screen shorter complaints with fewer words. Hence, conditional on other factors (e.g., defect severity, number of complaints), does complaint size associate with a recall decision? We observe that the average number of words per complaint is marginally higher for voluntary recalls (49.43) than mandatory recalls (Figure 3.7, Panel A). In terms of variation, values for the average number of words per mandatory recall complaint display higher dispersion than values for the average number of words per voluntary recall complaint (Figure 3.8, Panel A and B).

We also explore complaints' sentiment. We use a dictionary-based approach (Harvard IV dictionary) to calculate complaints' sentiment. Sentiment originating from user-generated content can be used to predict mindset metrics such as satisfaction (Kübler, Colicev, and Pauwels 2020). In this current setting, sentiment could be used to understand the type of text used to write complaints. If a complaint includes more technical description (e.g., low horsepower, engine, brake), the text sentiment is likely to be closer to neutral. However, if the complaint consists of more emotionally appealing words (e.g., "people are dying", "vehicle is dangerous"), the sentiment is likely to be more negative. This analysis may help us understand whether analysts are likely to pay more attention to complaints with more technical components or with more emotional appeal. In this data, we observe that complaints associated with a mandatory recall express more negative sentiment than complaints associated with a voluntary recall (Figure 3.7, Panel B). Average negative sentiment values for mandatory recall complaints also display less clustering than voluntary recall complaints (Figure 3.8, Panel C and Panel D).

We also consider the dimension of message consistency among consumer complaints.[32] Similarity/dissimilarity of messages in complaints could affect the probability of complaint being considered/ignored for further analysis. Let's assume an analyst observes ten vehicle complaints during a specific time period. Suppose most of these (or all) these complaints give consistent messages about the defect (e.g., engine heats up, engine is warm, engine temperature is very high). In that case, it may be easier for an analyst to process these complaints cognitively and spot the developing defect trend; this may increase the probability of these complaints being

[32] This analysis is currently in the process and has not been included in this draft.

considered for further analysis (thus affecting the recall probability). However, if these complaints give inconsistent messages, the analyst may find it difficult to process these complaints (combined with time-constraint) and may not spot the developing defect trend. This may reduce the probability of these complaints being considered for further analysis, affecting the recall probability. This rationale is consistent with a finding in Anand and Sternthal (1990), who discuss that time available for message processing and the time required for that task affect message effectiveness. Hence, if an analyst has less time to process complaints, inconsistent messages provided by complaints may motivate the analyst to ignore these complaints.

To define message consistency, we explore the underlined topics of complaints with the topic modeling approach. Topic modeling is an unsupervised machine learning technique, which could be used to identify patterns in the data (e.g., Berger et al. 2019). Topics are word distributions that commonly co-occur with a certain probability of appearing in a topic. Topic modeling could help understand the topics consumers write about and choose the words to express these topics (Netzer et al. 2019).

(Please see Figure 3.7, Figure 3.8)

Results and Discussion

This study aims to provide insight into the recall decision-making process. Specifically, it investigates the strategic interplay between an automaker and the regulator during their decision-making and how this interplay influences their choices. We employ a static discrete game approach, a framework frequently used in marketing and economics literature (e.g., Orhun 2013; Zhu et al. 2009) to model discrete decisions (e.g., whether to initiate a recall). We model our context as a simultaneous one-move game that consists of two players, the automaker and the regulator, making decision choices simultaneously.

Results show that players choose decisions suitable for the characteristics of the specific unit types (e.g., complaints level, product type). The impact of different payoff covariates corresponds closely to existing empirical studies of recalls and conventional wisdom. For example, we find that voluntary recall is favored by automakers that own a larger dealership network, possibly due to the advantage dealership network may provide in handling recalls. The regulator's resource constraint (indicated by administrative expenses) also affects the recall decision-making process. This finding is in line with the government sources (Office of Inspector General 2015), which discuss that resource constraint may hamper the recall process at NHTSA. Finally, with regard to strategic interaction, we find that the strategic interplay between an automaker and the regulators exists. Automakers are more likely to initiate recalls voluntarily when they anticipate that the regulator might recommend a mandatory recall. We do not find any such effect for the regulator, indicating that the regulator decision-making is indifferent to the automaker's possible action.

Our main empirical results are presented in Table 3.5. The coefficients, which represent the parameters of the payoff functions represented in Equation (6), are interpreted as follows: positive values indicate a positive impact on recall decision, increasing the probability that the recall action is selected relative to the outside option (no recall).

Characteristics

All three characteristics (complaints, crashes, and geodispersion) play a significant role in the recall decision-making process (Table 3.5).

Focusing more closely on the parameters, we find that, consumer complaints positively affect both voluntary ($\beta = .002, p < .01$) and mandatory recall ($\beta = .001, p < .01$) decisions. Complaints indicate how widespread the potential defect is. Controlling for complaints number, severity of the defect (number of reported crashes) have a positive effect on automakers voluntary recall action ($\beta = .017, p < .01$). Interestingly this variable, however, is not significant for the regulator ($\beta = -.011, n.s.$). Regulator's resource constraint could be the possible reason behind this result. Because it is costly for the regulator to determine whether a vehicle should have a mandatory recall, the regulator optimally uses its limited resources by leaving the more obvious recall candidates with more serious defects for the automakers. Hence, the regulator tends to initiate more recalls involving less serious defects. Complaints' geographical dispersion positively impacts both automaker ($\beta = .016, p < .01$) and regulator ($\beta = .017, p < .01$) recall decisions. As stated earlier, more geographical dispersion could create more negative buzz (e.g., more news coverage) around the potential defect and could affect automaker's reputation. It appears that more geographical dispersion also affects regulator's decisions as regulator might be motivated to act to allay public concerns.

Complexity of the component with defect is negatively associated with the regulator's action ($\beta = -.65, p < .001$). Conditional on other observables, regulator is less likely to take a mandatory recall action for components that are more complex in nature. As discussed before, regulator faces resource constraint. In addition, conducting a robust defect analysis is costly. Hence, regulator might prefer to avoid defect analysis of a complex component (e.g., engine), which might be costlier than defect analysis of a less complex component (e.g., lighting). This may affect regulator's recall decisions. Results also show that automakers are more likely to a voluntary recall action when a current year model is involved with the potential defect ($\beta = .114, p < .001$). Since the reputation loss or revenue loss is likely to be higher for a new vehicle model in comparison to an older model, automakers might be more proactive in initiating voluntary corrective actions when new models are involved. Entity specific covariates also influence recall decisions of automaker and the regulator. Conditional on observables, automaker's dealership network is positively associated with voluntary recall decision ($\beta = .002, p < .001$). Regulator's administrative expenses is negatively associated with mandatory recall decision ($\beta = -.031, p < .01$), supporting the idea that as expenses rise, lack of financial resources may prompt lower number of mandatory recall decisions.

Strategic Interaction

By constructing a formal model of strategic interaction, we are able to address the central question posed in this paper. Table 3.5 presents the result for strategic interaction analysis. γ_{maker} coefficient represents an automaker's belief of the regulator's mandatory action, and this is significant ($\beta = 6.722, p < .01$), which suggests that the automaker is more likely to initiate voluntary recalls when they anticipate that the regulator might recommend a mandatory recall. This result indicates that some part of automakers' recall decisions is driven by the regulatory dimension (regulator' presence); managers not only think about the cost associated with complaints and adverse reports, but they also think about the regulator's potential action and its associated cost. This result suggests that the automaker might see more value in initiating a voluntary recall than a mandatory recall. A voluntary recall may demonstrate that automakers are accepting responsibility for defects and are striving to provide safe products for their customers, despite facing substantial recall costs (Souiden and Pons 2009). A voluntary recall may also allow automakers to control their message during the recall, which could help manage reputation loss due to vehicle defects.

Importantly, results show an asymmetry in the strategic interaction. $\gamma_{regulator}$ coefficient represents the regulator's belief regarding the automaker's voluntary recall action, and this is not significant ($\beta = -.622, n.s.$); this suggests that regulator decision-making is indifferent to the automaker's possible action.

Information Exchange

Results suggest that the information exchange plays a significant role in the recall decision, even when a rich set of variables are employed in the model. Following previous research (e.g., Giroud 2013; Petersen and Rajan 2002), we use the geographical distance between these two entities as a proxy to indicate the cost of information exchange and coordination between an automaker and the regulator. Negative and significant coefficient for the automaker ($\beta = -.073, p < .01$) suggests that better information exchange between an automaker and the regulator (which could potentially lower the uncertainty around defect complaints) appears to lead to more voluntary corrective actions.

In contrast, a higher cost of monitoring and information exchange (a greater geographical distance) negatively affects the information exchange and is more likely to lead to mandatory actions ($\beta = .036, p < .01$). We also study the counterfactuals under changing levels of information exchange.

(Please see Table 3.5)

Complaints Text Analysis

Table 3.6 presents the results for this section. We add two additional covariates in the original discrete game model. Results indicate that the length variable (average number of words in a complaint) is negative and significantly associated with mandatory recall decisions ($\beta = -.0006, p < .01$). This result suggests that, conditional on other factors, shorter complaints are more likely to be associated with a mandatory recall outcome. The rationale for this result could be explained by the earlier discussion, which highlights that analysts at the regulatory agency are inundated with defect complaints. An analyst's decision to consider complaints for a further analysis is taken within seconds (Office of Inspector General 2015). Hence, after controlling for other observables (e.g., severity), an analyst may prioritize shorter complaints due to resource constraints. Such prioritization may affect final recall decisions.

Results also indicate that the negative sentiment variable is significantly ($\beta = .0205, p < .01$) associated with mandatory recall decisions. This result suggests that complaints with more negative sentiment (more emotional appeal) are more likely to be associated with a mandatory recall decision. Complaints containing words such as “someone may die while making a turn”, “this vehicle is dangerous”, “people may die in accidents” etc. are more likely to grab analyst’s attention and, hence, more likely to be associated with a mandatory recall decision.

(Please see Table 3.6)

Varying Conditions and Equilibrium Responses

The model parameters can be used to predict the equilibrium recall responses for different sets of conditions and provide insights on how these recall decisions might differ among different automakers. For instance, we evaluate recall decisions of the automaker and the regulator under different scenarios: 1) changes in underlying recall costs; (2) changes in automaker’s recall handing capability; and (3) changes in information exchange costs.

Underlying recall costs: This analysis is inspired by the idea that reputation loss is one of the primary factors considered by the automakers in recall decision-making (e.g., Chen et al. 2009). As discussed earlier, the geographical dispersion of complaints is used as a proxy for potential reputation loss (and potential legal costs) associated with defect complaints. More geographically dispersed complaints could create more negative social buzz about the automaker and could lead to greater reputation loss. The negative social buzz regarding the potential defect could also attract regulator’s attention and subsequently motivate the regulator to recommend a mandatory recall.

We reduce complaints' geographical dispersion by 10% and observe changes in automakers' recall behavior. Estimation results (Table 3.5) show that complaints' geographical dispersion is associated with recall probabilities of automaker and the regulator. Conceptually, when geographical dispersion reduces, the negative social buzz and adverse public attention are also likely to decline. Lower negative buzz would lead to less reputation loss for the automakers, lowering the automaker's recall choice probability. We consider a 10% reduction in complaints' geographical dispersion. With this change, we note down the top three vehicle makes (average rating = 3.27) with the highest drop in recall probabilities and the bottom 3 make (average rating = 2.38) with the lowest drop in recall probabilities. Results (Figure 3.9) indicate that, for a 10% drop in dispersion, automakers with lower quality are more likely to initiate a voluntary recall than the higher quality automakers. Since a stronger reputation can work as a buffer against the reputation loss, automakers with a higher quality rating can afford to drop their recall probabilities by a larger extent (hence less likely to initiate voluntary recalls). However, automakers with a lower quality rating don't enjoy a similar level of buffer, and hence they are more likely to initiate a recall when defects appear. This result highlights how changes in underlying reputation loss costs associated with geographical dispersion could lead to different recall responses by the automakers with different quality ratings.

Underlying information exchange: Since better information exchange and coordination between an automaker and the regulator could help reduce information asymmetry and uncertainty, the associated cost in such exchange process could affect recall decisions. We use the geographical distance, an exogenous variable, between the automaker and the regulator as a proxy to consider such costs. Estimation (Table 3.5) shows that, conditional on all the other observables, when the geographical distance reduces, we are likely to see more voluntary recalls and less number of mandatory recalls. Therefore, we run a counterfactual analysis to understand the effect of change in information exchange costs on the number of recalls initiated by automakers and the regulator.

We consider two scenarios with changes in geographical distance and observe automakers' recall behavior (Figure 3.10). When the distance goes down by a factor of .9, the mean voluntary recall choice probability goes up by 1.69% and mean mandatory recall choice probability goes down by .8%. This change is likely to lead to 12 additional voluntary recalls and one less mandatory recall. When the distance reduces by a factor of .7, we are likely to observe 38 additional voluntary recalls and four less mandatory recalls. This analysis suggests that efforts to make the information exchange more effective between an automaker and the regulator (lowering the potential cost) could lead to more net corrective actions.

Automaker's recall handing capability: We also evaluate the automaker's recall decision with respect to its dealership network size. The dealership network indicates an automaker's capability of handling recall repair and maintenance process. Estimation results (Table 3.5) show that dealership network positively associates with the automaker's voluntary recall probability. This analysis (Figure 3.11) shows that, when the dealership network increases by 6%, equilibrium response is likely to contain an additional voluntary recall.

(Please see Figure 3.9, Figure 3.10, Figure 3.11)

REFERENCES

Aguirregabiria, Victor and Chun-Yu Ho (2012), "A Dynamic Oligopoly Game of the US Airline Industry: Estimation and Policy Experiments," *Journal of Econometrics*, 168 (1), 156–173.

Aguirregabiria, Victor and Pedro Mira (2007), "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75 (1), 1–53.

Anand, Punam and Brian Sternthal (1990), "Ease of Message Processing as a Moderator of Repetition Effects in Advertising," *Journal of Marketing Research,* 75, 345–353.

Ater, Itai and Nir Yosef (2018), "The Impact of Product Recalls on the Secondary Market: Evidence from Dieselgate," Working Paper, Tel Aviv University.

Bala, Ram, Pradeep Bhardwaj, and Pradeep K. Chintagunta (2017), "Pharmaceutical Product Recalls: Category Effects and Competitor Response," *Marketing Science*, 36 (6), 931–943.

Berger, Jonah, Ashlee Humphreys, Stephan Ludwig, Wendy W. Moe, Oded Netzer, and David A. Schweidel (2019), "Uniting the Tribes: Using Text for Marketing Insight," *Journal of Marketing*, 84 (1), 1–25.

Bloomberg (2015), "Volkswagen Drops 23% After Admitting Diesel Emissions Cheat," (accessed July 8, 2020), [available at https://www.bloomberg.com/news/articles/2015-09-21/volkswagen-drops-15-after-admitting-u-s-diesel-emissions-cheat].

Borah, Abhishek and Gerard J. Tellis (2016), "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research*, 53 (2), 143–60.

Bromiley, Philip and Alfred Marcus (1989) "The Deterrent to Dubious Corporate Behavior: Profitability, Probability and Safety Recalls," *Strategic Management Journal,* 10 (3), 233–50.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises," *Journal of Marketing*, 73 (6), 214–226.

Chu, Ting-Heng, Che-Chun Lin, and Larry J. Prather (2005), "An Extension of Security Price Reactions Around Product Recall Announcements," *Quarterly Journal of Business and Economics*, 44 (3/4), 33–48.

Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises," *Journal of Marketing*, 77 (2), 58–77.

Cleeren, Kathleen, Marnik G. Dekimpe, and Harald J. van Heerde (2017), "Marketing research on product-harm crises: a review, managerial implications, and an agenda for future research," *Journal of the Academy of Marketing Science*, 45 (5), 593–615.

Cleeren, Kathleen, Marnik G. Dekimpe, and Kristiaan Helsen (2008), "Weathering Product-Harm Crises," *Journal of the Academy of Marketing Science*, 36 (2), 262–70.

Colak, Ahmet, and Robert Bray (2016), "Why Do Automakers Initiate Recalls? A Structural Econometric Game," Clemson University, Clemson, SC.

Committee on Energy and Commerce (2010), "Response by Toyota and NHTSA to Incidents of Sudden Unintended Acceleration," Hearing before the subcommittee on oversight and investigations of the committee on energy and commerce House of Representatives, (February 23), (accessed March 8, 2020), [available at https://www.govinfo.gov/content/pkg/CHRG-111hhrg76008/pdf/CHRG-111hhrg76008.pdf].

Consumer Reports (2015), "The truth about car recalls," (accessed July 8, 2020), [available at https://www.consumerreports.org/cro/magazine/2015/04/the-truth-about-car-recalls/index.htm].

Dawar, Niraj and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Customer Expectations," *Journal of Marketing Research*, 37 (May), 215–26.

Dranove, David and Chris Olsen (1994), "The Economic Side Effects of Dangerous Drug Announcements," *Journal of Law and Economics*, 37 (2), 323-348.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), "Does It Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry," *Journal of Marketing*, 81 (3), 111–129.

Ellickson, Paul B. and Sanjog Misra (2011), "Structural Workshop Paper —Estimating Discrete Games," *Marketing Science*, 30 (6), 997–1010.

Giroud, Xavier (2013), "Proximity and Investment: Evidence from Plant-Level Data," *The Quarterly Journal of Economics*, 128 (2), 861–915.

Hartman, Raymond S. (1987), "Product Quality and Market Efficiency: The Effect of Product Recalls on Resale Prices and Firm Valuation," *The Review of Economics and Statistics*, 69 (2), 367–372.

Han, Lu and Seung-Hyun Hong (2011), "Testing Cost Inefficiency Under Free Entry in the Real Estate Brokerage Industry," *Journal of Business & Economic Statistics*, 29:4, 564–578.

Haunschild, Pamela R., and Mooweon Rhee (2004), "The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls," *Management Science*, 50 (11), 1545–60.

He, Long, Ying Rong, and Zuo-Jun Max Shen (2020), "Product sourcing and distribution strategies under supply disruption and recall risks," *Production and Operations Management*, 29(1), 9– 23.

Hoffer, George, Stephen Pruitt, and Robert Reilly (1988), "The Impact of Product Recalls on the Wealth of Sellers: A Reexamination," *Journal of Political Economy*, 96 (3), 663–70.

Hora, Manpreet, Hari Bapuji, and Aleda V. Roth (2011), "Safety Hazard and Time to Recall: The Role of Recall Strategy, Product Defect Type, and Supply Chain Player in the U.S. Toy Industry," *Journal of Operations Management*, 29 (7), 766–77.

Hotz, V. Joseph and Robert Miller (1993), "Conditional Choice Probability and the Estimation of Dynamic Models," *The Review of Economic Studies*, 60(3), pp. 497–529.

Huang, Yan, Param Vir Singh, and Anindya Ghose (2015), "A Structural Model of Employee Behavioral Dynamics in Enterprise Social Media," *Management Science*, 61 (12), 2825–2844.

Jarrell, Gregg and Sam Peltzman (1985), "The Impact of Product Recalls on the Wealth of Sellers," *Journal of Political Economy*, 93 (3), 512-536.

Jayaraman, Vaidyanathan, Raymond A. Patterson, and Erik Rolland (2003), "The design of reverse distribution networks: Models and solution procedures," *European Journal of Operational Research*, 150 (1), 128–149.

Jibrell, Anisa (2018), "Auto Recall Bill Grew 26% to $22 Billion in 2016, Study Says," *Automotive News*, (January 30), (accessed June 17, 2020), [available at https://www.autonews.com/article/ 20180130/RETAIL05/180139974/auto-recall-bill-grew-26-to-22-billion-in-2016-study-says].

Josh, Lerner (1995), "Venture Capitalists and the Oversight of Private Firms," *Journal of Finance*, 50, 301–318.

Kedia, Simi and Shiva Rajgopal (2011), "Do the SEC's Enforcement Preferences Affect Corporate misconduct?" *Journal of Accounting and Economics*, 51 (3), 259–278.

Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer Based Brand Equity," *Journal of Marketing*, 57 (1), 1–22.

Kübler, Raoul, Anatoli Colicev, and Koen H. Pauwels (2020), "Social Media's Impact on the Consumer Mindset: When to Use Which Sentiment Extraction Tool?" *Journal of Interactive Marketing*, 50, 136–155.

Liu, Yan and Venkatesh Shankar (2015), "The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry," *Management Science*, 61 (10), 2514–2535.

Liu, Yan, Venkatesh Shankar, and Wonjoo Yun, (2017) "Crisis Management Strategies and the Long-Term Effects of Product Recalls on Firm Value." *Journal of Marketing*, 81 (5), 30–48.

Marsh, Thomas L., Ted C. Schroeder, and James Mintert (2004), "Impacts of Meat Product Recalls on Consumer Demand in the USA," *Applied Economics*, 36 (9), 897–909.

Mazzeo, Michael J. (2002), "Product Choice and Oligopoly Market Structure," *RAND Journal of Economics*, 33 (2), 221–42.

Netzer, Oded, Alain Lemaire, and Michal Herzenstein (2019), "When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications," *Journal of Marketing Research*, 56 (6), 960–80.

NHTSA (2017), "Vehicle Safety Recall Completion Rates Report," (accessed July 8, 2020), [available at https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/13376-recall_completion_rates_rtc-tag_final.pdf].

Office of Inspector General (2015), "Inadequate Data and Analysis Undermine NHTSA's Efforts to Identify and Investigate Vehicle Safety Concerns," *U.S. Department of Transportation*, (June 18), (accessed July 17, 2021), [available at https://www.oig.dot.gov/sites/default/files/NHTSA%20Safety-Related%20Vehicle%20Defects%20-%20Final%20Report%5E6-18-15.pdf].

Orhun, A. Yeşim (2013), "Spatial Differentiation in the Supermarket Industry: The Role of Common Information," *Quantitative Marketing and Economics*, 11 (1), 3–37.

Petersen Mitchell A. and Rajan Raghuram (2002), "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance*, 57, 2533–2570.

Rhee, Mooweon and Pamela R. Haunschild (2006), “The Liability of a Good Reputation: A Study of Product Recalls in the U.S. Automotive Industry,” *Organization Science*, 17 (1), 101–17.

Rupp, Nicholas G. (2004), “The Attributes of a Costly Recall: Evidence from the Automotive Industry,” *Review of Industrial Organization,* 25, 21–44.

Rust, John (1994), *Structural Estimation of Markov Decision Processes. In: Handbook of Econometrics*, Elsevier, Amsterdam, Vol. IV, Chapter 51, 3081–3143.

Salin, Victoria and Neal H. Hooker (2001), “Stock Market Reaction to Food Recalls,” *Review of Agricultural Economics*, 23 (1), 33–46.

Schwartz, Teresa M. and Robert S. Adler (1984), “Product Recalls: A Remedy in Need of Repair,” *Case Western Reserve Law Review*, 34 (4), 401.

Seim, Katja (2006), “An Empirical Model of Firm Entry with Endogenous Product-Type Choices,” *The RAND Journal of Economics*, 37(3), 619–640.

Souiden, Nizar and Frank Pons (2009), “Product Recall Crisis Management: The Impact on Manufacturer's Image, Consumer Loyalty and Purchase Intention,” *Journal of Product & Brand Management*, 18 (2), 106–114.

Strittmatter, Anthony and Michael Lechner (2020), “Sorting in the Used-Car Market After the Volkswagen Emission Scandal,” *Journal of Environmental Economics and Management*, 101, 102305.

Thirumalai, Sriram and Kingshuk K. Sinha (2011), “Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences,” *Management Science*, 57 (2), 376–92.

Unsal, Omer, M. Kabir Hassan, and Duygu Zirek (2016), “Corporate lobbying, CEO political ideology and firm performance,” *Journal of Corporate Finance*, 38, 126–149.

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), “The Impact of a Product-Harm Crisis on Marketing Effectiveness,” *Marketing Science*, 26 (2), 230–245.

Vitorino, Maria Ana (2012), “Empirical Entry Games with Complementarities: An Application to the Shopping Center Industry,” *Journal of Marketing Research*, 49 (2), 175–91.

Zhao, Yi, Ying Zhao, and Kristiaan Helsen (2011), "Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics after a Product-Harm Crisis," *Journal of Marketing Research*, 48 (2), 255–267.

Zhu, Ting, Vishal Singh, and Mark D. Manuszak (2009) "Market Structure and Competition in the Retail Discount Industry," *Journal of Marketing Research*, 46 (4), 453–466.

Table 3.1: Selected Product Recall Literature

Authors	Focus	Key points
Jarrell and Peltzman (1985)	Firm value	Product recall affects shareholder wealth negatively. Such costs are higher than costs emanating from recall.
Dawar and Pillutla (2000)	Brand Equity	Consumers interpret firm's responses to recall based on prior expectations with the firm. The study shows that existing consumers and potential future consumers expect different assurance from the recalling firm.
Haunschild and Rhee (2004)	Learning	Learning takes place within firms due to recalls. The study shows that greater learning takes place for firms, which recall voluntarily rather than mandatorily. Results also establish the difference in learning curve generalist and specialist automakers.
Marsh et al. (2004)	Category Demand	Meat recall events significantly affect category demand, with favorable effects on demand for meat substitutes, offset by more negative effects on meat demand.
Chen, Ganesan, and Liu (2009)	Recall strategy	The impact of proactive vs passive recall strategy on firm value. Results show that, regardless of the firm and product characteristics, proactive strategy has a stronger negative effect on firm value.
Freedman et al. (2012)	Sales	For firms with recalls, unit sales of the types of toys involved in the recall fall relative to sales of toys in other categories. The study does not find any evidence of within-manufacturer spillovers to dissimilar toys.
Cleeren, van Heerde, and Dekimpe (2013)	Advertising and Brand Share	Study analyses the effect of post recall advertisement and price changes on product's brand share and category purchase. The study also analyses the degree of moderation by two characteristics: extent of negative publicity surrounding recall and brand's public acknowledgement of recall.
Liu and Shankar (2015)	Brand and advertisement	When recalls are associated with greater media attention and severe consequences, consumer's response is more negative. Results also show that parent-brand advertising and sub-brand advertising effectiveness declines due to recall but the decline in latter is greater.
Bala et al. (2017)	Competitor Response	The authors focus on competitor reaction to product recalls where the competitor participates in multiple product categories that exhibit (dis)economies of scope in sales effort across them.
Eilert et al. (2017)	Recall timing	The authors test the effect of problem severity on time to recall, the role of brand characteristics in moderating this relationship. The results show that markets punish recall delays.

Ater and Yosef (2018)	Price (listing)	Volkswagen's emissions scandal had a statistically significant, negative effect on the number of transactions involving vehicles made by Volkswagen and their resale prices.
Strittmatter and Lechner (2020)	Price (asking), Brand share	Supply of used Volkswagen diesel vehicles increased after the emission scandal. The positive supply-side effects increase with the probability of manipulation. The negative impacts on the asking prices of used cars are subject to a high probability of manipulation.
This study	Recall decision-making	This study examines the underlying mechanism of the recall decision-making process. Using a discrete game framework, it captures the strategic interplay between an automaker and the regulator's recall decision process.

Table 3.2: Complaint Categories

OEM Categories	Percentage of OEM recalls
Electrical System	20.75%
Fuel system, Gasoline	20.68%
Power Train	15.82%
Engine and Engine Cooling	11.23%
Suspension	10.62%
Exterior Lighting	9.52%
Structure	7.47%
Fuel System, Other	1.64%
Hybrid Propulsion System	1.03%
Engine	0.62%
Forward Collision Avoidance	0.41%
Traction Control System	0.21%

Table 3.3: Recall Decisions

Complaint Category	Voluntary decisions	Mandatory decisions	% (mandatory/total)
Suspension	80	17	17.5%
Structure	66	14	17.5%
Power Train	121	16	11.7%
Fuel System, Gasoline	164	28	14.6%
Exterior Lighting	81	23	22.1%
Engine and Engine Cooling	94	20	17.5%
Electrical System	135	32	19.2%

Table 3.4: Key Data Sources

1	Consumer complaints	NHTSA
2	Vehicle recalls	NHTSA
3	Make sales	Ward's automotive
4	Dealership network (number of dealers)	Automotive News
5	Number of crashes	NHTSA
6	Geodispersion (number of states where complaints are reported)	NHTSA
7	Current year model dummy	NHTSA
8	Quality rating	Consumer reports
9	Component complexity data	NHTSA
10	Geographical distance between locations	Annual reports, Google
11	Quality rating	Consumer reports
12	Administrative expenses	NHTSA

Table 3.5: Estimation Results

	Automaker	Regulator
Intercept	-1.484***	-1.231***
Defect characteristics		
Complaints	.002***	.001***
Crashes	.017***	-.011
Geographic complaint dispersion	.016***	.017***
Product feature		
Complexity	-.087	-.650***
Current model	.114***	.118
Quality rating	-.011	-.193***
Entity specific		
Number of dealers	.002***	
Administrative expenses		-.031**
Information exchange		
Geographical distance	-.073***	.036***
Strategic interaction		
γ_{maker}	6.722***	
$\gamma_{regulator}$		-.622

**p*<0.05; ***p*<0.01; ****p*<0.001.*

Table 3.6: Results with Text Analysis

	Automaker	Regulator
Defect characteristics	Yes	
Product feature	Yes	
Entity specific	Yes	
Complaint characteristics	Yes	
Length	-.0002***	-.0006***
Negative sentiment	-.004	.0205**
Information exchange		
Geographical distance	-.073***	.040***
Strategic interaction		
γ_{maker}	8.27***	
$\gamma_{regulator}$		-.621

**p<0.05; **p<0.01; ***p<0.001.*

Figure 3.1: Recall Decision-making Process

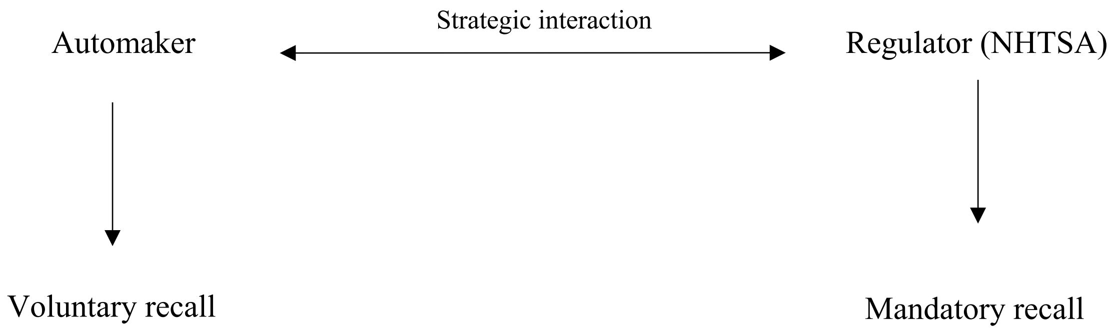
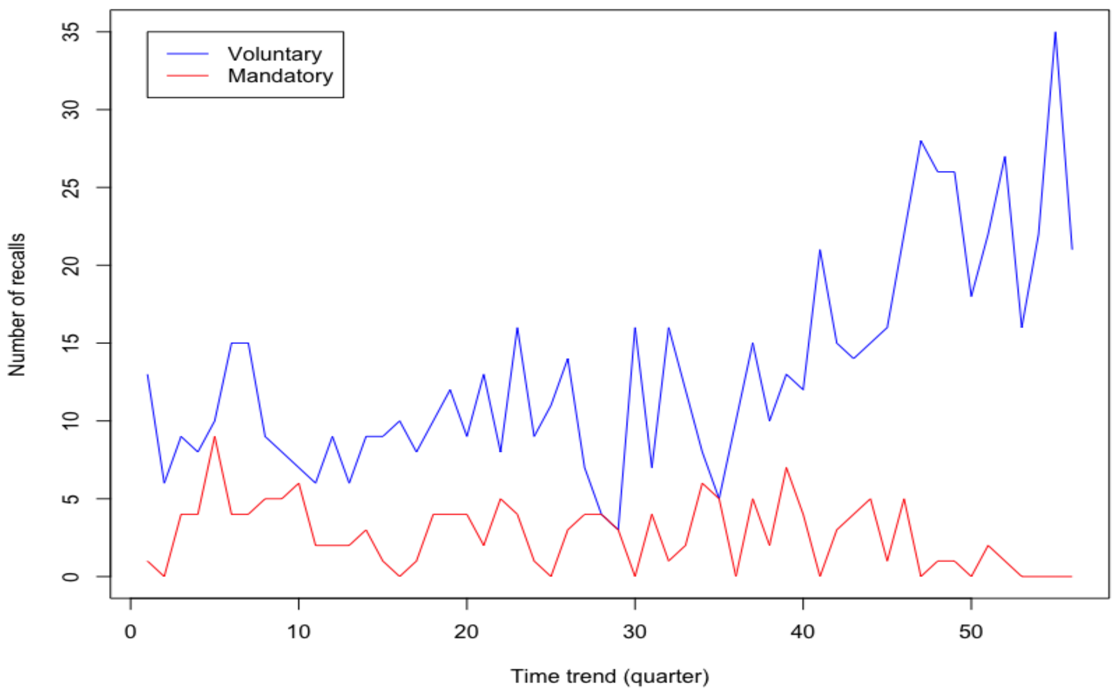
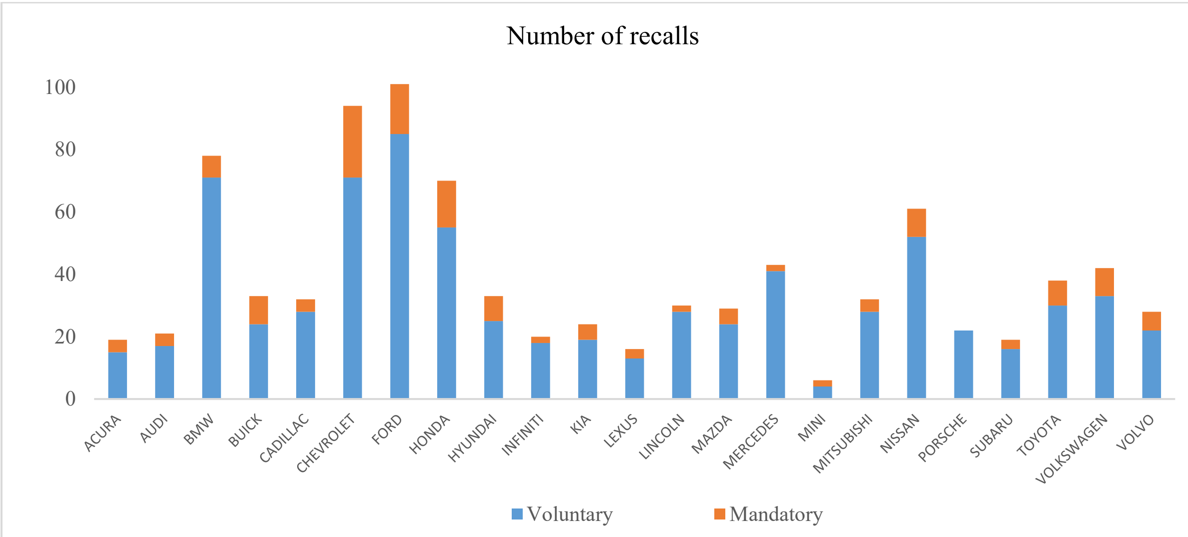


Figure 3.2: Aggregated Recalls per Quarter



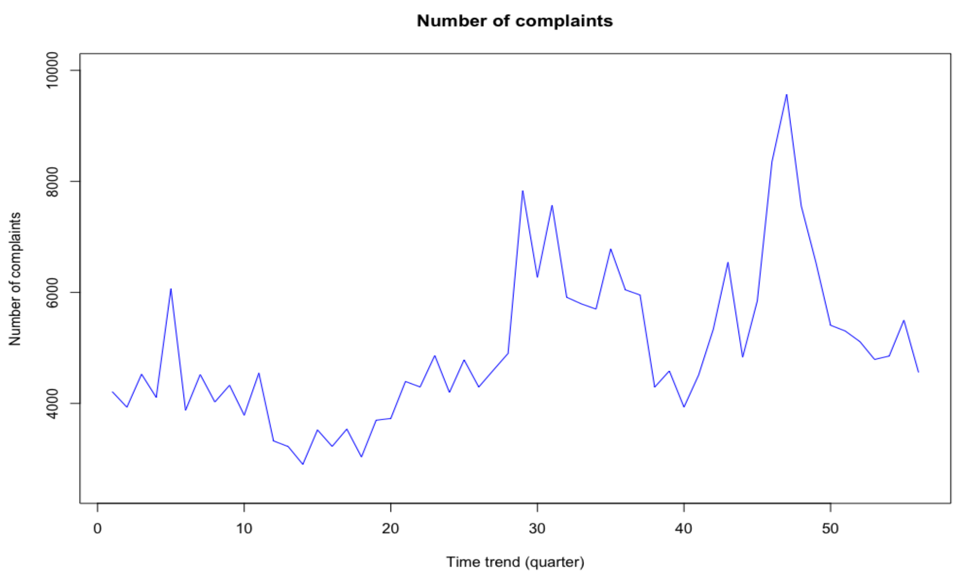
Note: These values are aggregated over vehicle makes.

Figure 3.3: Aggregated Recalls per Vehicle Make



Note: These values are aggregated over all periods (quarters).

Figure 3.4: Aggregated Complaints per Quarter



Note: These values are aggregated over vehicle makes.

Figure 3.5: Defect Characteristics per Recall Type

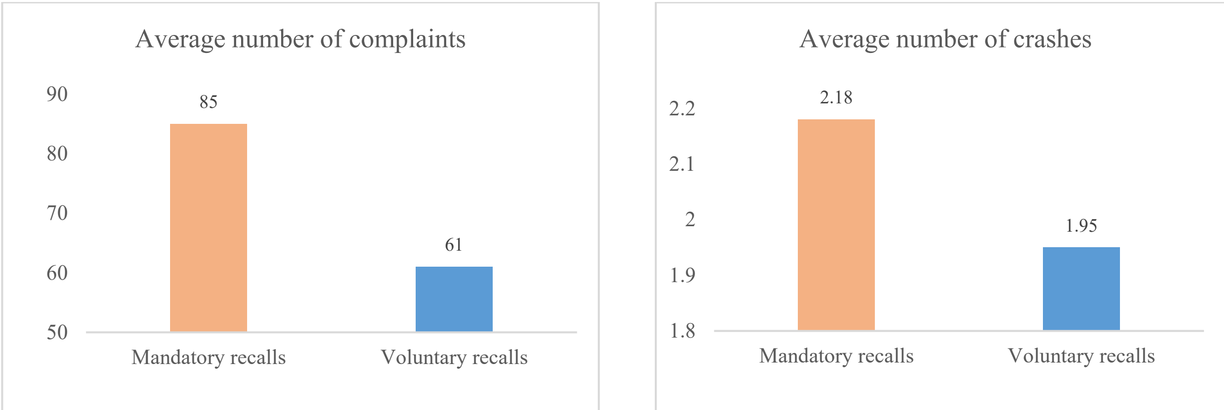


Figure 3.6: Examples of Defects Complaints by Consumers

*I BOUGHT MY 2016 MDX ON 02/01/2016 AND **WAS QUITE HAPPY WITH THE INITIAL PURCHASE**. AFTER DRIVING FOR TWO DAYS I STARTED SETTING UP THE CAR'S OPTIONS, I REALIZED THAT THE CARS DRIVE SYSTEM WAS SET TO START IN SPORT MODE. I CHANGED THE OPTION TO ALLOW THE CAR TO START IN 'NORMAL' MODE PERMANENTLY AND THAT'S WHEN I STARTED TO FEEL THE PROBLEM. THERE IS A NOTICEABLE 2 - 3 SECOND LAG AT TAKE OFF OR WHEN ATTEMPTED TO ACCELERATE FROM A REDUCED SPEED IN LOWER GEARS. A VERY UNCOMFORTABLE FEELING WHEN ATTEMPTING TO MAKE A LEFT TURN WHEN YOU HAVE ONCOMING TRAFFIC AND THE CAR FALLS TO ENGAGE AFTER YOU MAKE THE COMMITMENT TO DRIVE. I WAITED A FEW DAYS TO SEE IF THIS WAS JUST A KINK THAT WOULD GO AWAY SINCE THE CAR WAS NEW. NO SUCH LUCK. I TOOK THE CAR TO THE DEALER AND THEY SAID EVERYTHING WAS FINE. I ASKED ABOUT THE LAG AND THEY SAID IT IS NORMAL OPERATIONAL PART OF THE CAR. APPARENTLY THIS IS A KNOWN ISSUE WITH THE CAR FOR WHICH THEY DON'T THINK IT IS WORTH*

I GOT MY 2016 ACURA MDX IN JULY. SINCE THEN, I AM HAVING TRANSMISSION PROBLEMS. OFF-THE-LINE SHIFTS ARE ERRATIC, DEPENDING ON HOW MUCH THROTTLE I GIVE THE ENGINE. GIVE IT 3/4 THROTTLE AND ACCELERATION IS GREAT, BUT MILEAGE SUFFERS BADLY. GIVE IT ANY LESS THROTTLE AND ACCELERATION IS MEAGER, PLUS THE ENGINE REVS VERY HIGH BETWEEN SHIFTS. ONE TIME, I WAS PULLING AWAY FROM A STOPLIGHT AFTER SLOWING TO NEARLY A FULL STOP (THE LIGHT JUST CHANGED AS I APPROACHED), I PRESSED 1/2 WAY ON THE ACCELERATOR AND THE ENGINE BOGGED TO NEARLY ZERO RPMS. I THOUGHT IT DIED. I LET UP AND PRESSED DOWN AGAIN AND IT RETURNED TO NORMAL. MERGING ON THE HIGHWAY IS ALSO VERY DANGEROUS AND SCARY. AS I HIT THE GAS TO ACCELERATE ON THE ON-RAMP, THE ENGINE HESITATES SO BADLY, I NEARLY RUN OUT OF RAMP. PASSING ON THE HIGHWAY IS THE SAME, UNLESS I PRESS THE THROTTLE TO THE FLOORBOARD. ANOTHER TIME,

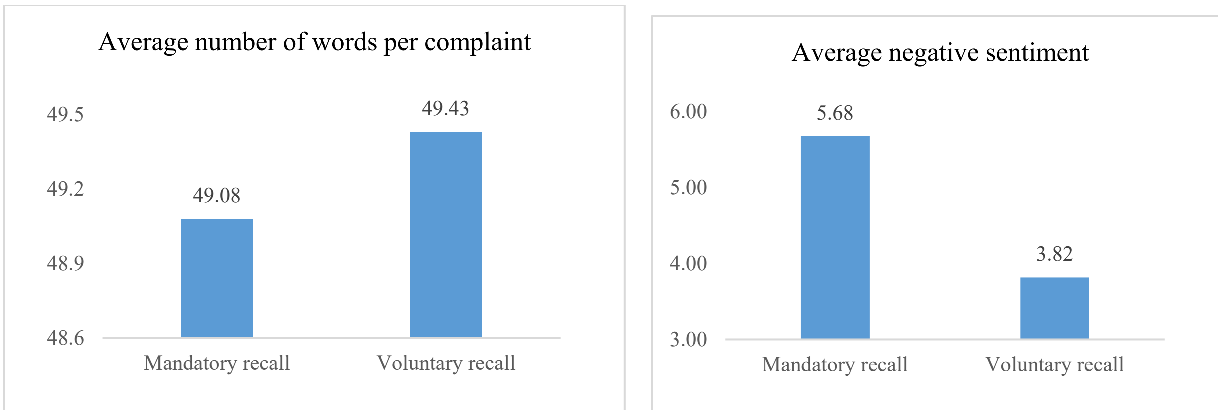
TRANSMISSION SLIPS FROM BETWEEN SHIFT 1-2 AND 2-3. CAR ALSO AT TIMES LUNGES FORWARD WHILE

ROUGH GEAR SHIFT AND CARS SEEMS TO BE REV-UP AT LOW GEARS . THIS CAN CREATE A DANGEROUS

Note: These consumers' complaints correspond to Acura MDX vehicle model and power train vehicle component.

Figure 3.7: Descriptive Statistics of Complaints Text Characteristics

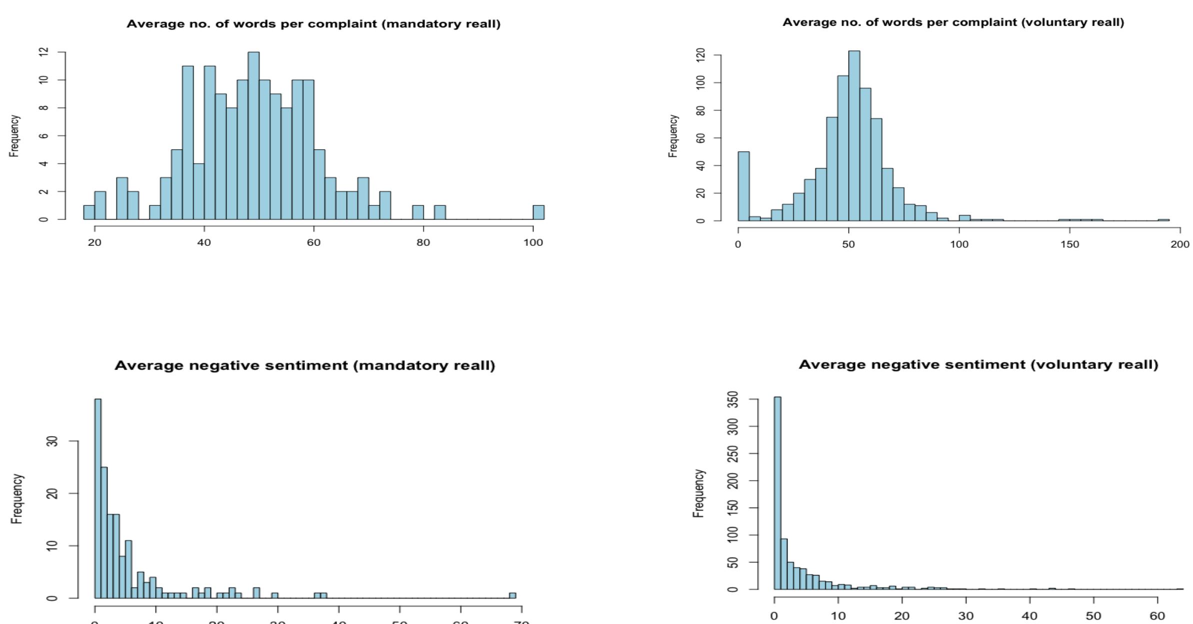
Panel A Panel B



Note: Panel A displays average value of number of words in complaints associated with corresponding recalls. Panel B displays average value of negative sentiment in complaints associated with corresponding recalls.

Figure 3.8: Frequency Plot of Complaints Text Characteristics

Panel A Panel B



Note: Panel A and Panel B display frequency plot of average number of words in complaints for corresponding recalls. Panel C and Panel D display frequency plot of average negative sentiment values in complaints text for corresponding recalls.

Figure 3.9: Changes in Recall Responses with Geographic Dispersion

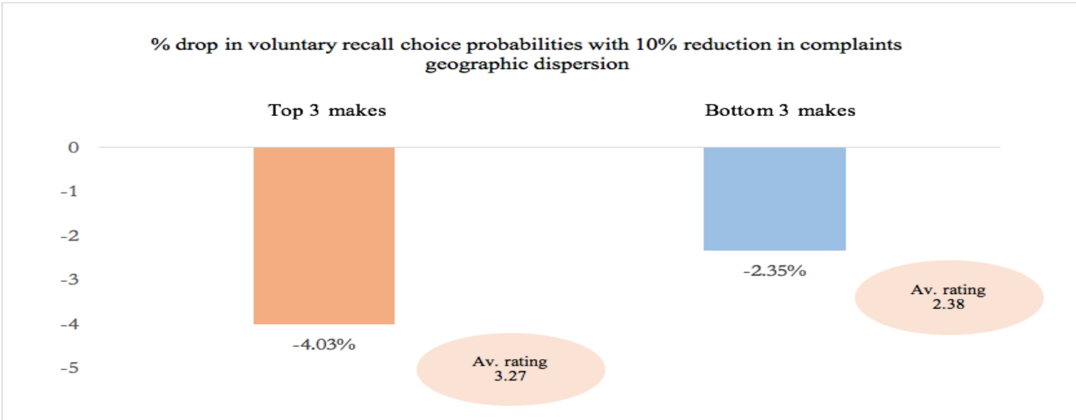


Figure 3.10: Changes in Recall Responses with Geographic Distance

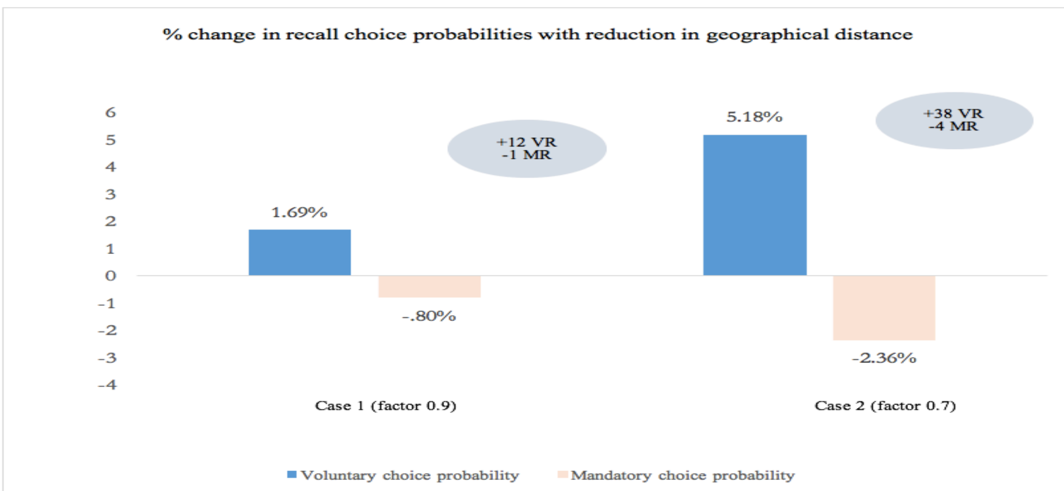
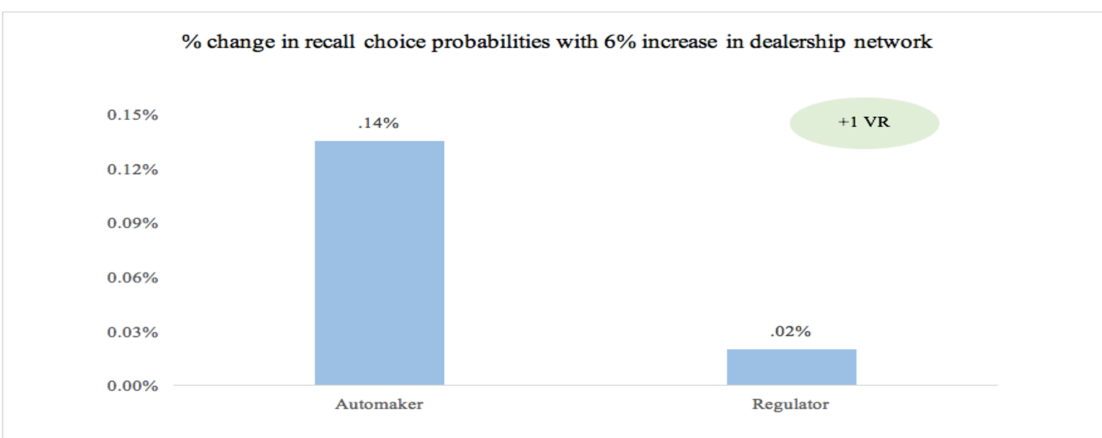


Figure 3.11: Changes in Recall Responses with Dealership Network



CHAPTER 4: DIRECT AND SPILLOVER EFFECTS OF PRODUCT RECALLS IN BUSINESS-TO-BUSINESS SECONDARY MARKETS: A STUDY OF THE US AUTOMOBILE INDUSTRY

Introduction

Many product markets (e.g., apparel, automobile, medical device, etc.) exhibits three noteworthy features that intersect to raise critical yet unaddressed research questions. First, the volume and the profitability from used products can be greater than new products. For example, in the U.S. used automobiles account for more than 70% of all automobile transactions.[33] The average gross profit for auto dealers from selling used vehicles is $2,354 compared to $1,944 for a new vehicle (NADA 2018).[34] Similarly, the resale market for apparel is projected to reach $64 billion by 2025 from $28 billion in 2019; this market grew 25 times faster than the overall retail market in 2019, with sixty-four million shoppers making a secondhand purchase.[35] Yet, used product markets receive limited academic attention. Consider, for example, the robust literature in marketing on the automobile industry (the empirical context of our study). Studies like Albuquerque and Bronnenberg (2012), Bucklin et al. (2008), Busse et al. (2006), Cachon et al. (2019), Fischer (2019), Morton et al. (2001), and Ozturk et al. (2016, 2019) focus on new vehicles. The economic significance of used product markets is now leading to growing

---

[33] In 2017, used vehicles comprised 39.3 million transactions (approximately worth $470 billion). See https://publish.manheim.com/content/dam/consulting/2018-Manheim-Used-Car-Market-Report.pdf, accessed July 2021.

[34] Similarly, in the used video games industry, pre-owned games represent about half of gross profit of GameStop, which is the largest retailer of new and used video games. See https://www.cnbc.com/2014/03/17/wal-mart-unveils-video-game-trade-in-program.html, accessed July 2021.

[35] See https://www.thredup.com/resale/, accessed July 2021.

academic scrutiny (e.g., Biglaiser et al. 2020; Bennett et al. 2015; Ishihara and Ching 2019; Shiller 2013; Yin et al. 2010), but many substantive questions pertaining to used product markets remain unexplored in marketing. We seek to add to this research.

Second, used product markets involve important interactions among B2B intermediaries (e.g., auto dealers) that are absent or less prevalent in new product markets. For example, auto dealers acquire their new vehicle inventory directly from auto manufacturers, which they then sell to the end-consumer (e.g., Lafontaine and Morton 2010; Cachon and Olivares 2009).[36] In contrast, auto dealers acquire and replenish their used product inventories by transacting with other dealers. These used vehicle trades among dealers are facilitated via business-to-business (B2B) wholesale auctions (Genesove 1995; Lacetera et al. 2012; Larsen 2020). In 2017, 83.8% of auto dealers availed of B2B wholesale auto auctions to acquire their used vehicles (NADA 2018). Gaming retailers also use online auctions to buy/sell second-hand games (Shiller 2013). Nonetheless, the so-called B2B knowledge gap is persistent across used product research (Lilien 2016). For example, in the case of automobiles, though some studies (e.g., Genesove 1993; Grether et al. 2009; Murry and Zhou 2020) provide B2B market insights, extant research primarily examines auto dealers' transactions with end-consumers in the used vehicle markets (e.g., Biglaiser et al. 2020; Gavazza et al. 2014). This consumer-focused research explores several elements including adverse selection, product search, and product quality (e.g., Kuruzovich et al. 2010; Peterson and Schneider 2014). Similarly, empirical research in other used product industries (e.g., used books, concert tickets) largely explores questions that revolve around B2C transactions such as cannibalization of new product sales or impact on primary market due to search frictions in secondary market (e.g., Bennett et al. 2015; Ghose et al. 2006;

[36] Influential studies in marketing like Purohit (1997), Albuquerque and Bronnenberg (2012), Busse et al. (2010), and Xu et al. (2014) advance insights on the interplay between auto manufacturers, auto dealers, and end-consumers.

Yin et al. 2010). As a result, there is a need for more empirical research on B2B transactions whereby intermediaries such as auto dealers acquire used products that they subsequently sell to end-consumers. Investigating this interplay among B2B intermediaries would augment the extant marketing literature focused on industries with a robust used products market.

Third, product recalls plague some of these industries (e.g., Borah and Tellis 2016, Thirumalai and Sinha 2011). For example, the auto industry faced 5,930 defect related recalls from 2012 to 2019. Likewise, medical device recalls have increased from 650 in 2003 to 1190 in 2012, with Class I recalls, in which serious adverse health consequences or deaths are possible, increased from 7 in 2003 to 57 in 2012.[37] While extant product recalls research advances valuable insights on consumer-side reactions (e.g., Barber and Darrough 1996; Chen et al. 2009; Liu and Shankar 2015; Zhao et al. 2011), managerially relevant research on B2B buyers' responses to product recalls and subsequent implications for their B2B transactions of these intermediaries remains untouched (e.g., Cleeren et al. 2017).

Many important and interrelated research questions that concern the impact of product recalls for intermediary B2B transactions arise. For example, the extant literature is silent on intermediary B2B buyers (e.g., auto dealers) response to product recalls (e.g., Cleeren et al. 2017). How do B2B buyers adjust the prices they are willing to pay if the used product faces a recall (direct effect)? What changes, if any, do B2B buyers make to replenish used product inventories in response to a recall? How do recalls influence these buyers' demand for non-recalled products (spillover effect)? Do B2B buyers switch to another non-recalled product, offered by the same manufacturer or a different manufacturer, in place of the recalled product?

[37] For automobile example see (accessed April 2021): https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/2019_recall_annual_count_final-031620-v1-tag.pdf. For medical device example see (accessed April 2021): http://fmdic.org/wp-content/uploads/2014/04/Medical-Device-Recall-Report-amf-2.pdf.

Do B2B buyers buy non-recalled products within the same product segment or a different segment? Answers to these managerial and policy-relevant questions would provide insights into product recalls' effects on intermediaries' B2B transactions and inventory management.

We investigate the aforementioned B2B-product-recall pertinent questions in the context of the US automobile market. We develop a descriptive, causal model that we calibrate with a unique database containing detailed information on the dealers' used vehicle purchases through a B2B auction. Our auction database span four years (2005–2008) and include several vehicle-level details including transaction price (price at which the dealer acquired the vehicle at the auction), vehicle condition report, and vehicle odometer reading. We augment these data with vehicle recall information from the National Highway Traffic Safety Administration (NHTSA). We exploit a narrow time window before and after recall announcement and then apply a difference-in-differences (DiD) identification strategy to estimate the causal impact of recall events. Our identification strategy involves comparing the difference in B2B transacted prices of vehicles pre- and post-recall in the recalled product category (i.e., passenger vehicles) with the difference in B2B transacted prices of vehicles pre- and post-recall in another product category (i.e., cargo vans) that is unlikely to be affected by the focal recall, to quantify the *direct effect* (on the recalled product). We leverage a similar identification strategy to quantify the *spillover effect* of product recalls on other products of the same automaker[38] and other automakers who are not simultaneously subject to recalls of their own products.

B2B transactions directly affect dealer's used vehicle purchases (stock management), which carries substantial economic significance. The used vehicles business contributes a higher

[38] Consistent with automotive recall studies (e.g., Haunschild and Rhee 2004), our unit of analysis is the "automaker" (e.g., Acura, Lexus), rather than the "auto firm" (e.g., Honda Motor Company) or the "model" (e.g., Accord, Civic). We use the term automaker to indicate this.

gross profit per used vehicle retailed ($2,354) than gross profit per new vehicle retailed ($1,944) (NADA 2018). Dealers use these B2B transactions to bolster and reshuffle their vehicle purchases to meet their appropriate retail needs (Genesove 1993). Dealers also use B2B used vehicle transactions to purchase substitutes for their new models when new models are too costly for customers. Therefore, any adverse marketplace event (e.g., vehicle recall) that could cause impromptu adjustments (e.g., changes in dealer's willingness to pay, deferring purchases, or switching to substitutes) in dealers' B2B purchases would directly affect dealer's stock management. Our study provides insights on these economically significant B2B transactions.

Several key findings emerge from our analysis. On average, recalls reduce the transaction prices for recalled products by about 10% (nearly $1,043) in the used vehicle market. The adverse direct effect on the recalled product is greater when it is a government-mandated recall (approximately $1,098 lower prices). A recall, which involves multiple models by the same automaker, causes approximately $1,819 drop in prices. The direct effect of product recalls is more damaging for older vehicles than younger vehicles with fewer miles. Specifically, a recall reduces the transaction price by about $21 for every 1000 miles accrued by the used vehicle. Beyond the direct effect, we also find significant spillover effects on unaffected products both for the recalled automaker and its competitors. For example, non-recalled products that belong to the same segment[39] as the recalled product and manufactured by the recalled product's automaker experience a price reduction of about 5.54%.[40] This suggests a negative within-segment spillover effect spanning recalled automaker's non-recalled vehicles. In addition, prices

[39] In line with Albuquerque and Bronnenberg (2012), we consider vehicle types (compact car, full-size car, luxury car, midsize car, minivan, sports car, sport utility vehicle, subcompact car, and wagon) to define segments.

[40] Any non-recalled vehicle model, which also belongs to the Honda make and compact segment would fall under this group. For example, if Honda Civic 2008 (compact segment) faces a recall and Honda Civic 2010 does not, then spillover would be considered on Honda Civic 2010

for non-recalled products that do not overlap segment with the recalled product but belong to the same automaker rise by about 4.91% following a recall notice.[41] This suggests that B2B buyers switch from a recalled product to a non-recalled product that belongs to a different segment but manufactured by the same automaker. Other automakers' non-recalled products that belong to the same product segment as the recalled product also suffer a price reduction of about 5.63%.[42,43] Results show that used vehicles sale benefit from franchise relationships. Dealers, which are affiliated with the recalled vehicle automaker, pay higher transaction prices (about 3.45% higher) for non-recalled models of the same make than the non-franchise dealers. These B2B findings are also relevant for the auctioneer, whose revenue is tied with vehicles' auction sale prices.

Our study also provides insights relevant for the current policy landscape of the used vehicle market in the US. On June 25, 2019, Senator Richard Blumenthal (D-CT) proposed the *The Used Car Safety Recall Repair Act* (116th Congress) that would require repairs on used vehicles subject to safety recalls before they are sold, leased, or loaned to consumers (Congress 2019). Although the legislation would reduce consumers' exposure to defective vehicles, it has evoked strong criticism from the NADA (2020), which asserted that this Act would increase dealers' cost of owning a recalled vehicle. Findings from our study can inform the ongoing policy debate on this Act. Specifically, the study advances empirical evidence on how dealers adjust their used vehicle purchases (both the direct- and spillover-effects) in the absence of the

---

[41] For example, if Honda Civic (compact segment) faces a recall, then any non-recalled Honda make vehicle such as Honda Accord, which does not belong to the compact segment, would fall under this group.

[42] For example, if Honda Civic faces a recall, then any non-recalled vehicle, which also belongs to the same segment as the Civic but different automaker (e.g., Acura, Lexus) would fall under this group.

[43] T test shows that the negative spillover coefficient for other automakers group (corresponding to 5.63%) is statistically different from the spillover coefficient for the same automaker group (corresponding to 5.54%).

proposed regulatory intervention. As stated earlier, used vehicles are a robust source of profits for dealers. Any policy intervention that could make the recalled vehicle a less attractive option, may further dampen dealers demand for the recalled product in the B2B and in doing so may have the unintended consequence of helping increase the price for other non-recalled vehicles.

We organize the rest of this paper as follows: In Section 2 we present the relevant literature; in Section 3 we describe the used vehicle market with a brief description of B2B vehicle sales and automotive recalls data; in Section 4 we detail the estimation approach with key model and identification considerations; in Sections 5 and 6 we describe the results and robustness checks respectively; and we conclude in Section 7.

Related Literature

Our research builds on the extant product recall literature and the literature on used products. We summarize the product recall literature in Table 4.1, and extend this research in three meaningful directions. First, we contribute to the literature stream that measures the direct effect of product recalls on financial outcomes. Jarrell and Peltzman (1985) and Hendricks and Singhal (2003) describe routes by which product recalls cause capital market losses for a manufacturer, including remedial costs (e.g., refund, repair), inventory losses, and lost sales. Others highlight direct negative impact of recalls on several other elements such as stock market returns (e.g., Barber and Darrough 1996; Chen et al. 2009) and marketing mix effectiveness (e.g., Liu and Shankar 2015; Zhao et al. 2011).

Second, we contribute to the literature on the spillover effects of a product recall on non-recalled products. An emerging literature studies how recalls may cause spillover effects on non-recalled products of the same manufacturer, non-recalled competitors in the category, or the industry as a whole (e.g., Bala et al. 2017; Borah and Tellis 2016; Freedman et al. 2012). For example, Borah and Tellis (2016) observe that negative online chatter about a recalled car model increases negative chatter for others with the same brand, while Freedman et al. (2012) find negative spillover effects of a large-scale toy recall on competing manufacturers' sales.

Third, our research contributes to the literature on the impact of recalls in secondary markets. In the automobile industry, the context for this study, the used vehicle market dwarfs the primary new-product market in terms of sales transactions, so understanding the impact of recalls on used vehicle markets is economically and managerially important. To the best of our knowledge, only five studies consider the effects of product recalls on the used vehicle markets, i.e., Ater and Yosef (2018), Che et al. (2020), Hammond (2013), Hartman (1987), and Strittmatter and Lechner (2020). These studies, however, explore B2C transactions and do not examine transactions further upstream from the end-consumer involving B2B intermediaries. For example, Hartman (1987) finds that safety recalls by General Motors (GM) diminish the resale value of the recalled products but do not affect the values of other GM products. In studying a 2010 Toyota safety recall, Hammond (2013) instead asserts that the effect on the resale prices of recalled products was null and short lived. Ater and Yosef (2018) and Strittmatter and Lechner (2020) study the supply-side implications of recalls in secondary markets, using the Volkswagen emission scandal; they both find statistically significant negative impacts on the supply of recalled products. Che et al. (2020) study changes in car prices due to the Volkswagen scandal to measure consumers' willingness to pay for brand reputation.

As stated previously and is clearly explicated in Table 4.1, extant research on product recalls emphasizes markets with consumers as the end-users, despite the significant value and size of B2B markets. Lilien (2016) notes that B2B transactions account for $10.7 trillion, i.e., 42% of all U.S. revenues and calls for rigorous empirical research of the B2B buying process. Recently, Cleeren et al. (2017) also assert the lack of empirical research on the effect of product recall effects in B2B markets. In response, we investigate the impact of product recalls on a used vehicle market with B2B buyers.

Our research also adds to the growing literature on used vehicle markets (e.g., Biglaiser et al. 2020; Che et al. 2020). Automobile is one of the prominent categories of the used product industry in the US.[44] Different features of this differentiated product, such as durability and lower prices than new product, have helped fuel the used vehicle market. Entry of new players (e.g., Carvana, Vroom), which are disrupting the used vehicle market with digital platform capabilities and big data analytics, has further boosted this market.[45] Empirical researchers have studied the used vehicle market across different dimensions such as allocative and welfare effects (Gavazza et al. 2014), consumer's myopic behavior (Busse et al. 2013), fuel economy (Sallee et al. 2016), and vehicle scrappage (Jacobsen and Benthem 2015), among others.

Finally, we also add to research that focuses on auto dealers and explores associated key dimensions such as dealers' colocation decision (Murry and Zhou 2020), price reactions of incumbent dealers due to another dealer exit (Ozturk et al. 2016), and quality pattern of cars sold through dealers (Biglaiser et al. 2020), among others. We contribute to the empirical strand of this literature by examining changes in B2B transactions of used vehicles among auto dealers, in response to product recalls.

Empirical Setting

The empirical setting for our study is based on B2B transactions in which new and used vehicle dealers buy vehicles from other dealers or from companies selling their fleets. The

[44] In 2017, approximate $470 billion worth used vehicle transactions took place in the US (an average $12,000 price per vehicle). In comparison, eBay, one of the leading platforms for used consumer durables, generated $89.82 billion in gross merchandise volume in 2018 (eBay annual report 2019).

[45] See https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/used-cars-new-platforms-accelerating-sales-in-a-digitally-disrupted-market, accessed December 2020.

wholesale used auto auction industry provides the largest source of inventory of used vehicles for car dealers. National Independent Automobile Dealers Association survey reported that up to 83.38% of dealers use auctions to acquire their used vehicles (NIADA 2018). Each year approximately 40 million used cars transactions occur the United States, 15 million of which pass through a wholesale auction house (Larsen 2020). The fragmented wholesale auction industry includes around 320 auction houses scattered across the country.

Data Description

The B2B transactions data that we use comes from one of the largest of auction operators that maintains 125 traditional (brick-and-mortar) and mobile auction sites and realizes $3 billion in revenues, mainly earned from fees paid by the buyers and sellers following a successful transaction. The B2B sellers mostly are automobile dealers selling their used vehicles in English-style auctions, and the B2B buyers are fellow dealers. Auto manufacturers also rely on wholesale auction houses to sell cars returned by consumers. Further, car rental agencies turn to auctions to sell used vehicles from their fleets, before the vehicles factory warranty expires. Financial institutions also use wholesale auctions to deal with their car inventories. Sellers bring the cars to the auction house, usually several days before the sale, and establish a secret reserve price. In the days preceding the sale, potential buyers may view car details and pictures online, including condition reports by fleet and lease sellers; they can visit the auction house to inspect and test-drive cars. The auction takes place in a large, warehouse-like space with multiple lanes. An auctioneer runs each lane, and simultaneously, vehicles move to the front of each lane. The auctioneers call out bids, raising the price until one bidder remains. If the final price falls short of the secret reservation price, the vehicle remains unsold. Auctioneers might try to sell unsold vehicles later, and might attempt to sell some vehicles several times over several days before successful transactions; sellers also have the option to pull vehicles from the auction. Genesove (1993) provides a detailed description of a typical wholesale used auto auction.

We obtain detailed information about more than 7.83 million successful transactions that occurred between January 2005 and November 2008, for the total sales value of about $97.66 billion; these transactions involved 26 automobile makes.[46] The average transaction prices in the broad passenger vehicle category (comprising compact, full-size, luxury, midsize, minivan, sports, sports utility vehicle, and subcompact) is $12,599, and an average of 1,236 vehicles sell in each auction region in a given day. The auctioneer prominently displays vehicle details on the windshield of each vehicle; we provide a condition report in Table WB 4.1 (Appendix).

The wholesale auction operator uses a proprietary, internet-based technology to allow sellers and buyers to participate in live physical auctions via real-time audio and video. Video cameras in auction lanes allow online users to view the vehicle, observe the physical bidding activity, and place their bids, which then appear on a screen located in the physical lane. Table 4.2 provides the summary statistics for key variables. For each automobile presented at auction, we observe its make (e.g., Audi, BMW, Ford, Honda), model (e.g., Accord, Altima, Civic, Sentra), and model year (year 2000 to 2008 include 94.31% of total observations). The wholesale auction house categorizes each vehicle into a segment (i.e., compact, full-size, luxury, midsize, minivan, sports, pickup, sport utility vehicle, subcompact, and wagon). We obtain the odometer reading for each vehicle, certified by the auctioneer; the mean and median odometer values (miles) for presented vehicles were 42,916 and 29,830, respectively. Vehicles with a 2005

[46] These makes include Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, Honda, Hyundai, Infiniti, Jaguar, Kia, Lexus, Lincoln, Mazda, Mercedes, Mini, Mitsubishi, Nissan, Porsche, Subaru, Toyota, Volkswagen, and Volvo.

model-year represent the largest year group in our data (20.57%). Vehicles with condition level[47] 3 were the most frequent group (58%). We also observe the vehicle source; majority were either leased vehicles (45.9%) or factory vehicle (29.3%). Approximately 87% of vehicles were registered to sell on the auction company owned proprietary online platform. Other key variables include the number of times a vehicle appeared in the auction before it was sold or removed from the auction, vehicle's sequence number in the auction (order in which it was presented), and whether the seller or buyer represents a large dealer group.

(Please see Table 4.2)

We augment our auction database with product recall data from the U.S. Department of Transportation (e.g., Eilert et al. 2017; Haunschild and Rhee 2004; Liu and Shankar 2015). A product recall occurs if an automaker or the National Highway Traffic Safety Administration (NHTSA) identifies a safety defect or violation in an automobile. The process generally starts with consumer complaints, though the automaker's own tests also might reveal defects. Consumers can submit complaints through multiple channels (e.g., phone, email, website, and questionnaires). Regardless of their source, the NHTSA is responsible for reviewing vehicle safety, initiating recalls (if necessary), and monitoring the effectiveness of ongoing recalls. NHTSA receives approximately 4,000 complaints about potential safety issues every month.[48] If an automaker initiates a recall on its own, it represents a voluntary recall, but if it occurs following the NHTSA's recommendation, it is a mandatory recall (Rupp and Taylor 2002). Vehicle recalls information includes the name of the recalling vehicle make, model, number of affected units, and a brief description of the defect. For a four-year period (2005–2008), 625

---

[47] Vehicle's condition score, as reported in the condition report (Table WB 4.1; Appendix) varies from 0 (worst condition) to 5 (best condition).

[48] See https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/810552.pdf, accessed December 2020.

recalls appear in the recall database and these recalls span different vehicle categories such as cars, trucks, and motorbikes. Figure 4.1 displays the number of recalls per week over this period.

(Please see Figure 4.1)

Empirical Model and Identification Strategy

We exploit a quasi-natural experimental setting and employ a difference-in-difference estimation strategy (DiD) to estimate the impact of product recalls on the recalled product and non-recalled products. Specifically, our quasi-experimental design leverages the as-if random variation in the timing of product recalls to clearly delineate treatment and control groups pre- and post-recall, to obtain an appropriate counterfactual to estimate our causal treatment effect. In particular, DiD can estimate the effect of a specific intervention or treatment (e.g., recall) by comparing changes in outcomes over time between a treatment population and a control population that is not exposed to the treatment.

Our DiD empirical strategy is not subject to endogenous sorting concerns that often plague other DiD designs. This is because product recalls are issued by the NHTSA or voluntarily exercised by the automaker and therefore exogenous to our B2B buyers. Furthermore, these recalls are unforeseen until announced by the NHTSA or the automaker, so the systematic selection of vehicles into the treatment and control group should not occur within a tight time-window pre- and post the recall announcement (1-day pre- and 1-day post recall in our setting). Given these unique institutional features of our empirical setting, our DiD can credibly estimate the causal impact of a product recall. We do so by comparing the price differential (post-treatment – pretreatment) of observationally identical vehicles in the treatment group with the price differential (post-treatment – pretreatment) of observationally identical vehicles in the control group, within a narrow time window pre- and post the product recall announcement. Formally,

$$P_{ij} = \beta_0 + \beta_1 T_i + \beta_2 R_j + \beta_3 (T_i \times R_j) + \epsilon_{ij} \quad (1)$$

where P_{ij} is the used vehicle's transaction price in group i in j period, and ϵ_{ij} is a random error that given our quasi-experimental design is assumed to be uncorrelated with our treatment indicator variable T_j. The data set contains two groups i (treatment and control) and two time-periods j (pre- and post-recall). The indicator variable T_i reflects the mean differences in prices between the treatment and control groups, indicated by the coefficient β_1. The indicator variable R_j captures naturally occurring mean differences in the post-recall period price, relative to the pre-recall period price, captured by β_2. Finally, β_3, the estimate of the treatment effect, indicates the difference in price (DiD) between treatment and control groups, after controlling for differences across groups and time shocks common to both, given as:

$$\beta_3 = [E(P_{ij}|i = 1, j = 1) - E(P_{ij}|i = 1, j = 0)] - [E(P_{ij}|i = 0, j = 1) - E(P_{ij}|i = 0, j = 0)] \quad (2)$$

Any deviation in differences in prices for the treatment versus control group provides a causal estimate of the treatment effect. The choice of the control group is critical to support a credible imputation of the counterfactual outcomes for the treated group. Passenger vehicle category (which includes segments of compact car, full-size car, luxury car, midsize car, minivan, sports car, sport utility vehicle, subcompact car, and wagon) represents our treatment group. In this context, one option is to use non-recalled models of the same make (e.g., non-recalled Honda Accord could be the control group for a recalled Honda Civic).

However, if buyers were to switch to Honda Accord following a Honda Civic recall, this control group would also be subject to a treatment and would bias the estimation. Considering the non-recalled passenger vehicles of a different automaker (e.g., Toyota) as a control group may also lead to bias if buyers were to switch to passenger vehicles of other makes. Therefore, we use vehicles from a different vehicle category (cargo van) as a control group. We believe such an identifying assumption is justified because B2B buyers are not likely to switch purchases between passenger vehicles and cargo vans following a product recall, due to their different uses, customer segments, and so forth.[49]

By choosing cargo vans as the control group in our DiD framework, our empirical strategy affords us the natural ability to explore the price implication of product recalls should our B2B buyers switch among passenger vehicle segments (e.g., midsize to fullsize) both within the recalled automaker and to the recalled automakers competitors. Thus, our choice of control group (cargo van) helps mitigate estimation biases that arise in studies that use non-recalled passenger vehicles as the control group (e.g., Ater and Yosef 2018; Che et al. 2020; Strittmatter and Lechner 2020). We also check that that cargo van recalls do not overlap with each other.

Focusing on passenger vehicle category[50] leads to a universe of 488 unique recalls (an average of 1 recall every 2.99 days). Due to such high frequency, to establish the causal impact of a single recall, we must carefully select events to avoid any potential contamination that may arise from overlapping recalls. Hence we use the following three steps to isolate specific recall events. First, similar to event studies (e.g., Agrawal and Kamakura 1995; Chen et al. 2009), we apply a narrow, one-day window {-1, +1} for vehicle transactions before and after the recall announcement. If a focal recall occurs on day 0, transactions one day prior and one day later enter the empirical analysis. The auction prices for yet-to-be-recalled make-model-year vehicles before the recall is announced constitute the credible counterfactual for post-recall prices, had the

[49] Conceptually, this is similar to the approach used by Liu and Shankar (2015), who use the characteristics of nonpassenger vehicle categories (e.g., minivan, light truck) to build instruments for the passenger car category. Moreover, in the automobile industry, competition occurs primarily within a vehicle segment (Albuquerque and Bronnenberg 2012), i.e., customers first select a segment (e.g., compact, full-size) and then choose among the various car brands within it (Zhou et al. 2019).

[50] We exclude recalls in other categories (buses, motorbikes, pickups, recreational vehicles, and trucks) as well.

recall not been issued. Transactions on day 0 are excluded; they arguably could be part of either the pre- or post-recall group.[51] The {-1, +1} transaction window assumes that B2B buyers quickly adjust in response to product recalls; any influence on used vehicle auction prices beyond day 1 is not addressed directly in our model (we test a different window as a robustness check, as detailed in Section 6.4). However, if the effects persist, our {-1, +1} window offers a conservative estimate of the full effect of product recalls. The narrow time window also is appealing, because it mitigates the potential for confounding effects by other exogenous shocks or proximate product recalls (Figure 4.1). To ensure that other trailing or following recalls do not influence pre-recall observations for a focal recall, we require that, for a focal recall on day 0, any trailing recall must be at least two days separate, and the following recall should be at least one day apart. This means that for the {-1, +1} period auction transactions to be valid for analysis, the focal recall event window is {-2, +1}. This step helps us avoid overlap among recall impact and filter recall events.

Second, to avoid correlational effects across makes, we consider single-make recalls only. For example, if a recall includes both Acura and Lexus vehicles, any post-recall changes for Acura vehicles cannot be credibly attributed to the Acura recall, because Lexus buyers might have switched to Acura due to the simultaneous Lexus recall, and vice versa. Third, as part of our mandate to include only passenger vehicles in the treatment group, we remove any recall that also includes other vehicle categories.[52] For example, a Dodge recall (campaign number 08E064000) included both sports utility vehicles (Durango) and pickup trucks (Dakota). We dropped this event from the analysis, because pickup trucks are not part of the treatment group.

[51] We do not observe the exact time during day 0 that a recall notice becomes public knowledge.

[52] These include buses, motorbikes, pickup trucks, recreational vehicles, and trucks.

Importantly, fewer makes are available for the control group than the treatment group of passenger vehicles, because fewer automakers compete in the cargo van category. Hence, to avoid unobserved factors and to ensure the similarity of automakers in both treatment and control group, we consider the same set of vehicle makes, which appear in both passenger vehicle and cargo van category. We observe four makes in the cargo van category (Chevrolet, Dodge, Ford, and Volkswagen). Therefore, the treatment group also consists of these four automakers, which correspond to 13 passenger vehicle models (e.g., Focus, Jetta) and 48 unique make-model-year units (e.g., Ford-Focus-2005, Dodge-Caravan-2002). Limiting the treatment group to these four makes produces 19 unique recalls (Table 4.3) for the estimation. This multistep procedure enables us to create recall events that do not overlap with other recalls and avoid other confounding factors. None of these events overlaps with any cargo van (control group) recall. We then collect B2B auction transactions around these chosen events for the DiD estimation.

(Please see Table 4.3)

We also apply several sample selection criteria to the raw data. The odometer readings and prices of sold vehicles must be positive. The vehicle condition value must be a non-negative number, because this variable can vary only from 0 to 5. To match the auction data period (2005-2008), we only consider vehicles with model year 2008 or earlier. We drop transactions where vehicle's model-year value is greater than the vehicle's auction year. To address missing segment information for vehicle observations, we refer to the EPA website.[53] To ensure uniformity, we also check the make and model names in both auction and recall data.

We create four product groups for the analysis (Figure 4.2). Product group 1 includes passenger vehicles recalled by the automaker or the regulator; NHSTA database provides make-

[53] See https://www.fueleconomy.gov/feg/download.shtml, accessed December 2020.

model-year of recalled vehicles (e.g., Ford Fiesta 2005). Product group 2 consists of passenger vehicles that do not face recall, though they belong to the same make as the recalled vehicle. If Acura MDX faces recall, its Product group 2 would comprise non-recalled Acura models (e.g., Acura RDX). Product group 3 vehicles did not experience a recall, and they belong to competing makes. For example, for Acura MDX recall, group 3 might refer to Toyota models. Finally, Product group 4 contains the cargo van category vehicles (control group).

(Please see Figure 4.2)

For each product group, we seek to answer various research questions. With product groups 1 and 4, we can apply the DiD estimator to quantify the direct impact of product recalls on transaction prices for the recalled product. Product groups 2 and 4 indicate the effect on the transaction prices of unaffected products that belong to the recalled automaker. Product groups 3 and 4 indicate the effect on the transaction prices of unaffected products of other automakers that do not face any recall.

Estimation

Using the naturally occurring variation in the timing of the various product recalls, coupled with our DiD estimator, we credibly estimate the causal impact of product recalls on the wholesale used vehicle transactions with auto dealers (buyers and sellers). Figure 4.3 displays the change in mean auction prices, before and after recalls, revealing that the mean auction price is lower one day after a recall than one-day prior. A product recall may have a negative impact on the transaction prices of recalled products in used vehicle markets. However, the mean prices for product group 2, non-recalled models with the same make, are higher one day after the recall than one day before, implying a positive spillover effect. We also observe changes in the auction prices of vehicles of other makes, in product group 3, reflecting a negative spillover effect on competitors. These results are exploratory, but they imply the possibility of determining direct and spillover effects of product recalls in the empirical context of B2B used vehicle sales.

(Please see Figure 4.3)

We use the following basic model specification for our analysis:

$$ln(P_{ij}) = \alpha_0 + \alpha_1 Treated_i + \alpha_2 Postrecall_j + \alpha_3 Treated_i * Postrecall_j + \epsilon_{ij} \quad (3)$$

where *i* corresponds to a particular group (treatment or control), and *j* corresponds to pre vs post recall period. P_{ij} is the used vehicle's transaction price in group *i* in *j* period. The indicator $Treated_i$ takes a value of 1 for the treatment group and 0 otherwise. $Postrecall_j$ equals 1 for the post-recall period and 0 otherwise. The coefficient α_3 captures the impact of the product recall on the treated group in the post-recall period.

To reduce threats from omitted factors, we include a battery of fixed effects that account for time-invariant differences between the treatment and control groups. First, vehicle-specific fixed effects (make and models) account for unobserved time-invariant differences that could affect both recall probability and prices. For example, a specific make might follow a higher manufacturing quality standard due to host country quality regulations, which could affect the vehicle's recall probability. The quality differential also would affect prices, because high-quality vehicles would be more desirable to buyers. Second, time fixed effects (year, month, and weekday) account for seasonality and macroeconomic trends. Kini et al. (2017) find that poor financial conditions affect quality, which may lead to more recalls. Therefore, we anticipate that economic cycles, such as recessions, not only affect the recall probability but also affect prices, if demand decreases during economic slowdowns. Third, we control for time-invariant cross-sectional differences in demand conditions across auction locations using regional fixed effects.

The secondary market setting also requires us to address some potential unobserved differences between otherwise identical vehicles, a problem absent in new vehicle markets. In particular, two identical make-model-year vehicles might differ greatly, depending on their levels of wear-and-tear or mileage. We include the condition score, as reported in the vehicle's condition report (Table WB 4.1; Appendix). We include the vehicle-specific odometer reading that provides a flexible measure of the effect of mileage on prices; vehicles with fewer miles generally attract more attention and potentially a price premium. These features also account for a vehicle's durability. A higher quality rating vehicle should be more durable than a lower quality rating vehicle. Therefore, the vehicle's condition score would account for its durability. Vehicle-specific odometer reading would also capture the variation in vehicles' durability levels. Make and model level fixed effects would control for time-invariant unobservables (e.g., better manufacturing facility) that influence a vehicle's durability. We also integrate an element of the competitive environment by considering if the auctioned vehicle was part of a closed sale (limited to specific franchised dealers). Auctioneer also provides a labor cost estimate to improve the vehicle condition. Controlling for labor costs, which could affect auction prices, helps delineate the true impact of the focal recalls.

Finally, we address some auction features. The lane in which a vehicle appears and its sequence within the lane can directly affect prices (Grether et al. 2009). This allow us to allay control for unobserved factors such as systematic differences (if any) in the number of potential bidders across lanes and over time within the same auction date. We do so because some buyers specialize in specific makes, models, or vehicle types; for example, franchise dealers will focus on lanes that contain the types of vehicles they want. In turn, auctioneers might group vehicles by particular criteria, such as make, in specific lanes or according to a particular sequence to attract larger crowds. Including the sequence number for each vehicle also allows us to incorporates the possibility that potential buyers may have less money to spend later in the auction than earlier in the auction (Grether et al. 2009).

In addition, we also condition on the number of times the vehicle moves through the auction lane, as well as whether the vehicle was registered on the auctioneer firm's proprietary online platform. Online auctions could increase competition among buyers and thus affect prices. Including proprietary platform dummy controls for any systematic differences (e.g., financial resources) that might mark buyers who tend to participate online. We also control for the seller's category (dealer/daily rental/factory/lease) for each vehicle. We also indicate if the seller/buyer is part of a mega group. Table 4.4 contains the definitions and sources for these covariates.

(Please see Table 4.4)

A key identifying assumption of a DiD setting is the parallel trend assumption; in the absence of treatment, the difference between the treatment and control groups should be constant over time. We validate this assumption by comparing the treatment group's prices with that of the control group during the pretreatment period. This assumption establishes that the treatment and control group prices would have changed at a similar rate in the absence of treatment. We estimate the following model to assess the parallel trends assumption:

$$ln(P_{it}) = \theta_0 + \theta_1 Treated_i + \sum_{t=1}^{t=5} \beta_t\, Day_t + \sum_{t=1}^{t=5} \gamma_t\, Treated_i * Day_t + \theta_2 Covariates + \epsilon_{it} \quad (4)$$

where Day_t takes value 1 when it is *t* day prior to the recall and 0 otherwise. We defined the other variables earlier. We consider a set of β coefficients for each day (day -5 to day -1) prior to the recall event (0^{th} day); these β coefficients estimate the difference in the price between the treatment and control groups on a specific day prior to the recall. As shown in Table WB 4.2

(Appendix), we do not find statistically significant differences in the pretreatment price between the treatment and control groups.

Building on equation 3, the final model specification takes the following form:

$$ln(P_{ij}) = \alpha_0 + \alpha_1 Treated_i + \alpha_2 Postrecall_j + \alpha_3 Treated_i * Postrecall_j + \alpha_4 Covariates + \epsilon_{ij} \quad (5)$$

where *i* corresponds to a particular group (treatment or control). $Treated_i$ takes a value of 1 for the treatment group and 0 otherwise. $Postrecall_j$ equals 1 for the post-recall period and 0 otherwise. Covariates include several vehicle features, auction features, and fixed effects.

A potential threat to identification stems from the concern that a recall may motivate sellers to sell recalled vehicles, which would cause selection bias. To temper any residual concern from potential selection bias, our main empirical analysis focuses on a narrow window {-1 day, +1 day} pre- and post recall announcement. We limit our sample to this small window because it is highly unlikely that a potential seller would be able to adjust the composition of vehicles they bring to the auction floor the day before/after the recall announcement. This lack of adjustment possibility arises because, in order to sell vehicle in the auction, the seller has to follow few administrative practices (e.g., bringing vehicles to the lot, competing vehicle registration, obtaining condition report), which happen at least few days in advance. Thus, we are unlikely to observe a surge in vehicles' supply in the auction on the 1^{st} day due to a recall on the 0^{th} day.

Results

Direct Effects

The net impact of recalls on dealers' demand responses during used vehicle purchase is not clear *ex ante*. On the one hand, negativity associated with the recall could make a defective vehicle an undesirable proposition. This could lead to lower demand for the recalled vehicle in the B2B auction. Federal law does not prohibit dealers from selling a used car with an outstanding recall; therefore, dealers can sell the vehicle without any recall repair. On the other hand, the dealer may decide to repair the defect to improve the vehicle quality. Since automakers pay for the repair costs, this quality improvement occurs at no cost for the dealer.[54,55] Such possible quality improvement might offset the negativity associated with the recall and encourage dealers to consider recalled vehicles' purchases. These two opposing factors (recall negativity and quality improvement) lead to a potential trade-off. The net impact on used vehicle auction prices from these two countervailing forces is not entirely obvious *ex ante* and remains an open empirical question in our used vehicles B2B context.

We first estimate Equation 5 with product group 1 (recalls) as the treatment group. The dependent variable (price) is a natural log, so the coefficients in the regression represent the proportionate change in price for a one-unit change in the independent variable. In Table 4.5 (Column 2), the interaction coefficient is negative and significant ($\beta = -.106, p < .05$), revealing that used vehicle prices in the treatment group decrease by 10.06% (100*$(1 - e^{-.106})$) relative to the control group in the post-recall period.[56] A used passenger vehicle with an average price of \$10,369 would experience a loss of \$1,043. It appears that any favorable demand effect, due to the improved, repaired condition of the vehicle (and potential profits) might be offset by

[54] Few dealers may even see the recall as an opportunity to enhance customer satisfaction and repeat business. See https://www.prnewswire.com/news-releases/despite-three-year-increase-in-recalls-satisfaction-among-recall-customers-continues-to-climb-300051934.html, accessed December 2020.

[55] The repair process may also carry some costs (e.g., storing and insuring the vehicle while it is waiting for the repair, depreciation costs), which might reduce recalled vehicle's future profitability. Dealers cannot completely control these costs, as repair process is also dependent on the affiliated entities (e.g., vehicle manufacturers). During 2010–2014, approximately 46% of recalls took more than 45 days to be repaired (NADA 2015). Currently, this study does not focus on the future profitability of used car transaction between dealer and the consumer.

[56] We repeat this analysis by replacing odometer reading with model-year variable and find similar results (Table WB 3).

the negative effect of the costs associated with the vehicle. Thus, recalled vehicles are less financially desirable, which lowers dealers 'willingness to pay at auction. Next, to address potential heterogeneity in these effects, we explore four key dimensions: whether the recall involved a single or multiple models, who initiated the recall, the vehicle mileage, and the type of buyer/dealer.

Breadth of Recall: We measure the breadth of a recall according to whether it involves one or more vehicle models (e.g., Civic). A recall that involves multiple models indicates a widespread issue, imposes a greater financial burden on the manufacturer, and may delay remedy actions. Such outcomes likely exacerbate dealers' concerns about buying such models. The "Multimodel" variable thus takes a value of 1 if more than one model is involved in the recall and 0 otherwise. For the recalled vehicles in product group 1 (Table 4.5, Column 3), we obtain separate interaction terms for single and multiple make recalls and find that the interaction coefficients, ($\beta = -.100, p < .05$) and ($\beta = -.193, p < .05$), respectively, are negative and significant.[57] A recall with multiple models appears to generate strong negative response from dealers, suggesting a 17.55% (100*($1 - e^{-.193}$)) lower prices (equivalent to $1,819). One possible explanation for this result could be that recalls involving multiple model likely increase dealers 'concerns about repair processes and associated costs.

Initiator of Recall: Dealers' responses to the recall could vary depending on who initiates the recall (automaker/regulator). On the one hand, a voluntary recall (initiated by a firm) might portray the firm as a socially responsible and could reduce the threat of regulatory actions (Govindaraj et al. 2004). A voluntary recall might also produce negative outcomes in the form of stock market losses (Chen et al. 2009). On the other hand, a mandatory recall (recommended by

[57] These two coefficients are not significantly different from each other ((F=1.22, p = .2701).

the regulator) may help the automaker avoid costs in the short-term but with the possible risk of future regulatory actions (Rupp 2001). A few studies explore the differential impacts of this dimension and report mixed results. For example, Jarrell and Peltzman (1985) find limited support for the differential impact of recall types on the stock market. In contrast, Liu et al. (2017) note positive long-term returns due to a voluntary recall. These studies consider stock market outcomes, which reflect investors' expectations of the present value of future cash flows associated with the firm. In the used vehicle market, the price response instead reflects dealers' perceptions of the value of purchasing a used vehicle. Thus, stock market findings might not extend to the used vehicle market.

To understand if automobile recalls impact dealers' transactions, we create a "MFRInflu" variable, which equals 1 for a voluntary recall and 0 otherwise. Results indicate that mandatory recalls exert a more negative impact ($\beta = -.112, p < .05$) on auction prices (Table 4.5, Column 4), suggesting 10.59% lower prices (approximately $1,098); one possible reason could be that dealers use mandatory recalls as a signal for the automaker's lack of willingness or financial resources to deal with the defect. Such perceptions likely worry dealers that rely on manufacturers to provide repair services and weaken demand for vehicles under mandatory recalls. Results do not indicate any negative impact of voluntary recalls; it suggests that buyers consider it a positive signal of the automaker's intentions and preparedness, which could allay dealers' concerns about the remedy plan.

Vehicle Mileage: We also explore heterogeneity with respect to a key vehicle-specific characteristic: mileage reading. We interact Treated X Postrecall with the vehicle's odometer reading to reflect the heterogeneity of vehicles at different stages of their lifecycle. Buyers may respond differently to recalls for vehicles that are relatively new and less used or older and frequently used. Older vehicles might require more frequent repair and maintenance due to natural wear and tear, so a recall might act as an additional signal of quality issue to accentuate the need for future maintenance; dealers would be hesitant about acquiring such products. In Table 4.5, for product group 1, the interaction coefficient ($\beta = -.002, p < .05$) is negative and significant, suggesting that recalled vehicles with more mileage suffer more negative impact in terms of their auction prices. An increment of 1000 more miles on the odometer reading leads to a .2% (100*($1 - \mathrm{e}^{-.002}$)) reduction in the auction prices of the treated units in the postrecall period. Put differently, a used vehicle with an open recall, with an average price of $10,369, would lose $20.7 for every additional 1000 miles.

Type of Buyer: Unlike B2C buyers, B2B auto dealers differ in terms of their affiliation with a vehicle manufacturer (i.e., franchise agreement). While franchise agreements apply only to new vehicles, it may limit the composition of used vehicles a franchise dealer may elect to acquire in the auction. For example, a Ford franchise dealer may be less willing to acquire a non-Ford used vehicle and/or have a higher willingness to pay for a Ford used vehicle than a used non-Ford vehicle in the auction. Therefore, a franchise dealer's differential preference and differential willingness to pay could temper the negative impact of the product recall. In contrast, a franchise dealer's business structure may also have an opposing influence. Franchise dealers earn revenue through two streams (new cars and used cars). If any unfavorable event (e.g., recall) influences one revenue stream (e.g., used car business), they could rely on the other stream (e.g., new car business). Possibility of this alternative source of revenue may make franchise dealers less likely to conduct any business transaction (e.g., purchasing vehicles subject to recall) that could incur additional costs (e.g., storing). In this scenario, franchise dealers may decide not to purchase recalled vehicles, unless the auction price is very low (so the dealer still can earn a reasonable profit even with the additional costs). Thus, franchise dealers may display a higher sensitivity to the product recall leading to an even greater downward pressure on transacted prices on the recalled products belonging the same franchise as the dealer. Given the countervailing forces, the net impact of dealer's franchise affiliation on transacted prices of the recalled product remains an open empirical question.

To study this effect, we categorize a dealer into one of the two groups (franchise or independent) based on its affiliation. A franchised dealer usually features the associated make or manufacturer name in its name (e.g., "Smith Honda Dealership"). Using this information, we create a "Franchised" variable that takes a value of 1 if the buyer is a franchise dealer and 0 otherwise. According to Table 4.5 (Column 6), the interaction coefficient that measures the impact on treatment unit prices in the post recall period ($\beta = -.001, \mathrm{n.s.}$) is negative but statistically non-significant. Thus, the type of buyer does not seem to systematically impact transacted prices of the recalled product.

(Please see Table 4.5)

Spillover Effects

The demand pattern for non-recalled vehicles (product groups 2 and 3) also might change with a recall, in line with evidence citing (e.g., Freedman et al. 2012; Marsh et al. 2004) spillover effects in consumers' reactions to recalls. Empirical studies document the spillover effect of negative events on other products of the same manufacturer (e.g., Borah and Tellis 2016). For example, Liu and Shankar (2015) find negative spillover effects of the recall of a sub-brand on the market shares of other sub-brands under the same parent-brand name. Previous research also highlights the presence of spillover effect among competitors in different settings (e.g., Ozturk et al. 2019; Roehm and Tybout 2006). For example, Freedman et al. (2012) find that competing manufacturers lose sales due to a large-scale toy recall's negative spillover effects; dubbed as a “contagion effect” (Ozturk et al. 2019). A recall signals negative information about the product’s industry, so it could lower consumers’ confidence and damage the competitors that produce non-recalled products. Similarly, Warner (1977) discusses that if a bankruptcy reveals negative information about the industry, the negative information could negatively affect competitors’ outcomes (i.e., stock prices).

Importantly, positive spillover effects are also possible (“competitive effect”) in our context; potential buyers of recalled products might switch to other non-recalled products following a recall crisis. The dealers want to maintain their business, so they likely seek alternatives if their preferred options face recalls; this could lead to higher demand for non-recalled vehicles at the auction. Again, positive spillover effects could be on other products of the same automaker or other automakers in the segment.

To shed light on these effects, we again estimate Equation 5 with product group 2 as the treatment group. In the {-1, +1} window, no other recall shocks occur, so any significant change in the auction prices of vehicles that were not recalled would suggest a contagion/competitive effect. In Column 1 of Table 4.6, we find a positive, significant coefficient ($\beta = -.120, p < .05$) for Treated X Postrecall interaction and evidence of the competitive effect, suggesting that used vehicle prices in the product group 2 increases by 12.74% (100*($e^{.120} - 1$)) relative to the control group in the post-recall period. This result may indicate that dealers substitute recalled models with non-recalled models of the same make, leading to a price increase for product group 2. When we incorporate other covariates (Column 2, Table 4.6), the coefficient remains directionally consistent ($\beta = -.024, n.s.$) but is not statistically significant. This finding warrants additional scrutiny. Thus, we explore heterogeneity across different dimensions, similar to those we tested in the main effects analysis in Section 5.1. We also analyze spillover to non-recalled vehicles of competing makes (i.e., product group 3) in Table 4.7.

Segment Overlap: Building on prior research (e.g., Ozturk et al. 2019), we explore heterogeneity along the vehicle segment (compact, full-size, luxury, midsize, minivan, sports, sport utility vehicle, subcompact, and wagon). We examine whether non-recalled models display any significant change in prices when (1) non-recalled and recalled models belong to the same segment, or (2) non-recalled and recalled models belong to different segments. Any significant change in non-recalled models' prices would highlight whether dealers substitute to non-recalled models due to recalls. Substitution could lead to increased demand and price in a B2B auction.

We also posit that non-recalled models, which belong to the same segment as the recalled model, may experience negative spillover effects (reduction in prices). This negative spillover may stem from dealers perceiving added uncertainty purchasing vehicles with the same segment of the recalled product. Importantly, this within-segment spillover could be on other products of the same automaker or other automakers in the segment.

In line with previous spillover research (e.g., Borah and Tellis 2016), we explore the possibility of a negative spillover effect on the demand for non-recalled vehicles that belong to the same segment as the recalled vehicle and the same automaker. For example, different models of the same automaker may share manufacturing processes or contain same vehicle parts, so a defect in one model could appear in the future in other, non-recalled model. Thus, dealers might avoid all vehicles of the segment, which includes the recalled model; lower demand for these non-recalled models would cause lower prices in the B2B auction market. Therefore, consistent with previous research (e.g., Freedman et al. 2012), we could also observe negative spillover effects on the non-recalled models that belong to a different automaker but the same segment as the recalled model, leading to lower prices in the B2B auction market.

Dealers (i.e., B2B buyers) may decide to defer their purchases to a later date or seek alternatives. Dealers are less likely to defer (in comparison to seeking an alternative vehicle) because they need to maintain their businesses. Thus, they likely seek vehicle alternatives in other segments, which do not include the recalled model. For example, let us consider that the Yaris model (subcompact vehicle segment) of Toyota automaker faces recall. Therefore, dealers might switch to non-recalled models in the compact vehicle segment (i.e., segments different from the recall model's segment). Higher demand for non-recalled models in the compact segment could lead to higher prices for these vehicles in the B2B auction (this positive spillover effect is similar to the "competitive effect" discussed in Ozturk et al. 2019). Importantly, dealers may switch segments either within the same automaker (e.g., Toyota-compact to Toyota-SUV) or across a different automaker (e.g., Toyota-compact to Honda-SUV). We consider both possibilities in our empirical analysis.

Switch within the same automaker (i.e., product group 2): We posit that dealers are more likely to switch to non-recalled models within the same automaker. The rationale is that dealers prefer to purchase used vehicles of the same make that their affiliated manufacturer produces (Hortaçsu et al. 2013). For example, a Toyota affiliated dealer is more likely to seek non-recalled models that belong to Toyota in the B2B market. Furthermore, auto dealers might be more historically popular for specific make vehicles (e.g., Lexus vs Toyota) among consumers. Such reputational association might also limit dealers' vehicle purchases in the used vehicle market as dealers would like to buy those vehicles that are more likely to be bought by the consumers. Dealers might also have vehicle part contracts with certain make-specific part suppliers. Due to these constraints (e.g., franchise association, reputation, supplier contracts), we expect dealers to switch to non-recalled models within the same automaker (for example, Toyota to Toyota) than across a different automaker (for example, Toyota to Honda). Thus, we are more likely to observe the aforementioned positive spillover effect (which leads to higher prices) for non-recalled models that belong to the same automaker as the recalled model.

In order to estimate this effect, we create a segment overlap dummy by matching the non-recalled vehicle segment with the recalled vehicle segment. For example, Ford Focus belongs to the compact car segment. Therefore, the Ford Focus recall would produce a segment overlap dummy value of 1 for any compact car and 0 otherwise. We interact Treated X Postrecall with overlap dummy in our main specification, as detailed in Column 3 of Table 4.6. The significant and positive interaction coefficient for Treated X Postrecall ($\beta = .048, p < .05$) confirms the positive spillover effect (when segment overlap dummy is 0). For product group 2, dealers' switch to non-recalled models that do not belong to the same segment as the recalled model leads to 4.91% (100*($e^{.048} - 1$)) higher prices for those non-recalled vehicles (an approximate increase of $509). The interaction coefficient for Treated X Postrecall X Segment overlap is negative ($\beta = -.105, p < .05$); the negative spillover leads to reduced demand for non-recalled vehicles in the same segment as the recalled vehicle (segment overlap dummy =1), causing 5.54% (100*($1 - e^{-.057}$)) lower prices (an approximate decrease of $574).

Switch across different automakers (i.e., product group 3): Dealers may also switch to non-recalled models from a different automaker. We repeat the aforementioned segment dummy analysis to examine changes in non-recalled models' prices for this group.

First consider the non-recalled vehicles belong to the same segment as the recalled vehicle. As discussed in the previous section, similar segment models (even though they belong to a different automaker) might still experience the negative spillover effect (contagion effect), which would lead to lower demand and lower prices. However, these non-recalled models might also experience the positive spillover effect (competitive effect due to dealers' switch), which could increase these vehicles' prices. Determination of which of these two effects would be dominant would require empirical scrutiny.[58]

In comparison, the non-recalled models that belong to a different segment may not experience the negative spillover effect (because of the different segments). However, these models may still experience a positive spillover effect (if dealers switch to these non-recalled models), leading to higher demand. But, this effect might be weak as dealers are less likely to switch across different automakers (as discussed previously). Determining whether this spillover effect would lead to significant change in prices needs to be empirically analysed.

Column 3 of Table 4.7 contains the spillover results for product group 3. The interaction coefficient ($\beta = -.058, p < .05$) for the Treated X Postrecall X Segment overlap (segment overlap dummy = 1) is negative, which suggests that negative spillover also affects non-recalled vehicles that belong to competing automakers but same segment and leads to 5.63% (100*$(1 - \mathrm{e}^{-.058})$) lower prices compared to competing automaker vehicles that belong to different segments (an approximate decrease of \$583 for a used vehicle with an average price of \$10,369). This negative spillover effect is consistent with prior research on contagion effect (e.g., Ozturk et al. 2019). Moreover, the non-significant Treated X Postrecall coefficient ($\beta = -.029, \mathrm{n.s.}$) suggests the positive spillover is limited to same-make vehicles (Table 4.7, Column 3). This result is consistent with our earlier discussion of dealers' affiliations; if dealers prefer

[58] As discussed in the previous section, dealers might be less likely to switch across different automakers (e.g., Toyota midsize vehicle to Ford midsize vehicle) due to dealers' constraints (e.g., affiliation with automakers, reputation). This might weaken the positive spillover (competitive) effect.

specific makes, due to their franchise relationship with the automaker, they are more likely to seek vehicles with affiliated makes as substitutes for a recalled model.

Breadth of Recall: We test this effect by interacting recall breadth (single vs. multiple model recall dummy) with the Treated X Postrecall effect. The interaction coefficient in Table 4.6 (Column 4) shows that recalls involving multiple models display significant positive spillover effects ($\beta = -.178, p < .05$) on the within-make product group 2; the prices for non-recalled models increase by 19.48% (100*(e$^{.178} - 1$)) due to a recall that spans across more than one model. Two factors likely underlie this positive spillover effect. First, a recall that involves multiple models affects more buyers, who now may look for possible substitutes among non-recalled models of the same make. Second, now there are fewer non-recalled substitutes with the same make because more models are part of the recall group. This combination should lead to higher demand for non-recalled models (positive spillover effects). We do not find this effect for product group 3 (Column 4, Table 4.7), so the positive spillover due to buyers 'inclination to look for non-recalled substitutes appears limited mainly to the within-make group.

Type of Buyer: We find heterogeneous responses by buyer types. For vehicles with the same make (Column 7, Table 4.6), the interaction coefficient ($\beta = .034, p < .05$) is positive and statistically significant, indicating that franchise dealers exert positive effects on the demand pattern for the make with which they are affiliated. Franchise dealers tend to be larger, with more resources (Genesove 1993), so all else being equal, they may be able to pay higher prices for non-recalled vehicles. Vehicles purchased by dealers with franchise affiliation with the vehicle display 3.45% (100*(e$^{.034} - 1$)) higher prices compared to the vehicles purchased by a dealer with no franchise affiliation with the vehicle. We do not find such effect for product group 3

(Column 7, Table 4.7), so positive spillovers (related to franchise dealers) are limited to the within-make group. We do not find heterogeneous spillover effects across recall initiators.

(Please see Table 4.6 and 4.7)

Robustness Assessment

Potential Selection Bias

Our empirical analysis thus far is limited to sold vehicles. Should recalls not only affect the transacted prices of sold vehicles but also affect the probability of selling a recalled vehicle, then our sold-only sample may be subject to selection bias. In order to address this concern, we apply a two-step Heckman correction model. In the first step, we model the likelihood of the vehicle being sold (Ti = 1 vs. Ti = 0) with a binary Probit structure, using vehicle characteristics and market variables. The Heckman method introduces a correlation between the error term of the selection equation and the price equation, in the form of the inverse Mills ratio (IMR) as a selection correction term. We use this IMR term in the second step (price model) to address potential selection bias.

For model identification purposes, the Heckman selection approach requires an exclusion restriction; there exists at least one predictor variable that affects the probability of sale of the vehicle but not impact the transacted price of the sold price (Chen et al. 2009). Therefore, we consider the number of similar vehicles offered for auction on a particular day in the same region.[59] For example, for a Honda-Accord-2006 auction on January 1, 2008, we count the number of Honda-Accord-2006 vehicles offered for auction on the same day in that region (e.g., Northeast, Southeast). More similar unit options may affect the probability of sale for the focal

[59] Each auction site belongs to one of six U.S. regions (Northeast, Southeast, Southwest, West coast, Midwest, and Florida). 07% of observations did not contain any region information so these were grouped as “other”. It has no effect on results.

units, but it should not affect a focal unit's auction price directly. We add this variable to the selection equation but exclude it from the second stage for identification (Puhani 2000).

The Heckman model results for the product group 1 (recalled vehicles) reveal a significant and positive IMR ($\beta = .115, p < .05$; Column 1, Table 4.8); this indicates that the error terms of the selection model and price model are positively correlated. However, even after correcting for the selection bias, the results remain consistent with our previous model (Column 2, Table 4.5). Recall does not affect the first-stage model ($\beta = -.190, \mathrm{n.s.}$ Column 1, Table 4.8). The exclusion variable vehicle count is significant and negative ($\beta = -.014, p < .05$), consistent with our intuition that more alternative, similar vehicles generally lower the sale probability of a specific, focal vehicle. The results for product groups 2 and 3 also are in line with previous results. *(Please see Table 4.8)*

Matching Analysis

As an additional robustness test, we combine our DiD estimation strategy with propensity-score matching (PSM) to address imbalances in the key variables between the treatment and control groups and create a control group in which the observable covariates are similar to those for an average treatment group. We first estimate the propensity score for the recall (treatment) group, then estimate the DiD model as a weighted least squares regression with the weights estimated from the PSM algorithms. Through this process, we ensure the treatment group features a similar average level of observable covariates as the control group. We use kernel matching method, so the weighted average of all controls for each treated observation is inversely proportional to the distance between propensity scores. The results for this analysis are reported in Table 4.9, Panel 1. Our main DiD finding remain robust even after undertaking propensity-score matching.[60]

Different Control Groups

We also check the robustness of recall's direct effect on B2B used vehicles market by considering different control groups. First, we consider the non-recalled vehicles of the same automaker as a control group. In Table 4.9 (Panel 2), we show that the results remain consistent; the interaction coefficient is significant and directionally negative ($\beta = -.069, p < .05$). Considering the non-recalled vehicles of other automakers as a control group also suggests similar results, with a negative and significant coefficient ($\beta = -.050, p < .05$).

(Please see Table 4.9)

Different Transaction Windows

For the same set of recalls in the main analysis, we also consider a {-2, +2} window for the auction transactions, such that the recall carryover effect would persist for two days. We present the results for product groups 1–3 in Table WB 4.5 (Appendix).

Concluding Remarks

Extant empirical research on product recalls has focused exclusively on consumer-side reactions to product recalls. Yet most industries that have been investigated thus far in this literature have distribution channels that comprise several B2B intermediary buyers, and the decisions of these buyers may also be impacted by product recalls. In parallel the extant literature on used products has paid limited attention to the impact of product recalls. Understanding B2B implications of product recalls is key to addressing the "B2B knowledge gap" (Lilien 2016) in the literature on used products. This study addresses this research gap. We do so by exploiting

[60] We obtained similar results with radius matching method (Table WB 4.4; Appendix).

the exogenous timing of automobile recalls in the empirical context of used vehicles acquired by auto dealers in a B2B wholesale auction market. Specifically, the study examines whether, and to what extent auto recalls influence B2B buyers' purchasing behavior of the recalled product (direct effect) and other products of the same automaker or other automakers (spillover effect).

Contribution: The current study presents several insights that contribute to the extant literature on various dimensions. First, this study helps integrate two related yet divergent strands of literature in marketing, namely: the literatures on B2B transactions of used goods and the literature on product recalls, which thus far has been exclusively focused on new goods and has not explored B2B implications of product recalls. The empirical setting is the used vehicle wholesale auction market where dealers engage in vehicle purchases from other dealers. We find that the wholesale prices for a used vehicle that faces a recall decreases by 10.06% (an average drop of $1,043). Several recall and vehicle characteristics moderate this impact. For example, recalls that involve multiple models (rather than single-model recalls) cause a stronger negative impact on transaction prices. Mandatory recalls, initiated by the government agency, have stronger adverse effects on prices than the voluntary recalls. We also observe asymmetric impacts on prices due to vehicle mileage; a used vehicle suffers greater negative impacts as the odometer reading rises (an approximate loss of $21 for every 1000 miles accrued).

Second, the study contributes to the literature by documenting the spillover effects of recalls in B2B markets. Previous studies identify recalls' negative spillover to non-affected products of the same manufacturer or non-affected competitors in the category (e.g., Borah and Tellis 2016). These studies, however, explore only consumer-side reactions. We find both negative and positive spillover effects of recalls on other non-recalled models that belong to the same automaker in B2B markets. Specifically, non-recalled models, which belong to the same vehicle segment as the recalled model, experience lower demand at B2B auction (thus about 5.54% lower prices). This effect is consistent with the aforementioned consumer-side reactions that find a negative spillover effect on non-recalled products (contagion effect) due to diminished consumer confidence. Competing automakers' non-recalled models, which belong to the same segment as the recalled model, also experience lower prices (about 5.63%) due to the contagion effect.

We also observe a positive spillover effect. For the same automaker vehicles, we find that non-recalled models, which belong to a different segment as the recalled model, experience higher demand at B2B auction (thus about 4.91% higher prices). Positive spillover suggests dealers' substitution to non-recalled models (competitive effect). Results also display interesting heterogeneity. For example, franchise dealers, which are affiliated with the recalled vehicle manufacturer, pay higher transaction prices (about 3.45% higher) for non-recalled models of the same make than the non-franchise dealers. This finding highlights that franchise relationships could be beneficial for associated automakers' used vehicle demand. Our findings (direct and spillover effect) also suggest implications for the auctioneer because the auctioneer's revenue is tied with vehicles' sale prices. A lower/higher transaction price could decrease/increase the auctioneer's revenue.

Policy landscape: Our findings are also timely and policy relevant. For example, this study can directly inform the ongoing policy debate surrounding the recently proposed Used Car Safety Recall Repair Act. This proposed Act would mandate repairs for used vehicles subject to safety recalls before being sold, leased, or loaned to consumers (Congress 2019). Although the legislation would reduce consumers' exposure to defective vehicles, it has evoked strong criticism from the NADA (2020), which asserted: "*Due to a lack of replacement auto parts, it* *can take months for recalled vehicles to be repaired. Since a used vehicle sitting idle on a dealer's lot depreciates by 2% per month on average, this bill would force dealerships to either pay consumers significantly less for trade-ins with open recalls or not accept trade-ins at all*." Such discussion might partly explain why previous versions of this bill (S. 900, S.1634)[61] did not pass in Congress.

Our findings can inform this debate. For dealers, we show that recalled vehicles are vulnerable to adverse demand reactions, whereas non-recalled models of the same make could earn higher prices. Without claiming direct evidence of policy interventions' impact, our study suggests how auto dealers adjust their demand for recalled products resulting in a spillover effects on non-recalled vehicles, even without any policy intervention. While we do not formally investigate the proposed guidelines advanced in the *Used Car Safety Recall Repair Act*, our findings do highlight a potential concern that the act may unintentionally further increase the demand for substitute (non-recalled) vehicles and prompt higher prices for them. Without a formal structural model we cannot speak to the welfare implications of such price adjustments to the end consumer.[62] Given the B2B focus of this paper, a structural model focused on end-consumers remains outside the scope of this study and a fruitful area of future policy research.

Research implications: This study raises the possibility of exploring new research angles regarding automakers' role in affecting dealers' B2B purchases during recalls. For example, what could be the impact on dealers' purchases if automakers invest in establishing more effective repair processes (e.g., quick availability of replacement parts for dealers during a

[61] See Bill S.900: https://www.congress.gov/bill/114th-congress/senate-bill/900.
See Bill S.1634: https://www.congress.gov/bill/115th-congress/senate-bill/1634, accessed April 2021.

[62] We do not observe retail prices for used vehicles sale to consumers, thus cannot assess implications for dealer's profit for each vehicle transaction.

recall)? As discussed earlier, auto industry experts cite a lack of replacement auto parts during the recall process as a serious concern for the dealers because slow availability of vehicle parts could lead to additional costs such as depreciation, insurance, and storage (NADA 2015). Ideally, if a defective vehicle gets repaired without any delay or additional costs, the dealer should not be concerned about acquiring recalled vehicles in auctions. In such a scenario, B2B transactions of recalled vehicles might not observe any price change. However, currently such concerns do arise, which possibly change vehicles' demand in auctions. Therefore, exploring how changes in the automaker's repair processes could allay dealers' concerns and provide buffer against a recall's impact on the B2B secondary market could be a future research area.

This study also carries research implications for the crisis communication between an automaker and the dealer. We find that focal automaker's non-recalled vehicles, which belong to the same segment as the recalled vehicle, face a negative spillover effect. Roehm and Tybout (2006) discuss that stakeholders might activate a scandal spillover target (e.g., a category) as the scandal information is processed. When the scandal attribute is associated with the category, activation of a category as a spillover target is especially likely to occur. Therefore, what actions (i.e., immediate communication) could the marketing managers of focal automaker take to limit a recall's spillover impact? What could be the key elements of such communication? Our study finds a negative spillover within the recalled vehicle's segment (e.g., compact). Therefore, we speculate that as soon as there is a recall, automakers should swiftly relay relevant information (e.g., common suppliers, scope of defect) to dealers to explain how the defect does not affect its non-recalled vehicles. Helping disassociate defect information from non-recalled products could reduce the negative spillover impact. In particular, impact of recall seems to be stronger when a recall is government mandated.

Similarly, focus on other automakers, who do not face a recall, could present another research opportunity. Marketing managers of non-recalled automakers should keep an eye on others' recall. We find that other automakers' vehicles that belong to the same segment as the recalled vehicle also face a negative spillover. Roehm and Tybout (2006) discuss that competitors of the scandalized brand might also be considered guilty by association. Social comparison theory suggests that firms can protect their image or status by avoiding comparisons with another firm undergoing a crisis (Snyder, Lassegard, and Ford 1986). Therefore, if the automaker, which does not face a recall, proactively communicates information regarding how the specific recall does not associate with its vehicles, it could help possibly minimize the negative spillover in the B2B market.

REFERENCES

Agrawal, Jagdish and Wagner Kamakura (1995) "The Economic Worth of Celebrity Endorsers: An Event Study Analysis," *Journal of Marketing*, 59 (3), 56–62.

Albuquerque, Paulo and Bart Bronnenberg (2012) "Measuring The Impact of Negative Demand Shocks on Car Dealer Networks," *Marketing Science,* 31 (1), 4–23.

Ater, Itai and Nir Yosef (2018) "The impact of product recalls on the secondary market: Evidence from dieselgate," Working Paper, Tel Aviv University.

Bachmann, Ruediger, Gabriel Ehrlich, Ying Fan, Dimitrije Ruzic, and Benjamin Leard (2019) "Firms and Collective Reputation: The Volkswagen Emissions Scandal as a Case Study," NBER Working Paper.

Bala, Ram, Pradeep Bhardwaj, Pradeep K. Chintagunta (2017) "Pharmaceutical Product Recalls: Category Effects and Competitor Response," *Marketing Science*, 36 (6), 931–943.

Barber, Brad M. and Masako N. Darrough (1996) "Product Reliability and Firm Value: The Experience of American and Japanese Automakers, 1973–1992," *Journal of Political Economy,* 104 (5), 1084–1099.

Bennett, Victor M., Robert Seamans, and Feng Zhu (2015) "Cannibalization and Option Value Effects of Secondary Markets: Evidence from the US Concert Industry," *Strategic Management Journal,* 36 (11), 1599–1614.

Biglaiser, Gary, Fei Li,Charles Murry, and Yiyi Zhou (2020) "Intermediaries and Product Quality in Used Car Markets," *RAND Journal of Economics*, 51 (3), 905–933.

Borah, Abhishek and Gerard J. Tellis (2016) "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research,* 53 (2), 143–160.

Bucklin, Randolph E., S. Siddarth, and Jorge M. Silva-Risso (2008) "Distribution Intensity and New Car Choice," *Journal of Marketing Research,* 45 (4), 473–486.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer (2013) "Are Consumers Myopic? Evidence from New and Used Car Purchases," *American Economic Review*, 103 (1), 220–256.

Cachon, Gérard P., Santiago Gallino, and Marcelo Olivares (2019) "Does Adding Inventory Increase Sales? Evidence of a Scarcity Effect in U.S. Automobile Dealerships," *Management Science,* 65 (4), 1469–1485.

Che, Xiaogang, Hajime Katayama, and Peter Lee (2020) “Willingness to Pay for Brand Reputation: Lessons from the Volkswagen Diesel Emissions Scandal,” Working Paper, University of London.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009) “Does a Firm's Product-Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives during Product-Harm Crises,” *Journal of Marketing Research*, 73 (6), 214–226.

Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013) Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises,” *Journal of Marketing*, 77 (2), 58–77.

Cleeren, Kathleen, Marnik G. Dekimpe, and Harald J. van Heerde (2017) “Marketing Research on Product-Harm Crises: A Review, Managerial Implications, and an Agenda for Future Research,” *Journal of the Academy of Marketing Science,* 45 (5), 593–615.

Collins, J. Michael, Kosali I. Simon, and Sharon Tennyson (2013) “Drug Withdrawals and the Utilization of Therapeutic Substitutes: The Case of Vioxx,” *Journal of Economic Behavior and Organization*, 86, 148–168.

Congress (2019) S.1971 - Used Car Safety Recall Repair Act, (accessed December 17, 2020), [available at https://www.congress.gov/bill/116th-congress/senate-bill/1971/text].

Dawar, Niraj and Madan M. Pillutla (2000) “Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations,” *Journal of Marketing Research,* 37 (2), 215–226.

Dranove, David and Chris Olsen (1994) “The Economic Side Effects of Dangerous Drug Announcements,” *Journal of Law and Economics*, 37 (2), 323–348.

Ebay (2019) Annual Report, (accessed May 17, 2020), [available at https://ebay.q4cdn.com/610426115/files/doc_financials/2019/ar/2019-Annual-Report-(3).pdf].

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017) “Does it Pay to Recall your Product Early? An Empirical Investigation in the Automobile Industry,” *J. Marketing*. 81 (3), 111–129.

Freedman, Seth M., Melissa Schettini Kearney, and Mara Lederman (2012) “Product Recalls, Imperfect Information, and Spillover Effects: Lessons from the Consumer Response to the 2007 Toy Recalls,” *Review of Economics and Statistics,* 94 (2), 499–516.

Gavazza, Alessandro, Alessandro Lizzeri, and Nikita Roketskiy (2014) “A Quantitative Analysis of the Used-Car Market,” *American Economic Review*, 104 (11), 3668–3700.

Genesove, David (1993) “Adverse Selection in the Wholesale Used Car Market,” *Journal of Political Economy,* 101 (4), 644–665.

Genesove, David (1995) “Search at Wholesale Auto Auctions,” *Quarterly Journal of Economics,* 110 (1), 23–49.

Ghose, Anindya, Michael D. Smith, and Rahul Telang (2006) “Internet Exchanges for Used Books: An Empirical Analysis of Product Cannibalization and Welfare Impact,” *Information Systems Research,* 17 (1), 3–19.

Ghose, Anindya, Rahul Telang, and Ramayya Krishnan (2005) “Effect of Electronic Secondary Markets on the Supply Chain,” *Journal of Management Information Systems*, 22 (2), 91–120.

Govindaraj, Suresh, Bikki Jaggi, and Beixin Lin (2004) “Market Overreaction to Product Recall Revisited—The Case of Firestone Tires and the Ford Explorer,” *Review of Quantitative Finance and Accounting,* 23 (1), 31–54.

Grether, David and Charles Plott (2009) “Sequencing Strategies in Large, Competitive, Ascending Price Automobile Auctions: An experimental examination,” *Journal of Economic Behavior and Organization*, 71 (2), 75–88.

Grether, David, David Porter, and Matthew Shum (2015) “Cyber-Shilling in Automobile Auctions: Evidence from a Field Experiment,” *American Economic Journal: Microeconomics,* 7 (3), 85–103.

Hammond, Robert G. (2013) “Sudden Unintended Used-Price Deceleration? The 2009–2010 Toyota Recalls,” *Journal of Economics & Management Strategy,* 22 (1), 78–100.

Hartman, Raymond S. (1987) “Product Quality and Market Efficiency: The Effect of Product Recalls on Resale Prices and Firm Valuation,” *Review of Economics and Statistics,* 69 (2), 367–372.

Haunschild, Pamela R. and Mooweon Rhee (2004) “The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls,” *Management Science,* 50 (11), 1545–1560.

He, Shu, Huaxia Rui and Andrew B. Whinston (2018) “Social Media Strategies in Product-Harm Crises,” *Information Systems Research*, 29 (2), 362–380.

Hendricks, Kevin and Vinod R. Singhal (2003) “The Effect of Supply Chain Glitches on Shareholder Wealth,” *Journal of Operations Management*, 21 (5), 501–522.

Hora, Manpreet, Hari Bapuji and Aleda V. Roth (2011) “Safety Hazard and Time to Recall: The Role of Recall Strategy, Product Defect Type, and Supply Chain Player in the U.S. Toy Industry,” *Journal of Operations Management,* 29 (7–8), 766-777.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman (2013) “Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers,” *Review of Financial Studies,* 26 (5), 1248–1290.

Ishihara, Masakazu and Andrew T. Ching (2019) “Dynamic Demand for New and Used Durable Goods Without Physical Depreciation: The Case of Japanese Video Games,” *Marketing Science,* 38 (3), 392–416.

Jacobsen, Mark R. and Arthur A. van Benthem (2015) “Vehicle Scrappage and Gasoline Policy,” *American Economic Review,* 105 (3), 1312–38.

Jarrell, Gregg and Sam Peltzman (1985) “The Impact of Product Recalls on the Wealth of Sellers,” *Journal of Political Economy,* 93 (3), 512–536.

Kini, Omesh, Jaideep Shenoy, and Venkat Subramaniam (2017) “Impact of Financial Leverage on the Incidence and Severity of Product Failures: Evidence from Product Recalls,” *Review of Financial Studies,* 30 (5), 1790–1829.

Kuruzovich, Jason, Siva Viswanathan, and Ritu Agarwal (2010) “Seller Search and Market Outcomes in Online Auctions,” *Management Science,* 56 (10), 1702–1717.

Lacetera, Nicola, Devin G. Pope, and Justin R. Sydnor (2012) “Heuristic Thinking and Limited Attention in the Car Market”. *American Economic Review,* 102 (5), 2206–36.

Lafontaine, Francine and Fiona Scott Morton (2010) “Markets: State Franchise Laws, Dealer Terminations, and the Auto Crisis,”. *Journal of Economic Perspectives,* 24 (3), 233–50.

Larsen, Bradley J (2020) “The Efficiency of Real-World Bargaining: Evidence from Wholesale Used-Auto Auctions,” *Review of Economic Studies,* 88 (2), 851–882.

Lilien, Gary L. (2016) “The B2B Knowledge Gap,” *International Journal of Research in Marketing,* 33 (3), 543–556.

Liu, Yan and Venkatesh Shankar (2015) “The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry,” *Management Science,* 61 (10), 2514–2535.

Liu, Yan, Venkatesh Shankar, and Wonjoo Yun (2017) “Crisis Management Strategies and the Long-Term Effects of Product Recalls on Firm Value,” *Journal of Marketing,* 81 (5), 30–48.

Marsh, Thomas L., Ted C. Schroeder, and James Mintert (2004) “Impacts of Meat Product Recalls on Consumer Demand in The USA,” *Applied Economics,* 36 (9), 897–909.

Murry, Charles and Yiyi Zhou (2020) “Consumer Search and Automobile Dealer Colocation,” *Management Science,* 66 (5), 1909–1934.

NADA (2015) NADA Commissions Report by J.D. Power to Assess Reductions in Trade-In Values Caused by Preventing Sale of Used Vehicles with Open Recalls, (accessed May 17, 2020), [available at https://www.nada.org/CustomTemplates/DetailPressRelease.aspx?id=21474842900].

NADA (2018) Annual financial profile of America’s franchised new-car dealerships, (accessed December 17, 2020),[available at https://www.nada.org/WorkArea/DownloadAsset.aspx?id=21474857318].

NADA (2020) Grounding All Recalled Used Vehicles Devalues Consumer Trade-ins, (accessed May 17, 2020), [available at https://www.nada.org/WorkArea/DownloadAsset.aspx?id=21474838324].

NIADA (2018) Used Car Industry Report, (accessed May 17, 2020), [available at https://www.niada.com/uploads/dynamic_areas/ei5l4ZznCkTc8GyrBKd6/34/UCIR_2018_Web.pdf].

Ozturk, O. Cem, Sriram Venkataraman, and Pradeep K. Chintagunta (2016) “Price Reactions to Rivals’ Local Channel Exits,” *Marketing Science,* 35 (4), 588–604.

Ozturk, O. Cem, Pradeep K. Chintagunta, and Sriram Venkataraman (2019) “Consumer Response to Chapter 11 Bankruptcy: Negative Demand Spillover to Competitors,” *Marketing Science,* 38 (2), 296–316.

Peterson, Jonathan R. and Henry S. Schneider (2014) “Adverse Selection in the Used-Car Market: Evidence from Purchase and Repair Patterns in the Consumer Expenditure Survey,” *RAND Journal of Economics,* 45 (1), 140–154.

Puhani, Patrick (2000) “The Heckman Correction for Sample Selection and Its Critique,” *Journal of Economic Surveys*, 14 (1), 53–68.

Roehm, Michelle L. and Alice M. Tybout (2006) “When Will a Brand Scandal Spill Over, and how Should Competitors Respond?” *Journal of Marketing Research,* 43 (3), 366–373.

Rupp, Nicholas G. (2001) "Are Government Initiated Recalls More Damaging for Shareholders? Evidence from Automotive Recalls, 1973-1998," *Economics Letters,* 71 (2), 265–270.

Rupp, Nicholas G. and Curtis R. Taylor (2002) "Who Initiates Recalls and Who Cares? Evidence from the Automobile Industry," *The Journal of Industrial Economics,* 50 (2), 123–149.

Sallee, James M., Sarah West, and Wei Fan (2016) "Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations," *Journal of Public Economics*, 135, 61–73.

Shiller, Benjamin R. (2013) "Digital Distribution and the Prohibition of Resale Markets for Information Goods," *Quantitative Marketing and Economics,* 11 (4), 403–435.

Snyder, C. R., MaryAnne Lassegard, and Carol E. Ford (1986) "Distancing After Group Success and Failure: Basking in Reflected Glory and Cutting Off Reflected Failure," *Journal of Personality and Social Psychology*, 51 (2), 382–388.

Strittmatter, Anthony and Michael Lechner (2020), "Sorting in the Used-Car Market After the Volkswagen Emission Scandal," *Journal of Environmental Economics and Management*, 101, 102305.

Thirumalai, Sriram and Kingshuk K. Sinha (2011) "Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences," *Management Science*, 57 (2), 376–392.

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007) "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230–245.

Warner, Jerold B. (1977) "Bankruptcy, Absolute Priority, and the Pricing of Risky Debt Claims," *Journal of Financial Economics*, 4 (3), 239–276.

Yin, Shuya, Saibal Ray, Haresh Gurnani, and Animesh Animesh (2010) "Durable Products with Multiple Used Goods Markets: Product Upgrade and Retail Pricing Implications," *Marketing Sci*ence, 29 (3), 540–560.

Zhao, Yi, Ying Zhao, and Kristiaan Helsen (2011) "Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics in the Wake of Product Harm Crisis," *Journal of Marketing Research*, 48 (2), 255–267.

Zhou, Chen, Shrihari Sridhar, Rafael Becerril-Arreola, Tony Haitao Cui, and Yan Dong (2019) "Promotions as Competitive Reactions to Recalls and Their Consequences," *Journal of the Academy of Marketing Science,* 47 (4), 702–722.

Table 4.1: Selected Literature

Articles	Industry	Market Type	Trans action Type	Spillover Effects	Dependent Variable	Key Findings
Dawar and Pillutla (2000)	Drinks	Primary	B2C	No	Brand equity	Existing consumers and potential future consumers expect different assurances from a recalling firm.
Chen et al. (2009)	Consumer goods	Primary	B2C	No	Stock	A proactive recall strategy has a stronger negative effect on the firm value.
Hora et al. (2011)	Toy	Primary	B2C	No	Time to recall	The time to recall, measured by the difference between recall announcement and product first sold date, is associated with the recall strategy (preventive vs. reactive) adopted by the firm.
Albuquerque and Bronnenberg (2012)	Auto	Primary	B2C	No	Sales	Strong consumer disutility for travel; dealers have local demand areas shared with a small set of competitors.
Eilert et al. (2017)	Auto	Primary	B2C	No	Time to recall	Markets punish recall delays.
Jarrell and Peltzman (1985)	Auto and drugs	Primary	B2C	Yes	Stock	With recalls, shareholders bear large losses, substantially greater than the costs directly from the recall.
Dranove and Olsen (1994)	Pharmaceutical	Primary	B2C	Yes	Stock	Dangerous drug announcements have no effect on other drugs sales and do not affect the share of European drug makers doing little business in the US.
Marsh et al. (2004)	Food	Primary	B2C	Yes	Price	Meat recalls significantly affected category demand, with favorable effects on demand for meat substitutes, offset by more negative effects on meat demand.
Van Heerde et al. (2007)	Food	Primary	B2C	Yes	Sales	Due to recalls, a firm may experience reduced own effectiveness for its marketing instruments and increased cross-sensitivity to rivals' marketing mix activities.
Freedman et al. (2012)	Toy	Primary	B2C	Yes	Sales	For firms with recalls, unit sales of toys involved in the recall fall relative to sales of toys in other categories. No evidence of within-manufacturer spillovers to dissimilar toys.
Cleeren et al. (2013)	Consumer goods	Primary	B2C	Yes	Brand share	Postrecall advertisements and price changes affect the product's brand share and category purchases.
Collins et al. (2013)	Pharmaceutical	Primary	B2C	Yes	Number of prescriptions	Withdrawal of Vioxx had positive and negative effects for specific substitute drugs in its own class (COX-2s) and led to an overall increase in the use of both its most direct competitor class (NSAIDs) and a class of older similar therapy (analgesics).
Liu and Shankar (2015)	Auto	Primary	B2C	Yes	Sales, Ads	When recalls are associated with greater media attention and severe consequences, consumers' responses are more negative.
Borah and Tellis (2016)	Auto	Primary	B2C	Yes	Social chatter	Negative chatter about one nameplate increases negative chatter for another,

						for nameplates within the same brand across segments and across brands within segments.
Bachmann et al. (2019)	Auto	Primary	B2C	Yes	Sales	The Volkswagen scandal reduced U.S. sales of other German auto manufacturers, principally driven by an adverse reputation spillover, reinforced by consumer substitution away from diesel vehicles.
He et al. (2018)	Airlines	Primary	B2C	Yes	Number of tweets	After the Germanwings Flight 9525 crash, on average, other airlines increased their defensive marketing efforts but decreased their offensive marketing efforts, possibly due to negative spillover.
Zhou et al. (2019)	Auto	Primary	B2C	Yes	Competitor promotions	Toyota recalls induced competitive promotions of approximately $850, but did not significantly affect sales.
Ater and Yosef (2018)	Auto	Secondar y	B2C	No	Price (listing)	Volkswagen's emissions scandal had a statistically significant, negative effect on the number of transactions involving vehicles made by Volkswagen and their resale prices.
Strittmatter and Lechner (2020)	Auto	Secondar y	B2C	No	Price (asking), Brand share	Supply of used Volkswagen diesel vehicles increased after the emission scandal. The positive supply-side effects increase with the probability of manipulation. The negative impacts on the asking prices of used cars are subject to a high probability of manipulation.
Hartman (1987)	Auto	Secondar y	B2C	Yes	Price (aggregated)	For GM cars, the resale market efficiently discounted new recall information. Recalls diminish the resale value of the recalled product but do not affect the values of its other products.
Hammond (2013)	Auto	Secondar y	B2C	Yes	Price	The 2009–2010 Toyota recall negatively affected the resale market for automobiles but they were quantitatively small (less than 2% of the vehicle's resale value), statistically indistinguishable from 0.
Che et al. (2020)	Auto	Secondar y	B2C	Yes	Price (Individual level)	The Volkswagen diesel emission scandal decreased final bid prices by 14% and 9% in the diesel and gasoline car markets, respectively.
This study	Auto	Secondar y	B2B	Yes	Price (Individual level)	In a B2B secondary market, buyers display lower demand for recalled models, leading to lower transaction prices for these vehicles. Non-recalled models with the same make as the recalled model, but different segment, experience higher prices, suggesting a positive spillover effect. Vehicles in the same segment as the recalled model experience negative spillover.

Table 4.2: Summary Statistics

Variables	Min	Max	Median	Mean	Standard deviation
Prices	1	341000	12000	12473	7018
Odometer Reading	0	999999	29830	42916	38525

Vehicle Condition (see Table WB 4.1; Appendix)

	Condition Level	# of Obs.	% Observations
1	Condition 3	5730314	58.58%
2	Condition 4	2081364	21.28%
3	Condition 2	1439340	14.72%
4	Condition 1	266478	2.72%
5	Condition 5	210945	2.16%
6	Condition 0	52985	.54%

Vehicle Model

	Model	No. of Obs.	% of Obs.
1	TAURUS	409042	4.18%
2	EXPLORER	331616	3.39%
3	CARAVAN	263645	2.70%
4	IMPALA	248915	2.54%
5	MALIBU	241193	2.47%
6	RAM	206042	2.11%
7	TRAILBLAZER	181310	1.85%
8	FOCUS	168337	1.72%
9	SEBRING	167660	1.71%
10	SILVERADO	163694	1.67%

Vehicle Make

	Make	No. of Obs.	% Obs.
1	FORD	2279047	23.30%
2	CHEVROLET	1643887	16.81%
3	DODGE	1124119	11.49%
4	CHRYSLER	735540	7.52%
5	TOYOTA	550298	5.63%
6	NISSAN	516465	5.28%
7	HYUNDAI	320271	3.27%
8	HONDA	296288	3.03%
9	MITSUBISHI	211117	2.16%
10	LINCOLN	205984	2.11%

Vehicle Category

	Category	No. of Obs.	% of Obs.
1	MIDSIZE CAR	2427149	24.81%
2	SUV	2391522	24.45%
3	COMPACT CAR	1228079	12.56%
4	LUXURY CAR	1090986	11.15%
5	PICKUP	1079542	11.04%
6	MINIVAN	818862	8.37%
7	SPORTS CAR	329973	3.37%
8	VAN	214794	2.20%
9	FULLSIZE	122506	1.25%
10	EXCLUDED	41637	.43%

Auction Location

	Location	No. of Obs.	% of Obs.
1	Region 5	1957369	20.0%
2	Region 4	1866685	19.1%
3	Region 3	1813881	18.5%
4	Region 6	1733025	17.7%
5	Region 2	1204531	12.3%
6	Region 1	1199069	12.3%
7	Region - other	6866	.07%

Table 4.3: Recall Events

Sr.	Campaign Number	Defects	Influenced By	Recall Date
1	05V030000	Latches/Locks/Linkages	NHTSA	2/1/05
2	05V061000	Seats	Firm	2/18/05
3	05V155000	Fuel System, Gasoline	NHTSA	4/14/05
4	05V206000	Electrical System	Firm	5/9/05
5	05V494000	Latches/Locks/Linkages	Firm	10/27/05
6	06E018000	Service Brakes	NHTSA	3/1/06
7	06E089000	Suspension	Firm	10/27/06
8	07V063000	Exterior Lighting	Firm	2/20/07
9	07V092000	Electrical System	NHTSA	3/9/07
10	07V328000	Seat Belts	Firm	7/20/07
11	07V482000	Exterior Lighting	Firm	10/16/07
12	08V082000	Air Bags	NHTSA	2/25/08
13	08V231000	Exterior Lighting	NHTSA	5/21/08
14	08V235000	Engine And Engine Cooling	Firm	5/28/08
15	08E039000	Exterior Lighting	NHTSA	6/10/08
16	08E048000	Exterior Lighting	NHTSA	8/8/08
17	08E064000	Suspension	Firm	10/20/08
18	08V577000	Steering	Firm	11/3/08
19	08V634000	Visibility	Firm	12/2/08

Table 4.4: Definition and Sources of Covariates

Variable	Definition	Source
Recalls	Number of recalls initiated by the firm/regulator	NHTSA
Transaction price	Final auction price of the sold vehicle	Auction company
Highest bid price	Highest bid received when the vehicle was not sold	Auction company
Make	Make of the vehicle	Auction company
Model	Model of the vehicle	Auction company
Model year	Model year of the vehicle	Auction company
Odometer reading	Odometer reading of the sold vehicle.	Auction company
Times run	Number of times vehicles was presented in auction earlier	Auction company
Lane number	Number of the auction lane where vehicle was presented	Auction company
Lane sequence	Vehicle's sequence number in the lane	Auction company
Buyer mega group	Whether buyer is a part of a mega group	Auction company
Seller mega group	Whether seller is part of a mega group	Auction company
Labor costs	Estimated labor costs required to improve vehicle condition	Auction company
Platform	Whether the vehicle was registered to sell on the proprietary platform	Auction company
Condition	Condition level of the vehicle	Auction company
Region	Region name of the auction site	Auction company
Vehicle source	Source of the vehicle (factory, lease, dealer, daily rental, repo)	Auction company
Auction year	Year when vehicle was auctioned	Auction company
Auction month	Month when vehicle was auctioned	Auction company
Auction day	Name of day when vehicle was auctioned	Auction company

Table 4.5: Direct Impact on Product Group 1 (Recalled Vehicles)

	No Covariates	Covariates	Multimodel	MFRInflu	Odometer	Franchised
Treated	.411**	.401**	.401**	.398**	.398**	.396**
Postrecall	-.02	.03	.040	.021	.055	.032
Treated × Postrecall	-.148**	-.106**				-.102**
Treated × Postrecall × Multimodel=0			-.100*			
Treated × Postrecall × Multimodel=1			-.193*			
Treated × Postrecall × MFRInflu =0				-.112**		
Treated × Postrecall × MFRInflu =1				-.043		
Treated × Postrecall × Odometer					-.002**	
Treated × Postrecall × Franchised						-.001
Constant	1.924***	.981***	.971***	.987***	.956***	.980***
Covariates	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes
Observations	4279	4279	4279	4279	4279	4279
R^2	.033	.77	.77	.77	.77	.77

Notes: Cargo van category is the control group. The dependent variable is log of sales price. FE = fixed effect. The covariates include vehicle condition, vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, auction region, vehicle source, make, and model). Franchised variable specification includes main effects. Model considers heteroskedasticity adjusted robust standard errors. $*p < .05$, $**p < .01$.

Table 4.6: Spillover Impact on Product Group 2 (Non-Recalled, Same Make)

	No Covariates	Covariates	Segment	Multimodel	MFRInflu	Odometer	Franchised
Treated	.189**	1.500**	1.474**	1.503**	1.505**	1.553**	1.501**
Postrecall	-.020	.145**	.162**	.142**	.138**	.146**	.150**
Treated × Postrecall	.120**	.024	.048*				.016
Treated × Postrecall × Segment			-.105*				
Treated × Postrecall × Multimodel=0				.021			
Treated × Postrecall × Multimodel=1				.178*			
Treated × Postrecall × MFRInflu =0					.027		
Treated × Postrecall × MFRInflu =1					-.0016		
Treated × Postrecall × Odometer						-.0004	
Treated × Postrecall × Franchised							.034**
Constant	1.924**	-.238	-.231	-.234	-.226	-.261	-.237
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21159	21159	21159	21159	21159	21159	21159
R-squared	.018	.79	.79	.79	.79	.79	.79

Notes: Cargo van category is the control group. The dependent variable is log of sales price. FE = fixed effect. The covariates include vehicle condition, vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, auction region, vehicle source, make, and model). Franchised specification includes main effects. Model considers heteroskedasticity adjusted robust standard errors. *$p < .05$, **$p < .01$.

Table 4.7: Spillover Impact on Product Group 3 (Non-Recalled, Different Make)

	No Covariates	Covariates	Segment	Multimodel	MFRInflu	Odometer	Franchised
Treated	.458**	-1.433**	-1.437**	-1.433**	-1.434**	-1.428**	-1.428**
Postrecall	-.020	-.162**	-.163**	-.163**	-.162**	-.152**	-.160**
Treated × Postrecall	-.016	.013	.029				.013
Treated × Postrecall × Segment			-.058**				
Treated × Postrecall × Multimodel=0				.012			
Treated × Postrecall × Multimodel=1				.013			
Treated × Postrecall × MFRInflu =0					.0112		
Treated × Postrecall × MFRInflu =1					.014		
Treated × Postrecall × Odometer						.00006	
Treated × Postrecall × Franchised							.0004
Constant	1.924**	3.479**	2.534**	3.480**	3.480**	3.470**	3.468**
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137125	137125	137125	137125	137125	137125	137125
R^2	.009	.81	.81	.81	.81	.81	.81

Notes: Cargo van category is the control group. The dependent variable is log of sales price. FE = fixed effect. The covariates include vehicle condition, vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, auction region, vehicle source, make, and model). Franchised specification includes corresponding main effects. Model considers heteroskedasticity adjusted robust standard errors. *p < .05, **p < .01.

Table 4.8: Robustness Check, Heckman Model Results

	Product Group 1		Product Group 2		Product Group 3	
Outcome equation						
Treated	.358	(.291)	.264	(.205)	-.897**	(.094)
Postrecall	-.177**	(.061)	-.049	(.026)	-.014	(.013)
Treated × Postrecall	-.103*	(.041)	.025	(.016)	.013	(.012)
Inverse Mills Ratio	.115*	(.047)	-.0047	(.021)	-.011	(.009)
Covariates	Yes		Yes		Yes	
Selection equation						
Treated	-2.050	(756)	.549	(.813)	-.845	(.665)
Postrecall	-5.42	(321.6)	-2.03**	(.138)	-.238**	(.065)
Treated × Postrecall	.19	(.143)	-.038	(.062)	.063	(.049)
Vehicle count	-.014**	(.002)	-.004**	(.0006)	-.003**	(.0001)
Covariates	Yes		Yes		Yes	
Observations	6103		25909		172986	

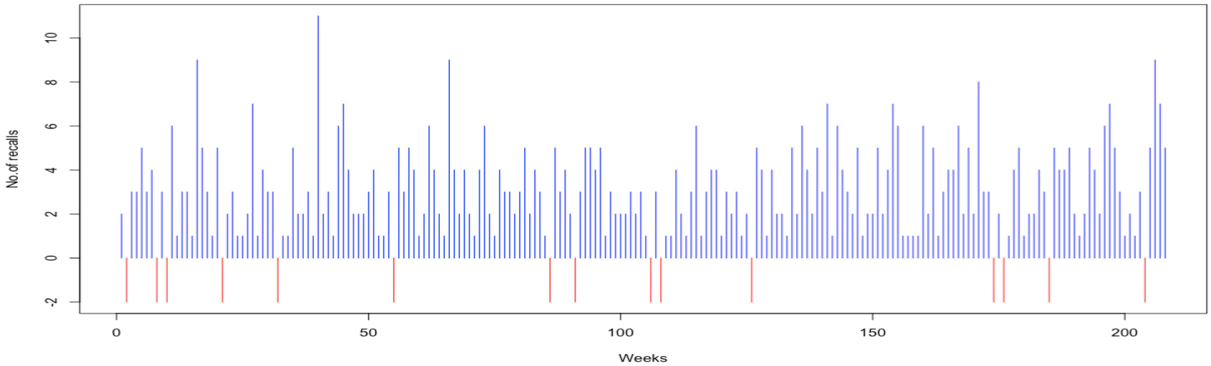
Notes: Cargo van category is the control group. For the outcome equation, the dependent variable is log of sales price. For the selection equation, the dependent variable is a dummy (1/0) indicating whether the vehicle was sold. The covariates include vehicle condition, vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (whether auction was closed to few dealers, platform registration, seller mega group, auction region, vehicle source, make, model, year, month, and day). **p* <.05, ***p* < .01.

Table 4.9: Robustness Check

	Panel 1						Panel 2			
Outcome equation	**Product Group 1**		**Product Group 2**		**Product Group 3**		**Control- Product Group 2** (Non-Recalled, Same Make)		**Control- Product Group 3** (Non-Recalled, Different Make)	
Treated	.455**	(.087)	1.492**	(.131)	1.418**	(.148)	.121**	(.011)	.052**	(.007)
Postrecall	-.132	(.197)	.115*	(.049)	.023	(.053)	.036**	(.006)	.009**	(.001)
Treated × Postrecall	-.134*	(.053)	.023	(.021)	.014	(.017)	-.069**	(.011)	-.050**	(.008)
Constant	1.354**	(.345)	-.430*	(.205)	-.309	(.196)	2.462**	(.136)	1.609**	(.231)
Covariates	Yes		Yes		Yes		Yes		Yes	
Propensity score matching	Yes		Yes		Yes		-		-	
Observations	4209		20701		53435		36190		653773	
R^2	.79		.77		.76		.81		.80	

Notes: Panel 1 analysis uses kernel matching method and displays direct and spillover effects on three product groups. Panel 2 displays the direct effects on product group 1 (recalled vehicles), with different control groups. The dependent variable is log of sales price. The covariates include vehicle condition, vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, auction region, vehicle source, make, model, year, month, and day). Heteroskedasticity adjusted robust standard errors are in parenthesis.**p* < .05, ***p* < .01.

Figure 4.1: Periodicity of Product Recalls



Notes: Blue lines indicate the number of recalls (Y axis) in a week across all makes. Red lines indicate weeks without any recall.

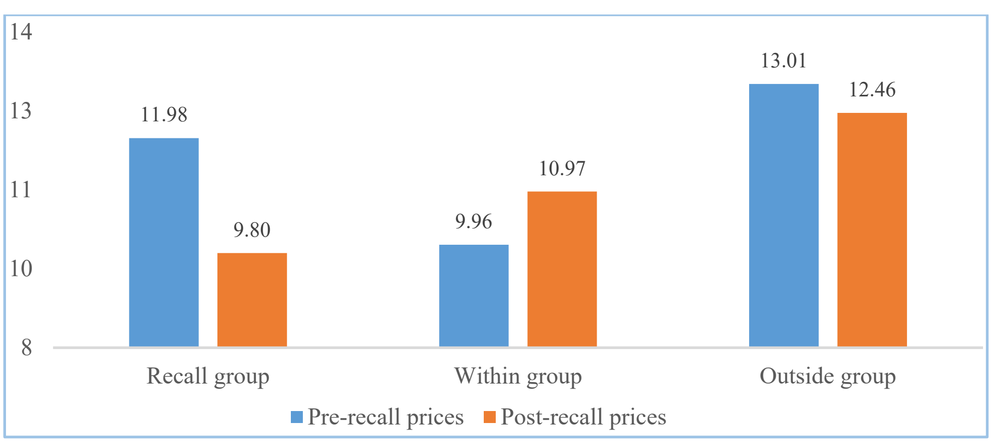
Figure 4.2: Classification of Product Groups Used in Analysis

Product group 1	**Product group 2**	**Product group 3**	**Product group 4**
Recalled- Make-Model-Year e.g., Honda Civic 2005 Honda Fit 2006	**Non-Recalled-** Make-Model-Year e.g., Honda Accord 2005	**Non-Recalled-** Different Make-Model-Year e.g., Toyota Camry 2005	**Non-Recalled** Cargo Van

Passenger vehicle (Product groups 1–3)

Cargo van (Product group 4)

Figure 4.3: Model-Free Evidence of Changes in Mean Prices across Product Groups



APPENDICES

Table WB 2.1: Lobbying Issue Names

Accounting	Homeland Security
Advertising	Housing
Aerospace	Immigration
Agriculture	Indian/Native American Affairs
Alcohol & Drug Abuse	Insurance
Animals	Labor Issues/Antitrust/Workplace
Apparel/Clothing Industry/Textiles	Intelligence and Surveillance
Arts/Entertainment	Law Enforcement/Crime/Criminal Justice
Automotive Industry	Manufacturing
Aviation/Aircraft/Airlines	Marine/Maritime/Boating/Fisheries
Banking	Medical/Disease Research/Clinical Labs
Bankruptcy	Media (Information/Publishing)
Beverage Industry	Medicare/Medicaid
Budget/Appropriations	Minting/Money/Gold Standard
Clean Air & Water (Quality)	Natural Resources
Commodities (Big Ticket)	Pharmacy
Chemicals/Chemical Industry	Postal
Civil Rights/Civil Liberties	Railroads
Communications/Broadcasting/Radio/TV	Real Estate/Land Use/Conservation
Computer Industry	Religion
Consumer Issues/Safety/Protection	Retirement
Constitution	Roads/Highway
Copyright/Patent/Trademark	Science/Technology
Defense	Small Business
District of Columbia	Sports/Athletics
Disaster Planning/Emergencies	Miscellaneous Tariff Bills
Economics/Economic Development	Taxation/Internal Revenue Code
Education	Telecommunications
Energy/Nuclear	Tobacco
Environmental/Superfund	Torts
Family Issues/Abortion/Adoption	Trade (Domestic & Foreign)
Firearms/Guns/Ammunition	Transportation
Financial Institutions/Investments/Securities	Travel/Tourism
Food Industry (Safety, Labeling, etc.)	Trucking/Shipping
Foreign Relations	Urban Development/Municipalities
Fuel/Gas/Oil	Unemployment
Gaming/Gambling/Casino	Utilities
Government Issues	Veterans
Health Issues	Waste (hazardous/solid/interstate/nuclear)

Table WB 2.2: Firm Names Considered

AMERICAN HONDA INC.	GENERAL MOTORS CO	NISSAN NORTH AMERICA
AMERICAN HONDA MOTOR	GENERAL MOTORS CO.	NISSAN NORTH AMERICA INC
AMERICAN HONDA MOTOR CO	GENERAL MOTORS COMPA	NISSAN NORTH AMERICA INC.
AMERICAN HONDA MOTOR CO.	GENERAL MOTORS COMPANY	NISSAN NORTH AMERICA, INC
AMERICAN HONDA MOTOR CO. INC.	GENERAL MOTORS COMPANY, LLC	NISSAN NORTH AMERICA, INC.
AMERICAN HONDA MOTOR CO., INC.	GENERAL MOTORS CORP.	NISSAN OF NORTH AMERICA
AMERICAN HONDA MOTOR CO.,INC	GENERAL MOTORS CORPERATION	PORSCHE CARS INC
AMERICAN HONDA MOTOR CO.,INC.	GENERAL MOTORS CORPORATION	PORSCHE CARS NORTH AMERICA
AMERICAN HONDA MOTOR COMPANY	GENERAL MOTORS INC	TESLA INC
AMERICAN HONDA MOTOR COMPANY INC.	GENERAL MOTORS INC.	TESLA INC.
AMERICAN HONDA MOTOR COMPANY USA	GENERAL MOTORS, CORP.	TESLA MOTORS
AMERICAN HONDA MOTOR COMPANY, INC.	GENERAL MOTORS, LLC	TESLA MOTORS INC
AMERICAN HONDA MOTOR CORP.	GENERAL MOTORS, LLC.	TESLA MOTORS INC.
AMERICAN HONDA MOTORS	GENERAL MOTORS/ UAW	TESLA MOTORS, INC
AMERICAN HONDA MOTORS CO	HONDA MOTOR CO	TESLA MOTORS, INC.
AMERICAN HONDA MOTORS, INC.	HONDA MOTOR CO.	TESLAMOTORS
BMW GROUP	HONDA NORTH AMERICA	TOYOTA MOT
BMW MANAGEMENT	HONDA NORTH AMERICA, INC	TOYOTA MOTOR CARS
BMW MANUFACTURING	HONDA NORTH AMERICA, INC.	TOYOTA MOTOR CORP.
BMW OF NORTH AMERICA	HYUNDAI AMERICA	TOYOTA MOTOR MANUFACTURI
DAIMLER A.G.	HYUNDAI KIA AMERICA	TOYOTA MOTOR MANUFACTURING
DAIMLER AG	HYUNDAI KIA AMERICA TECH CTR	TOYOTA MOTOR NORTH AMERICA
DAIMLER CHRYSLER	HYUNDAI KIA AMERICA TECH.	TOYOTA MOTOR SALES
DAIMLER CORPORATION	HYUNDAI MANUFACTURING	TOYOTA MOTOR SALES U
DAIMLER TRUCKS	HYUNDAI MOTOR	TOYOTA MOTOR SALES U.S.A.
DAIMLERCHRYLSER	HYUNDAI MOTOR AMERCIA	TOYOTA MOTOR SALES U.S.A. IN
FORD MOTOR	HYUNDAI MOTOR AMERIC	TOYOTA MOTOR SALES U.S.A. INC.
FORD MOTOR CO.	HYUNDAI MOTOR AMERICA	TOYOTA MOTOR SALES USA
FORD MOTOR COMPANY	HYUNDAI MOTOR AMRICA	TOYOTA MOTOR SALES USA INC
FORD AUTOMOTIVE	HYUNDAI MOTOR COMPANY	TOYOTA MOTOR SALES USA INC.
FORD COMPANY	HYUNDAI MOTOR GROUP	TOYOTA MOTOR SALES USA, INC.
FORD MOTER CO	HYUNDAI MOTOR MANUF	TOYOTA MOTOR SALES, INC.

FORD MOTER CO.	HYUNDAI MOTORS AMERICA	TOYOTA MOTOR SALES, U.S.A, INC.
FORD MOTER COMPANY	HYUNDAI-KIA	TOYOTA MOTOR SALES, U.S.A.
FORD MOTOR CO	HYUNDAI-KIA AMERICA	TOYOTA MOTOR SALES, U.S.A. INC.
FORD MOTOR CO,	HYUNDAI-KIA AMERICA TECH CTR	TOYOTA MOTOR SALES, U.S.A., INC.
FORD MOTOR CO.	HYUNDAI-KIA AMERICA TECH CTR.	TOYOTA MOTOR SALES, US HEADQUARTERS
FORD MOTOR COM	JAGUAR DISTRIBUTION CORP	TOYOTA MOTOR SALES, US. INC.
FORD MOTOR COMP	JAGUAR LAND ROVER	TOYOTA MOTOR SALES, US., INC.
FORD MOTOR COMPANY	JAGUAR NORTH AMERICA	TOYOTA MOTOR SALES, USA
FORD MOTOR CORP	KIA MOTORS	TOYOTA MOTOR SALES, USA INC
FORD MOTOR CORPORATION	KIA MOTORS AMERICA	TOYOTA MOTOR SALES, USA INC.
FORD MOTORS CO U.A.W.	KIA MOTORS AMERICA INC	TOYOTA MOTOR SALES, USA,
FORD MOTORS CO.	KIA MOTORS AMERICA, INC	TOYOTA MOTOR SALES, USA, INC
FORD/ MAZDA CORP.	KIA MOTORS AMERICA, INC.	TOYOTA MOTOR SALES, USA, INC.
FORD/UAW	LAND ROVER JAGUAR VENTURA	TOYOTA MOTOR SALES, USA, INC. COMPANY
GENERAL MORTORS	MAZDA MOTOR OF AMERICAN	TOYOTA MOTOR SALES, USA., INC.
GENERAL MORTORS CORP.	MAZDA NORTH AMERICA	TOYOTA MOTORS
GENERAL MOTERS	MAZDA NORTH AMERICAN OP.	TOYOTA MOTORS SALES
GENERAL MOTOR	MAZDA NORTH AMERICAN OPERATION	TOYOTA MOTORS USA
GENERAL MOTOR CO.	MAZDA NORTH AMERICAN OPERATIONS	TOYOTA NORTH AMERICA
GENERAL MOTOR COMPANY	MAZDA NORTH AMERICAN OPERTIONS	VOLKSWAGEN
GENERAL MOTOR CORP	MAZDA NORTH AMERICAN OPS	
GENERAL MOTOR CORP.	NISSAN AMERICAS	
GENERAL MOTOR CORPS	NISSAN AUTOMOTIVE	
GENERAL MOTOR LLC	NISSAN CORP	
GENERAL MOTORS	NISSAN MOTOR	
GENERAL MOTORS CO.	NISSAN MOTOR CORP.	
GENERAL MOTORS LLC	NISSAN N.A. INC.	

Table WB 2.3: Location Names

State	County	State	County
Alabama	Talladega	Mississippi	Madison
Alabama	Montgomery	Mississippi	Union
Alabama	Tuscaloosa	Missouri	Saint Charles
Alabama	Madison	New Jersey	Bergen
California	Los Angeles	New Jersey	Camden
California	Orange	New York	Schenectady
California	Santa Clara	North Carolina	Alamance
California	Alameda	North Carolina	Guilford
Georgia	Fulton	Ohio	Union
Georgia	Troup	Ohio	Lorain
Illinois	Cook	Ohio	Trumbull
Illinois	McLean	Ohio	Logan
Indiana	Huntington	South Carolina	Greenville
Indiana	Decatur	South Carolina	Florence
Indiana	Tippecanoe	Tennessee	Williamson
Indiana	Gibson	Tennessee	Maury
Kansas	Clay	Tennessee	Franklin
Kansas	Wyandotte	Tennessee	Rutherford
Kentucky	Jefferson	Tennessee	Hamilton
Kentucky	Warren	Texas	Tarrant
Kentucky	Scott	Texas	Bexar
Michigan	Oakland	Virginia	Fairfax
Michigan	Wayne	West Virginia	Putnam
Michigan	Eaton		
Michigan	Genesee		
Michigan	Ingham		

Table WB 2.4: Non-linear Estimates for Probit Model

Recall equation	Voluntary recall		Mandatory recall	
Constant	.825	(1.524)	-1.332	(1.609)
Lobbying	-1.356***	(.306)	-1.698***	(.305)
Complaints	.001	(.001)	.001	(.0004)
Deaths	-.029	(.051)	-.071	(.042)
States	.027	(.032)	.027	(.033)
Rating	-.559	(.346)	-.015	(.471)
Sales	-1.262	(1.841)		
Liabilities_std	-.031	(.017)		
Capex_std	.0003	(.0002)		
Agency_costs	-.206	(.38)		
Fixed effects	Yes		Yes	
Endogenous variable equation				
Constant	.244	(.70)	.394	(.571)
Contribution_hq	-.0003	(.003)	.000	(.002)
Contribution_plant	-.017***	(.003)	-.017***	(.003)
Complaints	8.04×10^{-6}	(.0003)	-.00001	.0003
Deaths	-.007	(.018)	-.010	(.023)
States	.003	(.005)	.005	(.008)
Rating	-.107	(.211)	-.189	(.147)
Sales	.668	(.993)		
Liabilities_std	.0004	(.0004)		
Capex_std	-.00003	(.00003)		
Agency_costs	.076	(.089)		
Fixed effects	Yes		Yes	

Notes: Lobbying amount is in millions of USDs. In recall equation, binary 0/1 (1= recall; 0= no recall) is the dependent variable. Errors are clustered at the firm level and shown in parenthesis.
**p* < .05, ***p* < .01, ****p* < .001.

Table WB 4.1: Condition Table

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

Table WB 4.2: Pretreatment Period Analysis

	Model 1	
	Estimates	Std. Error
Constant	-.112	(.447)
Treated	1.563*	(.617)
Eventday1	-.045	(.032)
Eventday2	-.007	(.038)
Eventday3	.029	(.040)
Eventday4	.03	(.033)
Treated:Eventday1	.02	(.043)
Treated:Eventday2	.052	(.045)
Treated:Eventday3	.065	(.043)
Treated:Eventday4	-.033	(.046)
Covariates	Yes	
Year FE	Yes	
Month FE	Yes	
Day FE	Yes	
Observations	7,219	
R^2	0.753	
F Statistic	208.2*** (df = 104; 7114)	

Notes: Data include pre-treatment observations (day-1 to day -5). Reference level is "day -5" observations. The dependent variable is log of sales price. Cargo van category is the control group. The covariates include vehicle's number of previous runs, lane number, sequence in lane, labor costs, vehicle condition, odometer reading, and dummies for several variables (make, model, whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, region, and vehicle source). *$p < .05$, **$p < .01$.

Table WB 4.3: Modelyear Analysis

	Model 1		Model 2	
	Estimates	Std. Error	Estimates	Std. Error
Constant	-.395	(1.357)	-.742	(1.153)
Treated	-.538**	(.07)	-.520**	(.068)
Postrecall	.0907	(.072)	.158*	(.066)
Treated # Postrecall	-.0697+	(.036)	-.0713*	(.034)
Residuals			.145**	(.012)
Covariates	Yes		Yes	
Observations	4,279		4,279	
R-squared	.81		.82	

Notes: Model 1 includes model year dummies as a covariate. For model 2, we first regress condition variable on model year, collect its residuals and incorporate this residual as an additional variable. Cargo van category is the control group. The dependent variable is log of sales price. The covariates include vehicle's number of previous runs, lane number, sequence in lane, labor costs, odometer reading, and dummies for several variables (make, model, whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, region, vehicle source, year, month, and day). +$p < .1$, *$p < .05$, **$p < .01$.

Table WB 4.4: Robustness Check

Outcome equation	**Product Group 1**		**Product Group 2**		**Product Group 3**	
Treated	.409**	(.085)	1.484**	(0.165)	1.422**	(0.164)
Postrecall	.0301	(.082)	0.166**	(0.0544)	-0.219**	(0.0536)
Treated × Postrecall	-.0880*	(.039)	0.0370	(0.0227)	0.00994	(0.0197)
Constant	1.141**	(.258)	-0.189	(0.193)	0.281	(0.190)
Covariates	Yes		Yes		Yes	
Propensity score matching	Yes		Yes		Yes	
Observations	4209		20701		53435	
R^2	.80		.80		.78	

Notes: This analysis considers the radius matching. The dependent variable is log of sales price. Cargo van category is the control group. The covariates include vehicle's number of previous runs, lane number, sequence in lane, labor costs, vehicle condition, odometer reading, and dummies for several variables (make, model, whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, region, and vehicle source). Robust standard errors are in parenthesis. *$p < .05$, **$p < .01$.

Table WB 4.5: Robustness Checks: Different Time Window

a. Product Group 1

	No Covariates	Covariates	Multimodel	MFRInflu	Odometer	Franchised
Treated	.452**	2.236**	2.236**	2.236**	2.243**	2.237**
Postrecall	-.055*	.077*	.077*	.077*	.078*	.078*
Treated × Postrecall	-.111**	-.093**				-.088**
Treated × Postrecall × Multimodel=0			-.092**			
Treated × Postrecall × Multimodel=1			-.119			
Treated × Postrecall × MFRInflu =0				-.093**		
Treated × Postrecall × MFRInflu =1				-.098		
Treated × Postrecall × Odometer					-.0018**	
Treated × Postrecall × Franchised						-.0026
Constant	1.921**	-.878**	-.877**	-.878**	-.874**	-.889**
Covariates	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes
Observations	7637	7637	7637	7637	7637	7637
R^2	.046	.76	.76	.76	.76	.76

b. Product Group 2

	No Covariates	Covariates	Segment	Multimodel	MFRInflu	Odometer	Franchised
Treated	.158**	1.557**	1.525**	1.559**	1.572**	1.595**	1.558**
Postrecall	-.055*	.042*	.056**	.040*	.047*	.068*	.045*
Treated × Postrecall	.225**	.010	.039**				.0027
Treated × Postrecall × Segment			-.13**				
Treated × Postrecall × Multimodel=0				.007			
Treated × Postrecall × Multimodel=1				.166*			
Treated × Postrecall × MFRInflu =0					.011		
Treated × Postrecall × MFRInflu =1					-.013		
Treated × Postrecall × Odometer						-.0005	
Treated × Postrecall × Franchised							.035**
Constant	1.921**	.228	.289	.226	.192	.194	.234
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38536	38536	38536	38536	38536	38536	38536
R^2	.026	.78	.78	.78	.78	.78	.78

c. Product Group 3

	No Covariates	Covariates	Segment	Multimodel	MFRInflu	Odometer	Franchised
Treated	.446**	-3.986**	-3.987**	-3.986**	-3.989**	-3.971**	-3.964**
Postrecall	-.055*	.026	.020	.0256	.0233	.048	.026
Treated × Postrecall	.053	.023	.039**				.025
Treated × Postrecall × Segment			-.064**				
Treated × Postrecall × Multimodel=0				.0252			
Treated × Postrecall × Multimodel=1				.0194			
Treated × Postrecall × MFRInflu =0					.016		
Treated × Postrecall × MFRInflu =1					.030*		
Treated × Postrecall × Odometer						-.008 X 10^{-3}	
Treated × Postrecall × Franchised							-.0065**
Constant	1.921**	5.478**	5.469**	5.477**	5.492**	5.463**	5.440**
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235890	235890	235890	235890	235890	235890	235890
R^2	.009	.80	.80	.80	.80	.80	.80

Notes: Cargo van category is the control group. The dependent variable is log of sales price. FE = fixed effect. The covariates include vehicle's number of previous runs, lane number, sequence in lane, labor costs, vehicle condition, odometer reading, and dummies for several variables (make, model, whether auction was closed to few firms, platform registration, buyer mega group, seller mega group, region, and vehicle source). **p* < .05, ***p* < .01.

Figure WB 2.1: Example of Lobbying Report

Clerk of the House of Representatives
Legislative Resource Center
135 Cannon Building
Washington, DC 20515
http://lobbyingdisclosure.house.gov

Secretary of the Senate
Office of Public Records
232 Hart Building
Washington, DC 20510
http://www.senate.gov/lobby

LOBBYING REPORT

Lobbying Disclosure Act of 1995 (Section 5) - **All Filers Are Required to Complete This Page**

1. Registrant Name ☑ Organization/Lobbying Firm ☐ Self Employed Individual
BMW of North America, LLC

2. Address
Address1 300 Chestnut Ridge Road Address2
City Woodcliff Lake State NJ Zip Code 07677 Country USA

3. Principal place of business (if different than line 2)
City State Zip Code Country

4a. Contact Name Mr. Bryan Jacobs | b. Telephone Number 2023932150 | c. E-mail bryan.jacobs@bmwna.com | 5. Senate ID# 400822436-12

7. Client Name ☑ Self ☐ *Check if client is a state or local government or instrumentality*
BMW of North America, LLC | 6. House ID# 418640000

TYPE OF REPORT 8. Year 2016 Q1 (1/1 - 3/31) ☐ Q2 (4/1 - 6/30) ☐ Q3 (7/1 - 9/30) ☐ Q4 (10/1 - 12/31) ☑

9. Check if this filing amends a previously filed version of this report ☐

10. Check if this is a Termination Report ☐ Termination Date 11. No Lobbying Issue Activity ☐

INCOME OR EXPENSES - YOU MUST complete either Line 12 or Line 13

12. Lobbying

INCOME relating to lobbying activities for this reporting period was:

Less than $5,000 ☐

$5,000 or more ☐ $

Provide a good faith estimate, rounded to the nearest $10,000, of all lobbying related income for the client (including all payments to the registrant by any other entity for lobbying activities on behalf of the client).

13. Organizations

EXPENSE relating to lobbying activities for this reporting period were:

Less than $5,000 ☐

$5,000 or more ☑ $ 110,000.00

14. REPORTING Check box to indicate expense accounting method. See instructions for description of options.

☑ **Method A.** Reporting amounts using LDA definitions only

☐ **Method B.** Reporting amounts under section 6033(b)(8) of the Internal Revenue Code

☐ **Method C.** Reporting amounts under section 162(e) of the Internal Revenue Code

Signature Digitally Signed By: Bryan Jacobs **Date** 1/19/2017 4:59:41 PM

LOBBYING ACTIVITY. Select as many codes as necessary to reflect the general issue areas in which the registrant engaged in lobbying on behalf of the client during the reporting period. Using a separate page for each code, provide information as requested. Add additional page(s) as needed.

15. General issue area code AUT

Figure WB 2.2: Other Sources for Recall Information

Source: ***https://www.cars.com***

Recall Number	Recall Date	Component
13V571000	**11/14/2013**	**POWER TRAIN:AUTOMATIC TRANSMISSION**

Summary

American Honda Motor Co., Inc. (Honda) is recalling certain model year 2014 Acura MDX AWD vehicles manufactured May 6, 2013, through October 14, 2013. The bolts that attach the drive shaft to the automatic transmission transfer assembly may not have been properly tightened. As a result, the bolts could loosen possibly allowing the shaft to detach.

Consequence

If the drive shaft detaches while driving it could cause excessive noise and possibly damage the vehicle, increasing the risk of a crash.

Recall Number	Recall Date	Component
16V777000	**10/26/2016**	**FUEL SYSTEM, GASOLINE:DELIVERY:FUEL PUMP**

Summary

Ford Motor Company (Ford) is recalling certain model year 2010-2012 Ford Escape vehicles manufactured February 26, 2009, to April 29, 2012, and 2010-2011 Mercury Mariner vehicles manufactured February 25, 2009, to December 12, 2010. On vehicles with a 3.0L engine, the Fuel Delivery Module (FDM) may crack, causing a fuel leak.

Consequence

A fuel leak in the presence of an ignition source increases the risk of a fire.

Source: *https://www.kbb.com*

Power train: automatic transmission

NHTSA CAMPAIGN ID:	Report Date:	Vehicles Affected:
13V571000	NOV 13, 2013	19197

Consequence:

If the drive shaft detaches while driving it could cause excessive noise and possibly damage the vehicle, increasing the risk of a crash.

What You Should Do:

Honda will notify owners, and dealers will inspect and tighten the drive shaft attaching bolts as necessary, free of charge. The recall began on July 3, 2014. Owners may contact Honda at 1-800-999-1009 or visit their website at www.recalls.honda.com. Honda's recall number is JC8.

Summary:

American Honda Motor Co., Inc. (Honda) is recalling certain model year 2014 Acura MDX AWD vehicles manufactured May 6, 2013, through October 14, 2013. The bolts that attach the drive shaft to the automatic transmission transfer assembly may not have been properly tightened. As a result, the bolts could loosen possibly allowing the shaft to detach.

Fuel system, gasoline

NHTSA CAMPAIGN ID:	Report Date:	Vehicles Affected:
16V777000	October 26, 2016	329,265

Consequence:

A fuel leak in the presence of an ignition source increases the risk of a fire.

What You Should Do:

Ford will notify owners, and dealers will replace the FDM flange with one that has a redesigned fuel supply port, free of charge. Remedy parts are currently unavailable. Interim notices were mailed to owners on December 13, 2016. Owners will recieve a second notice when remedy parts become available. Owners may contact Ford customer service at 1-866-436-7332. Ford's number for this recall is 16S41.

Summary:

Ford Motor Company (Ford) is recalling certain model year 2010-2012 Ford Escape vehicles manufactured February 26, 2009, to April 29, 2012, and 2010-2011 Mercury Mariner vehicles manufactured February 25, 2009, to December 12, 2010. On vehicles with a 3.0L engine, the Fuel Delivery Module (FDM) may crack, causing a fuel leak.

Source: ***https://www.nhtsa.gov/***

November 14, 2013 NHTSA CAMPAIGN NUMBER: 13V571000

Drive Shaft May Detach

If the drive shaft detaches while driving it could cause excessive noise and possibly damage the vehicle, increasing the risk of a crash.

NHTSA Campaign Number: 13V571000

Manufacturer Honda (American Honda Motor Co.)

Components POWER TRAIN

Potential Number of Units Affected 19,197

Summary

American Honda Motor Co., Inc. (Honda) is recalling certain model year 2014 Acura MDX AWD vehicles manufactured May 6, 2013, through October 14, 2013. The bolts that attach the drive shaft to the automatic transmission transfer assembly may not have been properly tightened. As a result, the bolts could loosen possibly allowing the shaft to detach.

October 26, 2016 NHTSA CAMPAIGN NUMBER: 16V777000

Fuel Delivery Module may Crack and cause Fuel Leak

A fuel leak in the presence of an ignition source increases the risk of a fire.

NHTSA Campaign Number: 16V777000

Manufacturer Ford Motor Company

Components FUEL SYSTEM, GASOLINE

Potential Number of Units Affected 329,265

Summary

Ford Motor Company (Ford) is recalling certain model year 2010-2012 Ford Escape vehicles manufactured February 26, 2009, to April 29, 2012, and 2010-2011 Mercury Mariner vehicles manufactured February 25, 2009, to December 12, 2010. On vehicles with a 3.0L engine, the Fuel Delivery Module (FDM) may crack, causing a fuel leak.