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Management of Product Recall in the Automobile Industry

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Management of Product Recall in the Automobile Industry

SUMMARY

A product recall occurs when products fail to meet certain safety standards or contain a defect that could cause serious harm to consumers. The objective of the thesis is to explore the sources of product recalls and the recall decision-making process. I test the proposed hypotheses in three related studies under the context of the US automobile industry. I propose novel complaint relevance and variety measures using text-based approaches to analyse the content of consumer complaints and product defects in recalls. The first two studies evaluate the impact of complaint relevance and complaint variety on the timing of recall decisions using a sample of 991 automotive recalls between 1993 and 2019. The third study examines the effect of chief executive officer (CEO) duality on the number of product recalls using a sample of 19 firms between 1994 and 2019.

In the first study, I examine the impact of complaint relevance on the time taken to make a recall decision and how such an impact varies depending on product characteristics. The results show that consumer complaints with high relevance to product defects lead to a faster recall decision. Additionally, the impact of complaint relevance on time to recall is greater for a recall that involves various brands or that involves older car models. In the second study, I investigate the influence of complaint variety on time to recall and how such an influence is contingent on complaint related factors. The findings indicate that consumer complaints with ambiguous defect signals result in a slower recall decision. Moreover, the relationship between complaint variety and time to recall is stronger when consumer complaints describe a severer product defect or when consumer complaints are collected from diverse sources. The third study tests the relationship between CEO duality and the frequency of product recalls and the boundary conditions for such a relationship. The estimates of negative binomial models show that the existence of CEO duality decreases the frequency of product recalls. The effect of CEO duality on product recalls is greater for a firm with high firm liquidity or for a firm led by a CEO with prior CEO experience. Taken together, the thesis contributes to several streams of research in marketing, operations management, and strategic management.

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List of Abbreviations

2SLS	Two-Stage Least Squares
ABV	Attention-Based View
BIC	Bayesian Information Criterion
BMW	Bayerische Motoren Werke
CEO	Chief Executive Officer
COO	Chief Operating Officer
CPSC	Consumer Product and Safety Commission
FDA	Food and Drug Administration
GM	General Motors
IPO	Initial Public Offering
IV	Instrumental Variable
LDA	Latent Dirichlet Allocation
LIWC	Linguistic Inquiry and Word Count
NHTSA	National Highway Traffic Safety Administration
OLS	Ordinary Least Squares
R&D	Research and Development
SEU	Subjective Expected Utility
SIC	Standard Industrial Classification
TF-IDF	Term Frequency-Inverse Document Frequency
TMT	Top Management Team
VOQ	Vehicle Owners Questionnaire
VW	Volkswagen

Chapter 1 Introduction

Product recalls occur when products are found to be defective or even dangerous (Van Heerde et al. 2007, Ball et al. 2017). Firms dread product recalls because of the high cost and negative publicity arising from recalls (Hora et al. 2011, Wowak et al. 2021, Mayo et al. 2022). This thesis aims to explore a set of factors that influence product recall decisions. Customer complaint is a common source of product quality feedback that may lead to a recall (Ball et al. 2018b, Wowak et al. 2021, Kini et al. 2022). Therefore, one could wonder the role of customer complaint in the recall process and the time taken for recall decisions. Importantly, characteristics of top managers may become reflected in the managerial decision of recalls (Hambrick and Mason 1984). Consequently, chief executive officer (CEO) duality as a widely used measure of CEO power can impact the frequency of product recalls (Joseph et al. 2014, Krause et al. 2014).

1.1 Motivation

A product recall can be viewed as the consequence of a product-harm crisis which is referred to as an incident in which a product fails to meet a mandatory safety standard, contains a defect that could cause harm to customer safety, or fails to comply with a voluntary standard of the specific industry (Liu et al. 2016, Shah et al. 2017). As depicted in Table 1.1, firms from various industries such as food, automobiles, drugs, medical devices, and consumer goods encounter product recalls (Haunschild and Rhee 2004, Thirumalai and Sinha 2011, Kalaignanam et al. 2013, Kini et al. 2017, Giannetti and Srinivasan 2022). Recalls are costly. Firms face both direct and indirect costs that arise from product recalls. Direct costs include the costs of managing reverse logistics, replacing or repairing the defective products, and litigation (Hora et al. 2011, Kini et al. 2022). Indirect costs, which may be substantially higher than the direct costs, include losses in reputation, market value, and sales (Eilert et al. 2017, Kini et al. 2017, Mayo et al. 2022).

Table 1.1 Number of Recalls between 2011-2020

Product categories	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Consumer products	412	439	373	387	415	428	381	265	259	240
Automobile	656	659	711	869	970	1,031	897	1,033	964	883
Food, drug, and medical device	3,640	4,075	3,844	2,924	2,789	2,847	2,945	2,790	2,601	2,655

Data sources: https://www.cpsc.gov, https://www.nhtsa.gov, https://www.fda.gov, CPSC Annual Report Fiscal Year 2011-2013, CPSC Annual Performance Report Fiscal Year 2014-2020, NHTSA 2022 Annual Report Safety Recalls, FDA Enforcement Statistics Summary Fiscal Year 2011-2017, FDA Data Dashboard.

Over the last decades, the product recall literature has explored the consequences and causes of product recalls (Jarrell and Peltzman 1985, Hoffer et al. 1988, Thirumalai and Sinha 2011). Researchers in operations management, finance, marketing, and strategic management have identified various factors that determine the likelihood or frequency of product recalls (Haunschild and Rhee 2004, Ball et al. 2018b). The factors include product scope (Thirumalai and Sinha 2011), CEO stock option pay (Wowak et al. 2015), and financial leverage and distress (Kini et al. 2017). Most recent work has noticed that factors such as plant inspections (Ball et al. 2017) and female directors (Wowak et al. 2021) could influence the timing of product recall decisions.

When a product is suspected of a safety defect, customers can report the safety problem to the regulator. The regulator analyses the complaints to decide whether to open an investigation. The firm may launch a recall voluntarily or initiate a recall mandated by the regulator if the safety defect is identified. Firms could be reluctant to launch a recall because of high recall cost and negative publicity. However, leaving defective products on market endangers customer safety and leads to significant recall cost and reputation damage for firms (Gao et al. 2022). Consequently, understanding the recall decision-making process and the time taken for the recall decisions is of great value for both firms and regulators (Astvansh et al. 2022a).

CEO and board members as powerful actors in a firm play an important role in strategic choice, organizational design, and performance (Hambrick and Mason 1984, Hambrick et al. 2005). CEO duality therefore may be a salient factor that relates to product recalls, as it represents power distributions in firms (Boyd 1995). The practice of combining CEO and board chair roles has long been referred to as a “double-edged sword” because of the balance between unity of command and entrenchment avoidance (Finkelstein and D’Aveni 1994). Therefore, it’s unclear how CEO duality influences the frequency of product recalls.

1.2 Research Context

The empirical setting for this study is the automobile industry in the United States. The US automobile industry has witnessed a high frequency of product recalls, thus providing an ample number of recall events for our analysis (Borah and Tellis 2016). For example, the sample for evaluating the effect of consumer complaint on product recall timing decisions in this study contains 991 observations, which represents a substantial sample in marketing and operations management settings (Chakravarty et al. 2022). Importantly, data on the recall process such as consumer complaint, investigation, and recall data files is publicly available in this industry. Other data, such as firm characteristics can also be accessed through diverse sources including Capital

IQ and LexisNexis database. In addition, the automobile industry is of considerable economic significance (Kalaignanam et al. 2013). By examining product recall decisions in one industry, one can eliminate confounding from extraneous industry-specific effects and enhance internal validity (Eilert et al. 2017). For these reasons, scholars have explored the consequences of product recalls (Kalaignanam et al. 2013, Borah and Tellis 2016, Pagiavlas et al. 2022), the antecedents of product recalls (Haunschild and Rhee 2004, Shah et al. 2017, Astvansh et al. 2022b), and the recall decision-making process (Rupp and Taylor 2002, Eilert et al. 2017, Ni and Huang 2017) using the automobile industry as empirical context.

In the United States, product safety is overseen by several federal government agencies, depending on the product category (Chen et al. 2009). Examples of the government agencies include National Highway Traffic Safety Administration (NHTSA), Food and Drug Administration (FDA), and Consumer Product and Safety Commission (CPSC). The National Traffic and Motor Vehicle Safety Act enacted in 1966 gives NHTSA the authority to formulate automobile safety standards and launch vehicle recalls. Recent years have seen a significant increase in automobile recalls in US, from 527 recalls in 2001 to 1,093 recalls in 2021 (NHTSA 2022). In 2016, NHTSA has overseen 919 vehicle recalls involving over 50 million vehicles and these recalls cost manufacturers almost $22.1 billion (Jibrell 2018).

1.3 Thesis Structure

Chapter 1 illustrates the research motivation, research context, and thesis structure. I first describe the motivation to conduct the research on product recalls. After that, I explain why I select the automobile industry as the empirical setting for this research. Finally, I present the thesis structure to provide an outline of this research.

Chapter 2 involves a literature review of prior work on product recall research. I first present three areas of topic focus: consequences of product recalls, antecedents of product recalls, and recall decision-making process. I then provide an overview of theories that help explain the product recall decisions. The theories include attention-based view of firm, decision-making under ambiguity, and upper echelons theory. Finally, I illustrate two categories of empirical methods for product recall research: text analysis methods and count models.

Chapter 3 tests the effect of complaint relevance on the time taken to make a recall decision and how such an effect varies depending on product characteristics. Drawing on the attention-based view of firm, this study argues that consumer complaints with high relevance to product defects are more likely to be attentional focus of decision-makers, thus leading to a faster recall. The hypotheses further propose that product characteristics including component sharing and product age negatively moderate the relationship between complaint relevance and time to recall. Using a sample of 991 automobile recalls between 1993 and 2019, I find that complaint relevance decreases the time taken for a recall decision. Furthermore, the relationship between complaint relevance and time to recall is stronger when the defective component is shared among various brands or when the car models are older.

Chapter 4 examines the influence of complaint variety on time to recall and how such an influence is contingent on contextual factors including complaint severity and complaint diversity. Building on the theory of decision-making under ambiguity, the research posits that high complaint variety is associated with a long time to recall because of the presence of ambiguity aversion. The hypotheses further argue that the long time to recall under high complaint variety is stronger when (1) consumer complaints describe a severer product defect and (2) consumer complaints are collected from more diverse sources. I verify the proposed hypotheses under the context of US automobile industry.

Chapter 5 investigates the relationship between CEO duality and product recalls, and the boundary conditions for such a relationship. The study builds on upper echelons theory to propose a negative relationship between CEO duality and product recalls. I posit that CEO-chairs have enhanced ability to deal with product quality issues, thereby decreasing the frequency of product recalls. I further propose that the relationship between CEO duality and product recalls varies depending on the level of managerial discretion. I test the hypotheses based on a sample of 19 publicly traded firms between 1994 and 2019. The estimates of negative binomial models show that CEO duality is negatively associated with the number of product recalls in a firm. Moreover, the findings suggest that a high level of firm liquidity creates a context in which CEO-chairs can tactically deploy assets to manage product quality, thus leading to a significant lower frequency of product recalls. Similarly, the influence of CEO duality on product recalls is greater for a firm led by a CEO with experience of working as CEO at another firm prior to appointment.

Chapter 6 concludes this thesis by summarising the results and discussing the directions for future research.

Chapter 2 Literature Review

The purpose of this chapter is to provide a literature review of prior work on the product recall topic and to illustrate the contributions of this thesis. In the following session, I review several streams of product recall literature: consequences of product recalls, antecedents of product recalls, and recall decision-making process. Next, I highlight a variety of theories related to product recall decisions: attention-based view of firm, decision-making under ambiguity, and upper echelons theory. Finally, I provide an overview of empirical methods for product recall research.

2.1 Empirical Studies on Product Recall Research

Empirical studies on product recalls can be broadly categorised into several streams. The first and second streams of literature focus on the consequences and causes of product recalls. The most recent stream of literature explores the recall decision-making process and the timing of recall decisions.

2.1.1 Consequences of Product Recalls

In the past decades, the product recall literature has evaluated the impact of product recalls on firms' performance outcomes (Gao et al. 2022). Scholars examined the consequences of product recalls on stock market returns (Jarrell and Peltzman 1985, Hoffer et al. 1988, Chen et al. 2009, Thirumalai and Sinha 2011, Mukherjee et al. 2022), brand equity (Dawar and Pillutla 2000), market share change (Rhee and Haunschild 2006), consumers and sales (Van Heerde et al. 2007, Liu and Shankar 2015), recall response rates (Rupp and Taylor 2002), and future accidents and recalls (Kalaignanam et al. 2013). Jarrell and Peltzman (1985) found that in drug and auto recalls the capital market losses are substantially greater than the costs directly emanating from the recall. Thirumalai and Sinha (2011) suggested that capital market penalties for medical device recalls are not severe and the market reaction to recall announcements is varied across heterogeneous firms. Kalaignanam et al. (2013) indicated that product recalls are negatively associated with future number of injuries and recalls.

2.1.2 Antecedents of Product Recalls

A significant stream of product recall research has explored various factors related to finance, marketing, operations management, and strategic management that explain the variation in the likelihood or frequency of product recalls (Haunschild and Rhee 2004, Kalaignanam et al. 2013, Wowak and Boone 2015, Ball et al. 2018b, Li et al. 2022). Examples include product scope (Thirumalai and Sinha 2011), outsourcing and offshoring (Steven et al. 2014), CEO stock option pay (Wowak et al. 2015), financial leverage and distress (Kini et al. 2017), product variety and plant utilization (Shah et al. 2017), product competition (Ball et al. 2018a), female board representation (Wowak et al. 2021), and foreign competition (Lam et al. 2022). Table 2.1 lists the related studies and relevant findings. Steven et al. (2014) found that outsourcing and offshoring are positively related to product recalls, and offshore outsourcing has a greater impact on recalls than offshoring without outsourcing. Wowak et al. (2015) indicated that the positive influence of CEO stock option pay on the likelihood of subsequent product safety problems will be weaker for longer-tenured CEOs as well as for founder CEOs. Kini et al. (2017) suggested that higher leverage, greater likelihood of financial distress, and more adverse cash-flow shocks adversely impact product quality. Ball et al. (2018a) revealed that whereas product competition is associated with an increase in high severity, low discretion recalls, it is associated with a decrease in low severity, high discretion recalls.

Table 2.1 Antecedents of Product Recalls: Research and Main Findings

Citation	Empirical setting	Relevant findings
Haunschild and Rhee (2004)	47 automakers between 1966 and 1999	Voluntary recalls result in a higher reduction in subsequent involuntary recalls than mandated recalls
Thirumalai and Sinha (2011)	Manufacturers in the medical device industry between 2003 and 2005	Whereas the prior recall experience of firms decreases the likelihood of future recalls, the product scope increases the likelihood of future recalls
Kalaignanam et al. (2013)	27 makes of 14 automobile firms between 1995 and 2011	Increases in recall magnitude lead to decreases in future number of injuries and recalls
Steven et al. (2014)	165 public firms within the US manufacturing sector between 2010 and 2012	Offshore outsourcing has a greater positive impact on recalls than offshoring without outsourcing; outsourcing domestically has the least influence
Wowak et al. (2015)	386 CEOs of public companies between 2004 and 2011	The positive influence of CEO stock option pay on the likelihood of subsequent product safety problems will be weaker for longer-tenured CEOs as well as for founder CEOs
Kini et al. (2017)	Public firms between 2006 and 2010	Higher leverage, greater likelihood of financial distress, and more adverse cash-flow shocks adversely impact product quality
Shah et al. (2017)	232 car model years between 2000 and 2006	Manufacturing-related recalls are positively related to product variety and plant utilization; the joint effect of plant variety and utilization is positively associated with increased recalls
Ball et al. (2018a)	64 publicly traded firm between 2002 and 2013	Whereas product competition is associated with an increase in high severity, low discretion recalls, it is associated with a decrease in low severity, high discretion recalls
Ball et al. (2018b)	167 managers from a Fortune 500 medical device firm and 614 subjects from Amazon Mechanical Turk	A physician's ability to detect a defect prior to product use decreases the likelihood to recall, while a manager's understanding of the root cause of the defect increases the likelihood to recall
Wowak et al. (2021)	92 publicly traded medical product firms between 2002 and 2013	An increase in female board representation is positively associated with the count of low-severity recalls, while it is negatively associated with the time-to-recall for high-severity recalls
Astvansh et al. (2022b)	22 passenger car manufacturers between 2009 and 2020	The volume of news reports about product safety increases high-severity voluntary recalls; the negativity in these news reports strengthens the main effect of news volume, whereas the media's product rating weakens the news volume effect
Giannetti and Srinivasan (2022)	86 US medical device firms between 2005 and 2018	The positive effect of corporate lobbying on a firm's product recalls via lower emphasis on product safety will be moderated by the firm's CEO functional experience and focus on radical innovation
Kini et al. (2022)	Firms within various industries between 2003 and 2013	Firms that are unionized and those that have higher unionization rates experience a greater frequency of quality failures
Lam et al. (2022)	948 US firms between 1991 and 2016	Increased foreign competition has a negative impact on the product quality of the US firms; US firms with more operational resources and research and development (R&D) intensity suffer less from foreign competition; firms pursuing product differentiation are also less affected by foreign competition
The current study	19 public firms within automobile industry between 1994 and 2019	CEO duality is negatively associated with the number of product recalls; the impact of CEO duality on product recalls will be greater for a firm with high firm liquidity or for a firm led by a CEO who has experience of working as CEO prior to appointment

Most recent research examined other factors such as news media (Astvansh et al. 2022b), corporate lobbying (Giannetti and Srinivasan 2022), and labour union (Kini et al. 2022). For example, Astvansh et al. (2022b) showed that the volume of news reports about product safety increases high-severity voluntary recalls. Kini et al. (2022) suggested that firms that are unionized and those that have higher unionization rates experience a greater frequency of quality failures. Nevertheless, the impact of CEO duality as a measure of CEO power on product recalls has not been explored. This study addresses the gap in literature by investigating the relationship between CEO duality and product recalls, and the boundary conditions for such relationship.

2.1.3 Recall Decision-Making Process

Recently, the product recall research attempts to open the "black box" of the product recall process (Wowak and Boone 2015). Scholars have devoted their attention to the recall decision-making process and the time taken to recall a defective product (Hora et al. 2011, Ball et al. 2017, Ni and Huang 2017, Wowak et al. 2021, Astvansh et al. 2022a). Prior literature has examined factors such as recall strategy, product defect type and supply chain player (Hora et al. 2011), plant inspections (Ball et al. 2017), problem severity (Eilert et al. 2017), female directors (Wowak et al. 2021), social media discussions (Gao et al. 2022), and CEO tenure (Mayo et al. 2022) that may impact the product recall timing decisions. The relevant studies are listed in Table 2.2. Eilert et al. (2017) showed that although problem severity increases time to recall, the relationship is weaker as brand reliability increases. However, the relationship between problem severity and time to recall is stronger as brand diversification increases. Gao et al. (2022) proposed two channels through which social media may accelerate the drug recall process: the information effect, which captures how extracting information from

Table 2.2 Recall Decision-Making Process: Research and Main Findings

Citation	Research focus	Main findings
Hora et al. (2011)	Identifying salient factors influencing time to recall a product	The time to recall, as measured by difference between product recall announcement date and product first sold date, is associated with the recall strategy, the type of product defect, and the supply chain entity that issues the recall
Ball et al. (2017)	Evaluating how well plant inspection outcomes predict the hazard of a future recall	Inspection outcomes reliably predict future product recalls; inspection outcomes become an unreliable predictor of recalls with an increase in site-specific investigator experience
Eilert et al. (2017)	Examining the effect of problem severity on time to recall	Although problem severity increases time to recall, this relationship is weaker when the brand under investigation has a strong reputation for reliability and has experienced severe recalls in the recent past; however, this relationship is stronger when the brand is diverse
Ni and Huang (2017)	Investigating how five recall attributes impact discovery-to-recall	Discovery-to-recall is longer for: recalls that are triggered by external initial reports, recalls that are attributed to suppliers, recalls that are associated with design flaws, and recalls with more models involved; cumulative recall experience shortens discovery-to-recall
Astvansh et al. (2022a)	Understanding the recall decision-making process	This data paper analyses textual disclosures on 2,120 recalls initiated in the United States; for each recall, the data set provides the time the firm took to make the recall decision, whether the recall was associated with a supplier, the number of events in the recall decision-making process, and the date and description of each event
Gao et al. (2022)	Investigating whether social media can accelerate the product recall process	More adverse drug reaction discussions on social media lead to a higher hazard rate of the drug being recalled and, thus, a shorter time to recall
Mayo et al. (2022)	Analysing how CEO tenure influences the hazard of subsequent recalls	The hazard of a recall is high immediately following a new CEO appointment, and then decreases significantly until the next CEO is appointed
The current study	Examining the impact of consumer complaint on time to recall	Consumer complaints with high relevance to product defects lead to a faster recall, whereas consumer complaints with ambiguous defect signals suggest a longer time to recall; the impact of complaint relevance on time to recall is greater for a recall that involves various brands or that involves older car models; the influence of complaint variety on time to recall is stronger when consumer complaints describe a severer product defect or when consumer complaints are collected from diverse sources

social media helps detect more signals and mine signals faster to accelerate product recalls, and the publicity effect, which captures how firms and government agencies are pressured by public concerns to initiate speedy recalls. Mayo et al. (2022) found that the hazard of a recall is high immediately following a new CEO appointment, and then decreases significantly until the next CEO is appointed.

In the US automobile industry, many of product recalls are voluntarily initiated by manufacturers, while others are either influenced by NHTSA investigations or ordered by NHTSA via the courts. Consumers report safety problems to NHTSA via website, telephone, or mail when they suspect that their vehicles or equipment may have a safety defect. NHTSA analyses data from diverse sources and then decides whether to open a formal investigation or not. If the government agency believes that a safety defect exists, it will notify the manufacturer and request the manufacturer to launch a recall. The manufacturer may protest the request and then the agency can make an "initial" defect decision and hold a public hearing. With strong evidence, NHTSA will make a "final" defect decision and the manufacturer has the right to challenge the final determination in federal court. The manufacturer may launch a recall voluntarily during the process (Rupp and Taylor 2002, Beene 2014). Figure 2.1 illustrates the NHTSA recall decision-making process.

However, little is known about the recall behaviour of the firm responding to customer complaint in the context of US automobile industry. This study explores the impact of consumer complaint on the time taken for recall decisions. This research proposes complaint relevance and complaint variety as drivers of product recall timing decisions. Furthermore, the research examines how the magnitude of the impact of complaint relevance and complaint variety on time to recall varies depending on contextual factors.

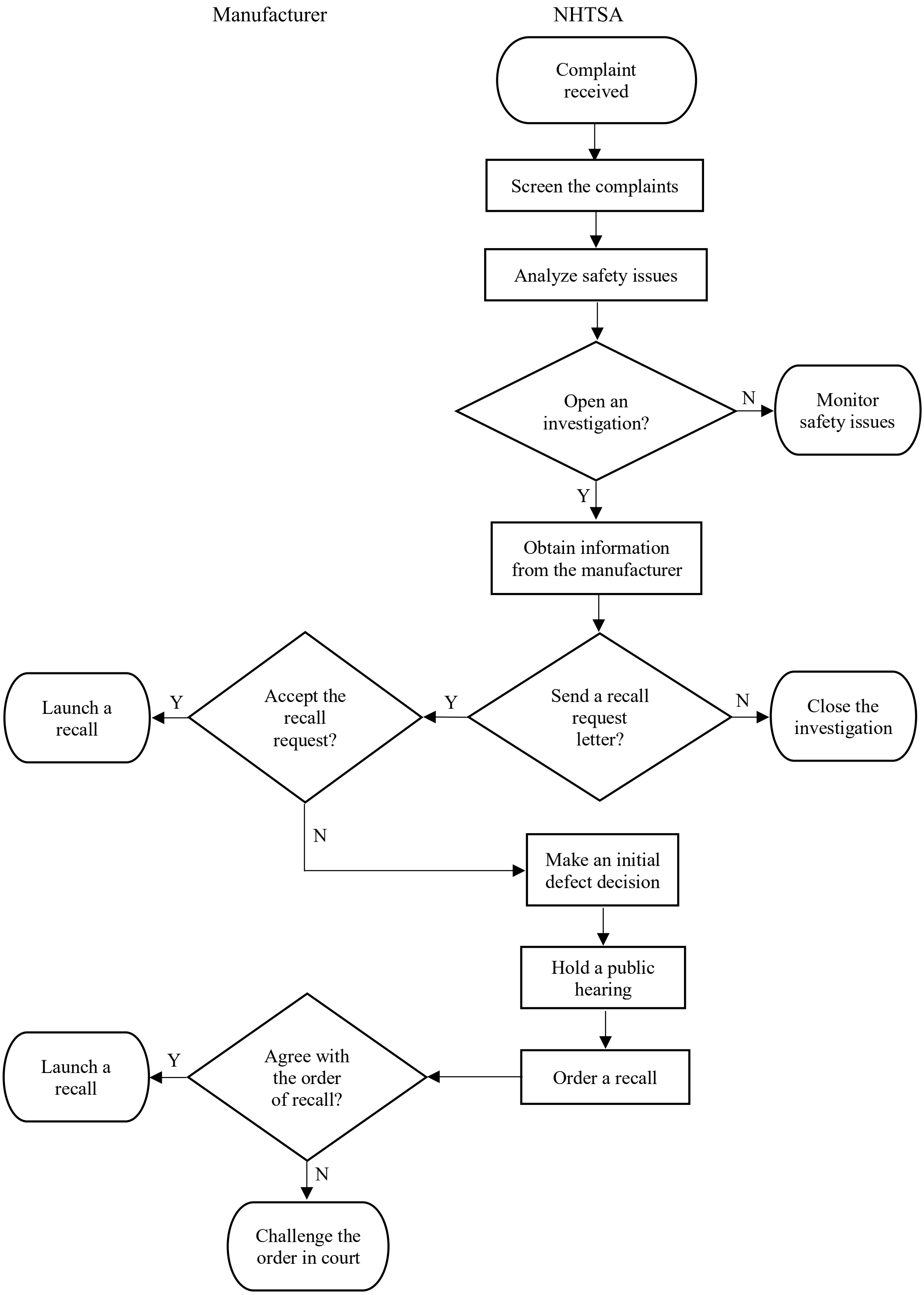

Figure 2.1 NHTSA Recall Decision-making Process

2.2 Theories of Product Recall Decisions

This session focuses on theories that help explain product recall decisions. I review product recall decisions through different theoretical frames of reference: attention-based view of firm, decision-making under ambiguity, and upper echelons theory. From the attention-based view of firm, I demonstrate why consumer complaints can affect the recall decision-making process. Drawing on the literature on decision-making under ambiguity, I illustrate how the quality of defect signals impacts the recall process and the timing of recall decisions. I also build on the upper echelons theory to explain why combining the CEO and board chair roles in a firm influences the frequency of product recalls.

2.2.1 Attention-Based View of Firm

Two decades ago, the attention-based view (ABV) of the firm was proposed to explain firm behaviours (Ocasio 1997). A central argument of ABV is that firm behaviour such as decision-making in organizations is the result of both the limited attentional capacity of humans and the structural influences of organizations on an individual's attention. Attention is defined as the noticing, encoding, interpreting, and focusing of time and effort by organizational decision-makers on both issues and answers.

The central idea of ABV is based on three premises drawn from different levels of analysis: focus of attention, situated attention, and structural distribution of attention. At the level of individual cognition, the principle of focus of attention states that decision makers act depending on what issues and answers they focus their attention on. Yadav et al. (2007) addressed the link between CEOs' attentional focus and innovation outcomes and found that greater CEO attention to the future will have a positive impact on innovation outcomes in firms. At the level of social cognition, the principle of situated attention highlights the role of situational context in shaping firm behaviours. Extant literature has examined a variety of contextual factors such as CEO characteristics, firm performance, and industrial regulations (Gulati and Higgins 2003, Cho and Hambrick 2006, Tuggle et al. 2010). At the organizational level, the principle of structural distribution of attention indicates that the rule, resources, players, and social positions of the firm can regulate and channel the attentional focus of decision makers. Using the real options reasoning as an example, Barnett (2008) developed a process of portfolio selection in which the contextual and concrete structures determine which options a firm holds at a point in time by controlling possibilities noticed by decision makers, the projects they championed, and the projects selected for inclusion in the firm's portfolio prior to that point in time.

According to their focus on structure, process, or outcomes, three varieties of attention have been identified: attentional perspective, attentional engagement, and attentional selection (Ocasio 2011). Attentional perspective is defined as the top-down cognitive structures that generate heightened awareness and focus over time to relevant stimuli and responses (Rhee and Leonardi 2018). The attentional engagement of managers involves the process of intentional, sustained allocation of cognitive resources to guide problem solving, planning, sense making, and decision-making. Attentional engagement encompasses attentional vigilance and executive attention. Empirical evidence has verified the role of executive attention in predicting firm behaviour (Eklund and Mannor 2021, Zhong et al. 2021). The third form of attention studies, attentional selection, is the emergent outcome of automatic or intentional attentional processes that result in focusing attention on selective stimuli or responses to the exclusion of others. Barreto and Patient (2013) found that attention patterns toward opportunity and threat aspects of a given exogenous shock among managers within a firm vary depending on desirability and feasibility.

Most recent research has extended the original theory and further explained the role of communication in shaping the ways in which organizational actors think and act (Ocasio et al. 2018, Nicolini and Korica 2021). Communication is defined as a process by which speakers interact with others to jointly attend to and engage with an understanding of organizational and environmental phenomena. In this vein, Weiser et al. (2020) have noticed that communication plays an important integrative role, both vertically and horizontally, in ensuring the development of a shared understanding of strategic goals across an organization. Vaara and Fritsch (2022) regarded language and communication as not only a representation of cognition or thinking but an inherent part of sensemaking and action in strategy work and strategic change. Tasselli et al. (2020) found that communication shapes the interindividual formation and use of vocabularies. Specifically, communication ties between managers within organizational subunits are more likely to develop similar vocabularies over time. Between subunits, the more two members share similar organizational vocabularies, the more they are likely to form a communication tie over time.

The ABV has been applied to investigate, for example, initial public offering (IPO) success (Gulati and Higgins 2003), innovation outcomes (Yadav et al. 2007), goodness of ideas (Rhee and Leonardi 2018), firm search behaviour (Zhong et al. 2021), and customer satisfaction (Vadakkepatt et al. 2022). Using the U.S. retail banking industry as the empirical context, Yadav et al. (2007) found that firms with CEOs whose attentional patterns exhibit greater future focus are faster at detecting new technological opportunities, faster at developing initial products, and better at deploying these initial products compared to other firms. Rhee and Leonardi (2018) showed that people with highly constrained networks generate good ideas by following a logic of interrogation, by which they focus their attention on information from a particular contact.

However, the application of the ABV in product recall studies is scant (Eilert et al. 2017). The study makes empirical contribution to the attention-based view by examining the relationship between complaint relevance and recall timing decisions. Complaint relevance denotes the similarity between description of consumer complaint and defect summary in a recall report. Drawing on the attention-based theory, I posit that consumer complaints with high relevance to product defects are more likely to be attentional focus of decision-makers, thus leading to a faster recall. I further argue that situational contingencies affect the attentional focus of managers and the subsequent organizational decision-making. Specifically, a high level of component sharing creates a context under which decision makers intentionally and sustainedly allocate cognitive resources to relevant consumer complaints, thus resulting in a much faster recall decision. Because safety issues relating to older car models are potential to be severer, relevant consumer complaints for older car models create a situation that trigger the decision-maker’s attention to quickly recall defective products.

2.2.2 Decision-making under Ambiguity

One of the most prevailing theories of choice in economics and psychology, the subjective expected utility (SEU) theory, assumes that people have subjective, or “personal,” probabilities of states (Savage 1954). However, the modern challenge to SEU as a descriptive theory was made by the Ellsberg paradox (Ellsberg 1961, Segal 1987, Halevy 2007). Ellsberg (1961) used the “three colour” problem to show that the principles of SEU do not seem plausible in some situations. Consider an urn contains 90 balls, 30 of which are known to be red (R). The remaining balls are either black (B) or yellow (Y) balls with unknown proportion (Einhorn and Hogarth 1985, Fox and

Tversky 1995, Trautmann and Kuilen 2015). A ball is drawn at random from the urn. Table 2.3 describes gambles where subjects are asked to bet on the colour of the ball.

Table 2.3 The Three-Colour Ellsberg Problem

	(30)	(60)	
	R	B	Y
A_1	\$100	\$0	\$0
A_2	\$0	\$100	\$0
A_3	\$100	\$0	\$100
A_4	\$0	\$100	\$100

Ellsberg predicted that most people would prefer A_1 to A_2, but A_4 to A_3. Such a pattern is inconsistent with the sure-thing principle of Savage (Ellsberg 2001). Suppose E is an event and $E = R \cup B$. As Table 2.3 shows, if the event E obtained, $A_1 = A_3$ and $A_2 = A_4$. If the event $\sim E$ (not E) obtained, $A_1 = A_2$ and $A_3 = A_4$. According to the sure-thing principle, A_1 is preferred to A_2 if and only if A_3 is preferred to A_4 (Segal 1987). In the "three-colour" problem, the common pattern A_1 is preferred to A_2 and A_4 is preferred to A_3 obviously violates the sure-thing principle (Camerer and Weber 1992). The thought experiment convincingly suggests that the principles of SEU can be violated under ambiguous situations (Ghirardato and Marinacci 2002).

Numerous subsequent studies, originated by the Ellsberg paradox, place emphasis on ambiguous situations that decision makers may face (Einhorn and Hogarth 1985, Sarin and Weber 1993, Rustichini 2005). Ambiguity is meant to represent situations in which the decision maker is not given a probabilistic information about the external events that might affect the outcome of a decision (Etner et al. 2012). Ellsberg (1961) characterized ambiguity as a quality depending on the amount, type, reliability, and "unanimity" of information, and giving rise to one's degree of "confidence" in an estimate of relative likelihoods. Experimental studies have ascertained the presence of the decision makers' averse attitudes to ambiguous situations and explored the psychological determinants of ambiguity averse such as knowledge, skill, and comprehension (Einhorn and Hogarth 1985, Camerer and Weber 1992, Trautmann and Kuilen 2015). Theoretical research has developed allowing ambiguity, and the decision makers' ambiguity attitudes to play a role in their choices (Ghirardato and Marinacci 2002). Several approaches for extending SEU include Choquet expected utility theory, maximin expected utility theory, and smooth ambiguity model (Klibanoff et al. 2005, Etner et al. 2012, Borgonovo and Marinacci 2015).

Recent empirical studies focus on the impact of ambiguity on firm decisions (Bali et al. 2017, Izhakian and Yermack 2017, Kostopoulos et al. 2022). Dimmock et al. (2016) tested the relation between ambiguity aversion and household portfolio choice puzzles. Their results revealed that ambiguity aversion is negatively associated with stock market participation, the fraction of financial assets in stocks, and foreign stock ownership, while it is positively associated with own-company stock ownership. Li et al. (2017) found that ambiguity-averse fund investors are more sensitive to the worst-case scenario when evaluating funds. Based on a static trade-off theory model, Izhakian et al. (2022) indicated positive associations between ambiguity and leverage.

Nevertheless, the research on product recall decisions under ambiguity is limited (Ball et al. 2018b). This study contributes to the stream of research on decision-making under ambiguity by establishing a relationship between information ambiguity and product recall timing decisions. Information ambiguity is measured as complaint variety that is the diversity of defect signals contained in the consumer complaints. This study argues that decision makers are more likely to respond slowly to ambiguous defect signals because of the presence of ambiguity aversion. The research further demonstrates that the longer time to recall under ambiguity is contingent on contextual factors related to the product recall process.

2.2.3 Upper Echelons Theory

The upper echelons theory views organization outcomes as reflections of the values and cognitive bases of top executives in the organization (Hambrick and Mason 1984, Finkelstein et al. 2009). Under the conditions of bounded rationality, the perceptual process of a decision maker takes three stages. First, the decision maker’s field of vision that are those areas to which attention is directed is restricted. Second, the manager selectively perceives only some of the phenomenon included in the field of vision. Third, the bunch of information selected for processing are interpreted through one’s cognitive base and values. The strategic choice is the result of combining the manager’s perception of situation with one’s values. In practice, several sets of executive background characteristics are used as proxies of the cognitive bases, values, and perceptions of top executives: executive tenure, functional experiences, formal education, international experience, and so on (Norburn and Birley 1988, Wiersema and Bantel 1992, Bigley and Wiersema 2002).

Subsequent theoretical development and empirical studies have extended the original theory and further examined factors such as managerial discretion and executive job demands as potentially important moderators of the association between executive characteristics and organizational outcomes (Hambrick 2007, Li and Tang 2010, Mannor et al. 2016). Managerial discretion represents the latitude of action available to top executives (Wangrow et al. 2015). The construct of executive job demands is defined as the degree to which a given executive experiences his or her job as difficult or challenging (Hambrick et al. 2005). In this vein, Finkelstein and Hambrick (1990) showed that the relationship between top management team tenure and firm strategies and performance will be stronger in contexts that allowed managers high discretion. Simsek et al. (2010) found that the influence of CEO core self-evaluation on firm's entrepreneurial orientation is particularly strong in firms facing dynamic environments, but negligible in stable environments. Chen (2015) revealed that new CEOs hired in turnaround situations, who face greater job demands, are expected to receive higher pay. Moreover, externally hired new CEOs will receive even higher pay because the job demands are particularly high if the successor is an outsider.

The upper echelons theory has been applied to investigate, for example, strategic attributes (Finkelstein and Hambrick 1990), firm performance (Carpenter 2002, Hsu et al. 2013), investor decisions (Higgins and Gulati 2006), financial misconduct (Koch-Bayram and Wernicke 2018), and marketing strategy (Whitler et al. 2021). Higgins and Gulati (2006) indicated that investor decisions are influenced by the employment affiliations and roles of top management teams (TMT) members and by a young firm's partnership with a prestigious lead underwriter. Hsu et al. (2013) found that age, educational level, international experience, and duality of the CEO have moderating influence on the relationship between internationalization and firm performance. However, the application of upper echelons theory in product recall studies is limited (Wowak and Boone 2015). Building on the upper echelons theory, the research proposes that CEO-chairs, who hold both the CEO and board chair roles, have enhanced ability to avoid product safety problems, thereby resulting in a lower frequency of product recalls. Moreover, this study establishes boundary conditions for the relationship between CEO duality and the frequency of product recalls. Specifically, the research argues that a CEO-chair in a firm with ample slack resources is expected to experience lower frequency of product recalls compared to a CEO without the role of board chair. Likewise, a CEO-chair with prior experience of working as CEO at another firm will experience a significantly lower frequency of product recalls.

2.3 Empirical Methods for Product Recall Research

2.3.1 Text Analysis Methods

Text analysis approaches are widely adopted in marketing, and operations management research (Choi et al. 2018). Text analysis methods encompass top-down approaches and bottom-up approaches. Top-down approaches involve analysing occurrences of words based on a dictionary or a set of rules, such as dictionary-based approaches and rule-based approaches (Humphreys and Wang 2018). In contrast to top-down approaches, bottom-up approaches involve extracting information about the semantic similarity of words by analysing their usage across a large body of texts (Mehl 2006). Examples of bottom-up approaches are supervised classification, Latent Dirichlet Allocation (LDA) model, and text similarity. I provide an overview of both top-down, dictionary-based approach as well as bottom-up approach such as similarity measures.

2.3.1.1 Dictionary-Based Analysis. The top-down approach, dictionary-based analysis represents counting word usage over predetermined categories of words (Schwartz et al. 2013, Eichstaedt et al. 2015). Traditional approaches use standardized dictionaries such as Regressive Imagery Dictionary, Linguistic Inquiry and Word Count (LIWC) Dictionary, Minnesota Contextual Category System, Lasswell Value Dictionary, and Harvard IV Dictionary (Tausczik and Pennebaker 2010, Humphreys and Wang 2018). Cohn et al. (2004) constructed four linguistic indicators including emotional positivity, cognitive processing, social orientation, and psychological distancing based on the occurrences of particular words relating to specific linguistic categories in LIWC Dictionary. Using the diaries of U.S. users of an online journaling service, linguistic analyses revealed pronounced psychological changes in response to the September 11 attacks. Brett et al. (2007) used LIWC word categories to reflect both the affective and cognitive linguistic dimensions of social interactions and found that giving face facilitates the resolution of disputes, while attacks on face reduce the likelihood of dispute resolution. By measuring CEO past, present, and future focuses through use of the LIWC dictionary, Nadkarni and Chen (2014) showed that, in stable environments, the rate of new product introduction is higher in firms led by CEOs with high past focus, high present focus, and low future focus. In dynamic environments, the rate of new product development is higher in firms led by CEOs with low past focus, high present focus, and high future focus.

Alternatively, one can construct a custom dictionary that contains specific categories of words according to a specific research question. Following the procedures set forth by Pennebaker et al. (2007) and Ertimur and Coskuner-Bali (2015), the dictionaries are developed and validated through three steps. The first step is to create a word list from a corpus of documents pertaining to the focus of construct. Second, the list of words is classified into several categories. The final step involves validating the dictionary, for example, using human coders to check and refine the dictionary (Humphreys and Wang 2018). Ertimur and Coskuner-Balli (2015) qualitatively analysed the articles from *The New York Times* and *The Washington Post*, coding for logics and their characteristics. Then they generated a list of words representing each of four logics: spirituality, medical, fitness, and commercial. The word list was validated with three judges and finalised according to certain criteria. Gamache et al. (2015) created a list of words that capture regulatory foci of CEOs from letters to shareholders and asked experts to code whether each word reflected a promotion focus or a prevention focus. The dictionary was then validated via survey method as well as correlation and regression analyses.

2.3.1.2 Text Similarity Measures. Text similarity measures play a fundamental role in text related tasks such as information retrieval, topic discovery, and data clustering (Jain et al. 1999). Text similarity measures capture the association between pairs of words, sentences, and documents. This session overviews five commonly used text similarity measures in text-based analysis: Jaro-Winkler similarity, Euclidean distance, cosine similarity, Jaccard index, and term frequency-inverse document frequency.

The Jaro-Winkler metric is an advancement of the Jaro similarity measure, which gives values of partial agreement between two textual strings (Winkler 1990, Winkler 1999). Jaro similarity is computed based on the number and order of the common characters between two strings. As an extension of Jaro similarity, the Jaro-Winkler similarity uses a prefix weight which gives favourable values to strings that match from the first few characters. Section 3.3.3 provides the calculation details of Jaro-Winkler similarity.

The Euclidean distance is the square root of the difference between the occurrences of two terms (Feldman and Sanger 2006).

$$D_E = \sqrt{(X_i - X_j)^2} \tag{2.1}$$

where X_i is the occurrence of term i.

The cosine similarity is one of the most popular similarity measures applied to text documents (Feldman and Sanger 2006, Netzer et al. 2012, Liu and Toubia 2018).

$$Cosine_{ij} = \frac{X_{ij}}{\sqrt{X_j X_i}} \tag{2.2}$$

where X_{ij} is the co-occurrence between terms i and j.

The Jaccard coefficient measures similarity as the number of common terms over the number of all unique terms in both strings (Netzer et al. 2012).

$$Jaccard_{ij} = \frac{X_{ij}}{X_j + X_i - X_{ij}} \tag{2.3}$$

The term frequency-inverse document frequency (*tf-idf*) is used to weigh the occurrence of each term by its role in the document (Manning et al. 2008, Netzer et al. 2012, Liu and Toubia 2018). The tf-idf weighting scheme assigns to term t a weight in document d given by: $tf\text{-}idf_{t,d} = tf_{t,d} \times idf_t$. The term frequency $tf_{t,d}$ is the number of occurrences of term t in document d. The inverse document frequency of a term t is defined as: $idf_t = log \frac{N}{df_t}$, where N is the total number of documents in a collection and df_t is the number of documents in the collection that contain a term t.

Surprisingly, very few studies explore the utility of text-based methods on the content of consumer complaints and product defects in recalls provided by the National Highway Traffic Safety Administration (NHTSA) dataset (Ghazizadeh et al. 2014). This research develops new measures derived from unstructured text data in automobile recalls via text-based approach. The study proposes a novel complaint relevance measure that relates the description of consumer complaints to defect summary in a recall report using text similarity method. The research also offers a new complaint variety measure that reflects the degree of diversity of defect signals contained in the consumer complaints. The first step is to construct a custom dictionary of defect signals via dictionary-based analysis and then the diversity of defect signals is calculated using Blau's index. An alternative complaint variety measure is calculated by combining tf-idf term weighting scheme and Blau's index.

2.3.2 Count Models

Over the last decades, researchers in economics, marketing, and operations management typically use count regressions for count-based outcomes, in which the dependent variable takes only non-negative integer values relating to the number of events occurring in each interval. Examples include number of new products (Katila 2002), annual innovation launches (Greve 2003), number of items purchased

(Bryniolfsson et al. 2009), number of citations (Corredoira and Rosenkopf 2010), number of recalls (Thirumalai and Sinha 2011), number of patents (Atanassov 2016), and number of patent subclasses (Tandon and Toh 2022). The basic regression model for count data is the Poisson regression model. Alternative count models include negative binomial model and zero-inflated Poisson and negative binomial models.

Poisson regression fits models of the number of occurrences of an event (Cameron and Trivedi 1986)[1]. Let y_i denote the number of occurrences for the *ith* of N individuals. The Poisson regression model assumes that y_i given the explanatory predictors $\boldsymbol{x}_i$ is Poisson distributed with probability density:

$$f(y_i|\boldsymbol{x}_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \qquad y_i = 0,1,2,\ \ldots, \quad i = 1,2,\ \ldots\ , N \tag{2.4}$$

and mean parameter:

$$E[y_i|\boldsymbol{x}_i] = \mu_i = \exp\,(\boldsymbol{x}_i'\boldsymbol{\beta}) \tag{2.5}$$

The model comprising (2.4) and (2.5) is commonly referred to as the Poisson regression model (Johnson et al. 2005, Cameron and Trivedi 2013). The Poisson model is also named as a log-linear model because the logarithm of the conditional mean is linear in the parameters: $\ln E[y_i|\boldsymbol{x}_i] = \boldsymbol{x}_i'\boldsymbol{\beta}$.

The Poisson likelihood function is expressed as:

$$lnL(\boldsymbol{\beta}) = \textstyle\sum_{i=1}^{n}\{y_i\boldsymbol{x}_i'\boldsymbol{\beta} - \exp(\boldsymbol{x}_i'\boldsymbol{\beta}) - \ln y_i!\} \tag{2.6}$$

In practice, the Poisson model is restrictive in several ways. First, the Poisson model is based on the likelihood independence of observations assumption. Also, the Poisson model assumes that the conditional mean and variance of the dependent variable are equal. Overdispersion occurs when any of the assumptions is violated (Hilbe 2011). The negative binomial model addresses the issue of overdispersion by allowing for an

[1] For detailed derivations of the count models, see Johnson et al. (2005), Hilbe (2011), and Cameron and Trivedi (2013). See Hilbe (2011) and Long and Freese (2014) for a discussion of count models with Stata and R examples. Johnson et al. (2005) provides an extensive review of the application of count models.

estimated variance that exceeds the mean (Cohn et al. 2022). Cameron and Trivedi (2013) considered a general class of negative binomial models with mean μ_i and variance function $\mu_i + \alpha\mu_i^p$. The NB1 model sets $p = 1$, with mean μ_i and variance function $(1 + \alpha)\mu_i$. The NB2 model, which sets $p = 2$, is the standard formulation of the negative binomial model. It has density:

$$f(y|\mu, \alpha) = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(y + 1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1} + \mu}\right)^{y},$$

$$\alpha \geq 0, y = 0,1,2, \ldots \tag{2.7}$$

where $\Gamma(\cdot)$ is the gamma function. Given that $\frac{\Gamma(y + a)}{\Gamma(a)} = \prod_{j=0}^{y-1}(j + a)$ for y as an integer, the log-likelihood function for the NB2 model is:

$$\ln L(\alpha, \beta) = \sum_{i=1}^{n}\{(\sum_{j=0}^{y_i-1}\ln(j + \alpha^{-1})) - \ln y_i! - (y_i + \alpha^{-1}) \ln(1 + \alpha \exp(\boldsymbol{x}_i'\boldsymbol{\beta})) + y_i \ln\alpha + y_i \boldsymbol{x}_i'\boldsymbol{\beta}\} \tag{2.8}$$

The zero-inflated models are appropriate for analysis when count-based outcomes have an excessive number of zero values (Lambert 1992). To account for excess zeros, zero-inflated models assume that excess zeros come from a logit or probit model. The zero-inflated Poisson model assumes that the remaining counts come from a Poisson model and the zero-inflated negative binomial model assumes that these remaining counts come from a negative binomial model (Cameron and Trivedi 2013). Other count models such as zero-truncated count models are suitable when data structurally exclude zero counts. A common feature of zero-truncated models is that the mean of the distribution is shifted left, resulting in under dispersion (Hilbe 2011).

Researchers have applied count models to product recall research (Haunschild and Rhee 2004, Shah et al. 2017, Ball et al. 2018a). By examining the sources of product recalls with negative binomial model, Thirumalai and Sinha (2011) found that prior recall experience decreases the likelihood of recalls, whereas product scope increases the likelihood of recalls. Kini et al. (2022) estimated Poisson regression models to examine the impact of unionization on the frequency of product recalls. They revealed that unionized firms and firms with higher rates of unionized workers experience a greater frequency of product recalls. However, the existing literature has overlooked the influence of CEO duality on product recalls. To bridge the gap in literature, this research estimates the effect of CEO duality on product recalls using panel negative binomial models.

2.4 Summary

I develop a conceptual framework of the thesis by drawing on the insights from theories and empirical research relating to product recall. As depicted in Figure 2.2, this thesis makes several noteworthy contributions to the existing literature by addressing important questions in the area of product recall research. First, this research proposes novel complaint relevance and variety measures to analyse the content of consumer complaints and product defects in automobile recalls. In Chapter 3, I develop a complaint relevance measure that relates the description of consumer complaints to the defect summary in a recall report via text similarity approach. Chapter 4 offers a new complaint variety measure that reflects the diversity of defect signals contained in the consumer complaints. I adopt dictionary-based approach to divide the defects signals into several categories and then calculate complaint variety using Blau's index of heterogeneity. An alternative complaint variety measure is obtained by combining a term weighting scheme and Blau's index.

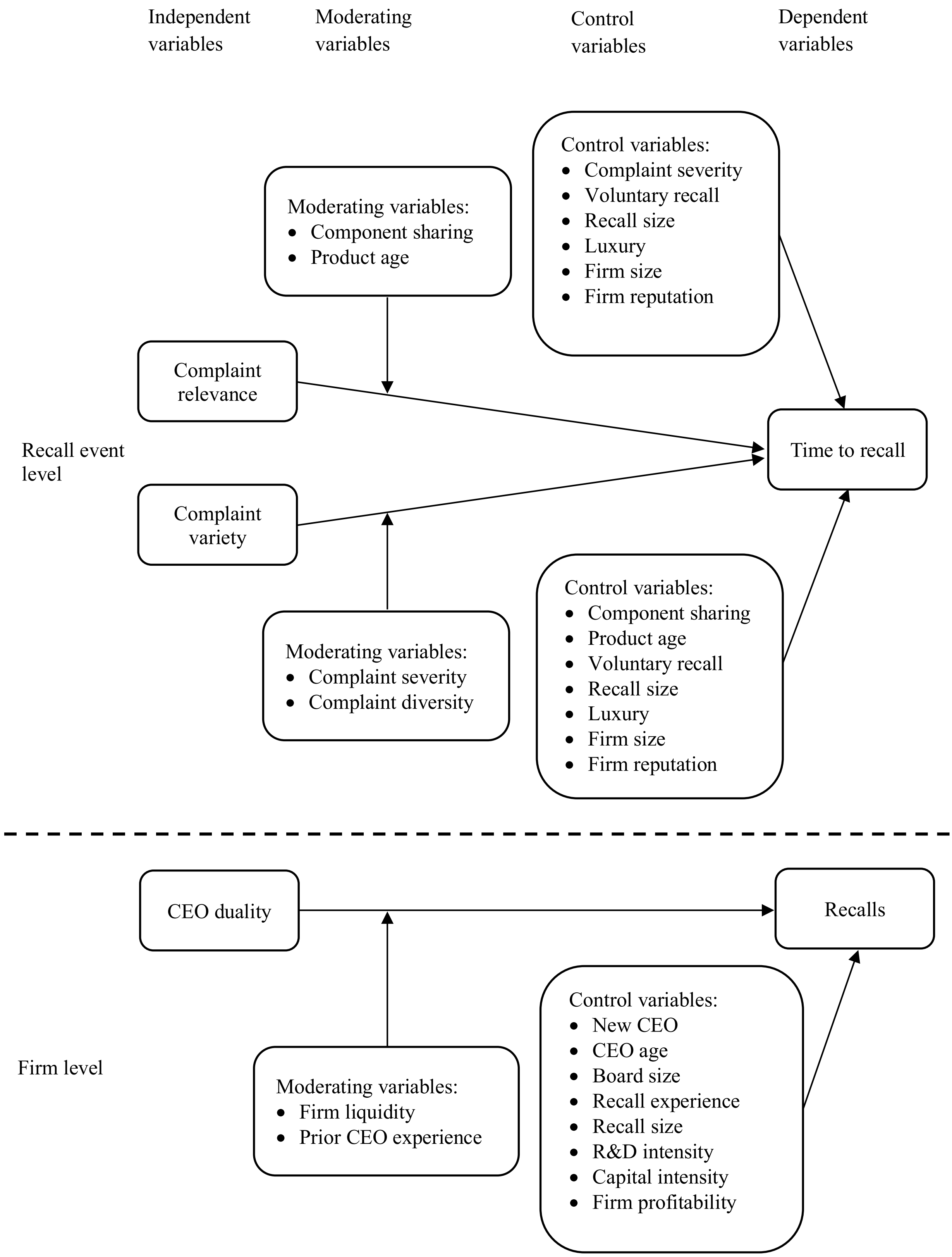

Figure 2.2 Conceptual Framework

This research also provides a contribution to the recall process literature by establishing a relationship between customer complaint and the time taken to make a recall decision. Despite that the existing literature has explored factors that can influence the timing of product recall decisions (Eilert et al. 2017, Gao et al. 2022), the impact of consumer complaint on the time taken for recall decisions has not been investigated. In Chapter 3, I leverage attention-based view of firm to explain how consumer complaints with high relevance to product defects lead to a faster recall decision. In Chapter 4, I demonstrate that the theory of decision-making under ambiguity may explain the reason why consumer complaints with ambiguous defect signals can result in a long time to recall.

Moreover, this research contributes to the marketing research by examining how contextual factors affect the relationship between consumer complaint and time to recall. The marketing literature focuses on the financial impact of customer complaint (Luo and Homburg 2008, Luo 2009). Nevertheless, it overlooks whether and how customer complaint can influence operational decision-making. In Chapter 3, I test the moderating effect of product characteristics including component sharing and product age on the relationship between complaint relevance and time to recall. Chapter 4 evaluates how complaint related factors that are complaint severity and complaint diversity influence the strength of the impact of complaint variety on time to recall.

This research extends the corporate governance literature by investigating the impact of corporate governance structure on the frequency of product recalls. Although CEO duality is a common corporate governance phenomenon (Krause et al. 2014), very little empirical research exists with respect to quantifying the impact of CEO duality on product recalls. Drawing on the upper echelons theory, I argue that CEO-chairs, who hold both CEO and board chair roles, have greater abilities to deal with product quality issues, which results in a decrease in the frequency of product recalls. I further posit that the level of managerial discretion will moderate the negative association between CEO duality and product recalls.

Finally, this research contributes to the literature on the antecedents of product recalls. Researchers in marketing, operations management, and strategic management have examined various factors that explain the variation in the likelihood or frequency of product recalls (Wowak and Boone 2015, Li et al. 2022). Examples include product scope (Thirumalai and Sinha 2011), CEO stock option pay (Wowak et al. 2015), and corporate lobbying (Giannetti and Srinivasan 2022). This research adds to the product recall literature by identifying CEO duality as a new antecedent of product recalls. In Chapter 5, I find that existence of CEO duality reduces the number of product recalls. Furthermore, the results show that the effect of CEO duality on product recalls is greater when the level of managerial discretion is higher.

Chapter 3 Impact of Complaint Relevance on Time to Recall: Empirical Investigation of the Automobile Industry

3.1 Introduction

Product recalls are pervasive in wide-ranging industries such as automobiles, pharmaceuticals, toys, and food (Hora et al. 2011, Ball et al. 2018a, Kini et al. 2017, Mayo et al. 2022). Besides the direct cost of managing reverse logistics, customer compensations, and litigation, firms face the indirect cost of reputation damage and erosion of market values that arise from product recalls (He et al. 2020, Mukherjee and Chauhan 2021). When receiving safety-related consumer complaints, firms analyse information related to the reported safety problems to decide whether to initiate a recall (Ball et al. 2017, Eilert et al. 2017). We uncover a phenomenon in the recall decision-making process: firms respond quickly to consumer complaints with high relevance to product defects.

Typically, when products are suspected of defects, consumers can report safety problems to the regulator. Consumer complaints filed to the regulator are often in the form of unstructured, text-based data. Complaints describe the safety issues but may not identify the defective components. Therefore, it takes time for the regulator to analyse and process complaints to confirm the defective components. Moreover, firms could be reluctant to initiate a recall because of high cost and adverse publicity. Despite the importance of the recall decision, little is known about the recall decision-making process and the time taken for the recall decisions (Astvansh et al. 2022a).

To help bridge the gap, we propose a novel measure of *complaint relevance* derived from unstructured text data in automobile recalls. We apply text similarity method to calculate complaint relevance that is the similarity between description of consumer complaints and the defect summary in a recall report. The objective of this study is to investigate whether and how complaint relevance impacts the time taken to make a recall decision.

Building on the attention-based view of firm, we argue that consumer complaints with high relevance to product defects are more likely to be attentional focus of decision-makers, thus indicating a faster recall. We test the impact of the complaint relevance on the *time to recall*[2] using a sample of 991 automotive recalls between 1993 and 2019 in US. The study finds that complaint relevance decreases *time to recall*. Furthermore, our findings provide evidence on how the relationship between complaint relevance and time to recall varies under various scenarios. When the defective component is shared among various brands, an increase in complaint relevance will result in a much faster recall. Likewise, the magnitude of the impact of complaint relevance on time to recall is larger for older car models. We verify that our findings are robust to alternative explanations, models, and specifications.

Our research is one of the first studies to apply text-based approach to analyse unstructured text data in automobile recalls (Ghazizadeh et al. 2014). We propose a novel complaint relevance measure that relates consumer complaints to defect summary in a recall report using text similarity method. Beyond offering a novel complaint relevance measure, our research contributes to product recall research and marketing research involving consumer complaint. The product recall literature has examined factors that influence the time taken to make a recall decision in the context of toy industry (Hora et al. 2011) and medical industry (Wowak et al. 2021). This study extends the line of research by showing that customer complaint impacts the time to recall. In another vein, the marketing literature has tested the financial impact of

[2] Time to recall denotes the number of days from the date of the first consumer complaint to the date of a recall.

customer complaint (Luo and Homburg 2008, Luo 2009). This study contributes the strand of research by establishing a relationship between consumer complaint and operational decisions. Our research can provide insights to help government agencies and manufacturers make recall decisions with lower recall costs.

This chapter proceeds as follows. Section 3.2 presents a foundation and explanations for why complaint relevance influences time to recall. Section 3.3 presents the data, variables, and summary statistics. Section 3.4 reports the main results evaluating the relationship between complaint relevance and time to recall. Section 3.5 presents further analyses and robustness checks to our baseline regression. Section 3.6 discusses the results, managerial implications, and directions for future research.

3.2 Theory and Hypotheses

We build on the attention-based view (ABV) to examine the relationship between the complaint relevance and the time taken for recall decisions, resulting in a decrease in time to recall. This leads to Hypothesis 3.1. We define time to recall as the time elapsed between the date of the first consumer complaint and the date of a recall report received by NHTSA. We introduce theoretical mechanisms that may describe circumstances under which the time taken to make a recall decision is even shorter, leading to Hypothesis 3.2 and 3.3.

3.2.1 Complaint Relevance and Time to Recall

Rooted in the concept of bounded rationality, attention-based theory views organizations as systems of structured attention by decision-makers (Simon 1947, Ocasio 1997). Psychologists understand attention as a variety of interrelated processes carried out in various brain networks, including maintaining the alert state, selection of information, or regulation of conflict (Posner and Rothbart 2007). Attention in organization science is characterized as the noticing, encoding, interpreting, and focusing of time and effort by decision-makers on both issues and answers. ABV focuses on how attention embedded in the organization’s economic, social, and institutional structure shapes organizational decision-making. According to ABV, decision-makers attend to environmental stimuli both internal and external to organizations, and through their attentional processing construct the mental models that result in organizational moves (Ocasio 2011).

Within the framework of ABV, situated attention indicates that the focus of attention of decision-makers depends on the characteristics of situations they confront themselves with, and the situations are shaped by the organization and its environment. As a key dimension of an organization’s demand environment, customers shape an organization’s actions and cognitions through their interaction with the organization (Coviello and Joseph 2012). Griffin and Hauser (1993) attach the importance of incorporating the “voice of the customer” into the product development process. They address the questions of identifying customer needs, arraying customer needs into several categories, and fulfilling customer needs. Danneels (2003) presents a “model of enactment” in which organizations take actions upon their environment, produce cognitions about the environmental responses to their actions, and the cognitions guide their subsequent actions. Zhong et al. (2021) argue that customers may affect the development of executive attention and executive attention in turn may drive organizational behaviour. Executive attention is defined as an attentional process that involves allocating controlled cognitive resources in working memory to planning, problem solving, conflict resolution, and decision-making (Ocasio 2011). Eklund and Mannor (2021) describe the key aspects of executive attention as “opportunity identification” and “opportunity executive”, and further illustrate how organizations should allocate their attention to improve firm performance.

Our research proposes a novel measure of complaint relevance and then examine the impact of complaint relevance on the manufacturer's recall timing decisions. We expect complaint relevance to be negatively associated with recall timing because of its impact on the allocation of time and effort, and the attentional focus of organizational decision-makers in the recall decision-making process. Consumer complaints, as rare external events to organizations serve as a set of stimuli for decision-makers. In this regard, organizations generate highlighted awareness and focus to consumer complaints. However, senior managers are faced with numerous problems, opportunities, and threats, and they are limited in their capacity to construct and enact strategic actions such as proposals and procedures (Ocasio et al. 2018). Therefore, organizational decision-makers are more likely to allocate nonautomatic cognitive resources in working memory to more relevant consumer complaints and provide a quicker response to these complaints. Thus, we hypothesize:

Hypothesis 3.1: The *complaint relevance is negatively related to the time to recall.*

3.2.2 Moderating Effect of Component Sharing

The attention-based view of firm has addressed how contextual variables affect attention allocation. Sullivan (2010) proposes two possible effects of new problems on solving old problems: the "distraction effect" when an organization is distracted by new problems and allocates more attention to new problems and the "urgency effect" when the new problems create a sense of pressure compelling an organization to attend to old issues. Stevens et al. (2015) show that low performance creates a context in which the organization shifts attention away from social goals to economic goals. Therefore, low performance exacerbates the relationship between utilitarian identity and the relative attention to social goals by enhancing the focus of decision makers on commercial activities. Also, decision makers will use available resources to pursue economic goals when firm performance is low. Berchicci and Tarakci (2022) posit that attention rules are shaped by environmental volatility and vary by locus of attention across firms.

Empirical studies have examined the effect of contextual factors such as firm performance, firm size, capacity utilization, product variety, and product age on operational decisions (Azadegan et al. 2013; Shah et al. 2017). Component sharing, which refers to the use of the same version of a component across various products is often adopted by manufacturers to improve product variety while maintaining cost at a lower level (Fisher et al. 1999). Component sharing may affect product quality and performance in different ways. Component sharing positions manufacturers to respond quickly to new opportunities, reduce design and manufacturing costs, and enhance economies of scale and scope (Patel and Jayaram 2014). On the other hand, a component designed uniquely for a product is associated with high reliability, while the effect is attenuated when the component is shared among various products (Ramdas and Randall 2008). Therefore, one could also wonder how the level of component sharing affects the relationship between the complaint relevance and the time to recall.

In this study, we argue that component sharing influences decision-making by shaping the focus of attention and cognitive processing of organizational decision-makers. Given that a component is shared among various brands, decision-makers are required to search for and analyse information from diverse sources during the recall process. Senior managers are faced with more complex situations under which the attentional processing is highly demanding of attentional capacity, and the action of decision-makers is triggered by those issues they are mindful of. Moreover, the component sharing strategy introduces uncertainty to the process of recall decision-making. When a defect is discovered in a brand, the manufacturer should recall all brands that are using the same component. Therefore, a high level of component sharing creates a context under which decision makers intentionally and sustainedly allocate cognitive resources to consumer complaints with high relevance to product defects to avoid the astonishingly high recall costs. By this way, the process of decision-makers attending to consumer complaints and taking actions will take place quickly, which results in a much faster recall. Thus, we hypothesize:

Hypothesis 3.2: *The level of component sharing negatively moderates the relationship between the complaint relevance and the time to recall.*

3.2.3 Moderating Effect of Product Age

Recall research has revealed that product age affects the manufacturer's product recall decisions (Ball et al. 2018a). The product age indicates the number of years that a car model has been on market. It reflects the stage of product life cycle that products are in, thus shaping the situations that decision makers are faced with. For newer car models, the manufacturer may identify safety issues and initiate recalls through a quality control program (Rupp and Taylor 2002). However, potential safety issues for older car models are more likely to be reported to NHTSA through consumer complaints. Therefore, we posit that the relationship between the complaint relevance and the time to recall will be contingent upon the product age.

Manufacturers may have identified some quality issues for old car models by collecting information from sources such as quality control programs and consumer complaints at the dealership. Our data indicates that the level of complaint severity is higher for older car models compared to new car models. In other words, safety issues reported to the NHTSA for older car models are more likely to be severer compared to that for newer car models. In the context of ABV, relevant consumer complaints for older car models create the situation that trigger the decision-maker's attention to the related safety issues, thereby leading to a much faster recall (Ocasio 1997). Consequently, we propose that the impact of complaint relevance on time to recall is greater for older car models. Thus, we hypothesize:

Hypothesis 3.3: *The level of the product age negatively moderates the relationship between the complaint relevance and the time to recall.*

3.3 Data and Variables

3.3.1 Data

Our study uses vehicle recalls data in the US automobile industry from National Highway Traffic Safety Administration (NHTSA) website. The data includes three data files. The complaint file involves information such as complaint unique number, manufacturer name, automobile make and model, complaint severity, date complaint received, description of complaint, dealer name, telephone number and address on 1,048,576 safety-related defect complaints received by NHTSA since 1984. The investigation file contains information about the investigation number, vehicle make and model, component description, date opened, date closed, campaign number, summary description and details on 132,195 investigations opened since 1972. The recall file includes detailed information about the campaign number, vehicle make and model, component description, date of manufacturing, recall size, recall date, recall initiator, defect summary, consequence summary, corrective summary and recall notes on 145,415 recall campaigns since 1966. Appendix presents the description of variables in the data files. The end date of all three data files is 30th of October in 2019.

We conducted pre-processing and cleaning on the texts of manufacturer names, in terms of removing punctuations and un-wanted symbols (such as “&” and blank spaces), conversing cases and abbreviations, correcting of name variations[3]. In this way, the same manufacturer with different name variations can be accurately identified and linked.

We matched the recall data with the investigation data by using the NHTSA recall campaign number. To examine the impact of the complaint relevance on the time to recall, we then merged the combined dataset with complaint data by manufacture name, vehicle or equipment make, vehicle or equipment model, model year, and component’s description. After combining the three data files, we obtained a dataset with of 81 variables and 4,148,787 observations.

Considering that this research examines the effect of complaints on the recall timing decision, the observations where the date of complaint received was later than the date of recall were removed. Moreover, only observations that complaint data matched with recall data were maintained. Our study regards each recall as a unit of analysis. After dropping the duplicated records, the final sample has 991 recalls for the period 1993-2019.

3.3.2 Dependent Variable

The dependent variable is *time to recall*, which is measured as the number of days from the date of the first consumer complaint to the date of a recall. Of 991 recalls, 803 recall decisions were made within 2,000 days after the first consumer complaint. The

[3] For example, name variations of a firm such as “volkswagen group of america, inc.”, “volkswagen of america, inc”, “volkswagen of america, inc.”, “volkswagen of america, inc” were all corrected as ‘“volkswagen of america”.

average number of days from consumer complaint to recall is about 1,096 days. This research uses two forms of time to recall. In the main analyses, time to recall denotes the number of days from the date of the first consumer complaint to the date of a recall report received by NHTSA. An alternative measure of time to recall is defined as the number of days from the date of the first consumer complaint to the date owner notified by the manufacturer of a recall. The average time to recall by recall year is illustrated in Figure 3.1.

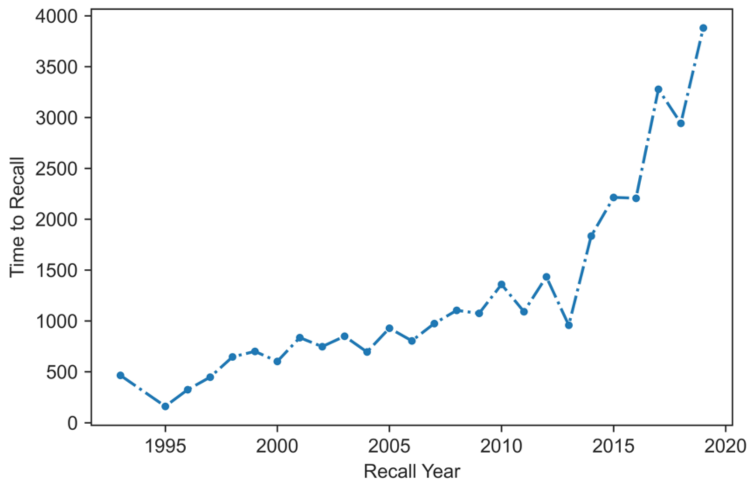

Figure 3.1 Average Time to Recall by Recall Year

3.3.3 Independent Variable

Our focal explanatory variable is the *complaint relevance*, which is the Jaro-Winkler similarity between description of consumer complaints and the defect summary in a recall report. The Jaro-Winkler metric is a string comparator measure that gives values of partial agreement between two textual strings (Jaro 1995, Winkler 1999). The higher the Jaro-Winkler similarity for two textual strings is, the more similar the strings are, and as a result, the complaint and the defect summary are more relevant. It is an advancement of the Jaro similarity measure (Jaro 1989) which is defined as:

$$\Phi_j = w_1 \cdot c/d + w_2 \cdot c/r + w_t \cdot (c - \tau)/c \tag{3.1}$$

where w_1 is weight associated with characters in the description of consumer complaint, w_2 denotes weight associated with characters in the defect summary, and w_t is weight associated with transpositions. We set up those weights as 1/3, which is a typical value widely used in practice and past literature (Larsen and Rubin 2001, Christen 2012, Lampe and Hilgers 2015, Meertens et al. 2020, Stringham 2022). c is the number of characters in common in two files. d and r are the length of the description of consumer complaint and the defect summary respectively. τ is the number of matching characters that are not in the right order divided by two.

The Jaro-Winkler metric Φ_w introduces the prefix weight p which gives favourable values for Jaro similarity measure to strings that match from the first few characters:

$$\Phi_w = \Phi_j + p \cdot (1 - \Phi_j) \tag{3.2}$$

The standard value for the prefix weight sets to 1/10 in Winkler (1990). Therefore, the complaint relevance used in the main analyses is derived by specifying the prefix weight p at 1/10. The similarity score is adjusted upwards when the Jaro Similarity exceeds the boost threshold. Following Winkler (1990), the boost threshold sets to 7/10 when calculating the *complaint relevance2* that is an alternative measure of complaint relevance.

3.3.4 Moderation Variables

We investigate how the impact of the complaint relevance on the time to recall is contingent on the product characteristics including the level of component sharing and the product age. The *component sharing* is the use of the same version of a component among various products (Ramdas and Randall 2008). Considering that a recall is related to components, we operationalize component sharing in terms of the number of brands that is makes for each recall. Nearly 67% and 20% of recalls involve 1 brand or 2 brands respectively. The minimum, first quartile, and median of component sharing are all just one (brand). The third quartile and maximum of component sharing is 2 or 40 brands. Figure 3.2 shows the boxplot of component sharing. Following Rupp and Taylor (2002) and Mayo et al. (2022), we use the *product age* to indicate the number of years that a car model has been on market. The starting year of each observation was the model year of the oldest model involved in a recall, and the ending year was the year of recall[4]. Figure 3.3 presents the boxplot of product age.

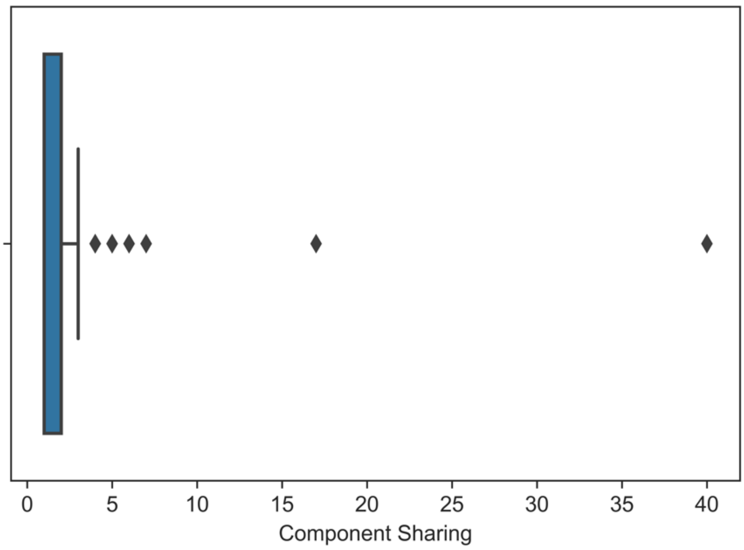

Figure 3.2 Distribution of Component Sharing

[4] According to NHTSA, the term "model year" denotes "the year used to designate a discrete vehicle model, irrespective of the calendar year in which the vehicle was actually produced". Of 991 observations, 8 recall decisions were made one year earlier than the model year. That's because the car models were manufactured before the model year of the products. For example, the Hyundai Motor Company recalled 2011 Hyundai Sonata vehicles manufactured December 2009 through September 2010 in September 2010.

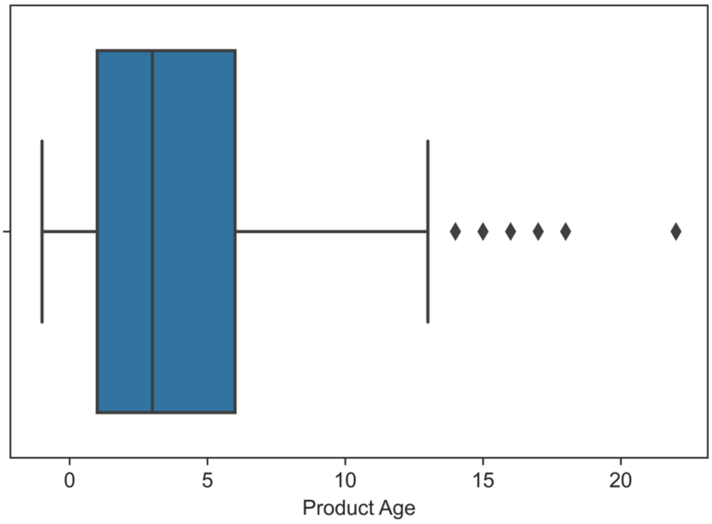

Figure 3.3 Distribution of Product Age

3.3.5 Control Variables

Our research includes various control variables. The more severe the defect, the more likely a firm is motivated to avoid accountability (Eilert et al. 2017). We measure complaint severity to control the possible association. The *complaint severity* is a confirmatory factor analysis of the number of complaints, investigations, crashes, injuries, deaths and polices aggregated by recall. We standardize these six items, perform a confirmatory factor analysis on them and create scores to operationalize complaint severity. The magnitude of the impact of consumer complaint on time to recall might differ greatly across the types of recalls. To deal with this concern, we use the *voluntary recall* that is an indicator variable set to one if the recall was launched by a manufacturer and zero if it was launched by a government agency (Haunschild and Rhee 2004). It is possible that the number of days from the date of consumer complaint to the date of a recall is longer for larger product recalls (Kalaignanam et al. 2013, Eilert et al. 2017). To control for the possibility, we include the *recall size* that is the natural log of the potential number of vehicles or equipment affected by each recall.

Luxury brands that are cars of higher price signals a higher quality of products, which may impact the likelihood of a recall (Ramdas and Randall 2008). We measure the *luxury* as an indicator variable that takes the value of 1 if at least one luxury car model is involved in a recall using data obtained from the US Consumer Reports.

To control for heterogeneity at the firm level, we use the firm size and firm reputation. Larger firms are likely to be of higher motivation and ability to respond to the external event (Haunschild and Rhee 2004, Shah et al. 2017, Bray et al. 2019). We measure the *firm size* as the number of employees at a firm using data from Capital IQ database. Extant literature implies that firm reputation is possible to affect product quality (Rhee and Haunschild 2006, Eilert et al. 2017). Following Chakravarty et al. (2022), the *firm reputation* is measured as media visibility, or the number of mentions about the firm in the prior year of the current year. The data is obtained from LexisNexis News and Business database.

Table 3.1 shows the summary statistics and correlation matrix of the variables.

3.4 Complaint Relevance and Time to Recall

We investigate how complaint relevance impacts the time to recall as well as how such an impact is contingent on product characteristics including component sharing and product age. Considering the unbalanced nature of our data, we estimate ordinary least squares (OLS) regression with a set of control variables[5]. We also check for normality of residuals, multicollinearity, and heteroscedasticity. Our baseline regression specification is:

[5] Our sample comprises 108 manufacturers, 39 of which have experienced product recall for one time. For a few manufacturers such as Ford Motor and General Motors, our sample contains data spanning more than 20 years. Moreover, manufacturers may face product recalls for multiple times in a certain year.

Table 3.1 Descriptive Statistics and Correlation Table for Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable															
(1) Time to recall	991	1095.626	1168.101	0	7287	1									
Independent variables															
(2) Complaint relevance	991	0.554	0.139	0	0.941	-0.323*	1								
Moderating variables															
(3) Component sharing	991	1.583	1.615	1	40	0.065*	0.030	1							
(4) Product age	946	4.290	3.751	-1	22	0.861*	-0.256*	0.071*	1						
Control variables															
(5) Complaint severity	991	0.000	2.175	-3.355	38.594	0.231*	-0.003	0.066*	0.198*	1					
(6) Voluntary recall	991	0.572	0.495	0	1	-0.068*	-0.117*	-0.010	-0.157*	-0.114*	1				
(7) Recall size	991	10.545	2.511	1.386	16.380	0.228*	-0.028	0.146*	0.237*	0.195*	-0.237*	1			
(8) Luxury	991	0.211	0.408	0	1	0.074*	-0.081*	0.130*	0.068*	0.013	0.022	0.146*	1		
(9) Firm size	989	118109.200	130665.400	20	371702	-0.074*	0.083*	0.161*	-0.134*	0.110*	-0.083*	0.293*	0.054	1	
(10) Firm reputation	991	1606.355	3875.215	0	21530	0.097*	0.015	0.091*	0.036	0.088*	-0.043	0.070*	0.108*	0.282*	1

Note. Correlation coefficients significant with *p<0.05.

$$
\begin{aligned}
Y_i = \alpha_0 &+ \alpha_1\, \textit{complaint relevance}_i + \alpha_2\, \textit{component sharing}_i \\
&+ \alpha_3\, \textit{complaint relevance}_i * \textit{component sharing}_i \\
&+ \alpha_4\, \textit{product age}_i + \alpha_5\, \textit{complaint severity}_i \\
&+ \alpha_6\, \textit{voluntary recall}_i + \alpha_7\, \textit{recall size}_i + \alpha_8\, \textit{luxury}_i \\
&+ \alpha_9\, \textit{firm size}_i + \alpha_{10}\, \textit{firm reputation}_i + \varepsilon_i
\end{aligned} \tag{3.3}
$$

where i indexes recall. The dependent variable Y_i denotes *time to recall*$_i$ that is the number of days from the date of the first consumer complaint to the date of a recall. The focal explanatory variable is *complaint relevance*$_i$ that is the similarity between the description of consumer complaints and the defect summary in a recall report. *Component sharing*$_i$ is the moderating variable operationalized by the number of brands for recall i. As mentioned above, we also include a series of control variables, that is, complaint severity, voluntary recall, recall size, luxury, firm size, firm reputation.

To estimate the moderating effect of the product age, we add interaction between the complaint relevance and the product age, using the following specification:

$$
\begin{aligned}
Y_i = \beta_0 &+ \beta_1\, \textit{complaint relevance}_i + \beta_2\, \textit{product age}_i \\
&+ \beta_3\, \textit{complaint relevance}_i * \textit{product age}_i \\
&+ \beta_4\, \textit{component sharing}_i + \beta_5\, \textit{complaint severity}_i \\
&+ \beta_6\, \textit{voluntary recall}_i + \beta_7\, \textit{recall size}_i + \beta_8\, \textit{luxury}_i \\
&+ \beta_9\, \textit{firm size}_i + \beta_{10}\, \textit{firm reputation}_i + u_i
\end{aligned} \tag{3.4}
$$

The moderating factor *product age$_i$* represents the number of years that a car model has been on market.

Table 3.2 presents the regression results using time to recall as dependent variable. Column (1) is the regression with all control variables. In column (2), we add the explanatory variable complaint relevance in the regression; in column (3) we study how complaint relevance and component sharing interact in the recall process. In column (4), we further examine the moderating influence of product age on the relationship between complaint relevance and time to recall. Consistent with Hypothesis 3.1, the coefficient on complaint relevance is negative and statistically significant. Specifically, 1 unit increase in complaint relevance will decrease time to recall by 801.637 days. Considering that complaint relevance indicates the quality of real-time information, attention is likely to be focused on safety issues associated with more relevant consumer complaints, thus resulting in a faster recall (Bakker and Shepherd 2017).
In column (3), the coefficient on the interactive term between complaint relevance and component sharing is negative and significant, indicating that the higher the level of component sharing, the stronger the relationship between complaint relevance and time to recall. This provides support for Hypothesis 3.2. If component sharing is at its mean value of 1.583, increasing complaint relevance by one unit is expected to decrease time to recall by 855.432 days. Similarly, if complaint relevance is at its mean value of 0.554, one more brand involved in a recall will increase time to recall by 56.587 days. To gain a better understanding of this interaction effect, we calculate the impact of complaint relevance on time to recall at low and high levels of component sharing. We set low and high levels of component sharing at 10% and 90%, respectively. The results indicate that 1 unit increase in complaint relevance decreases time to recall by 605.952 days at low levels of component sharing and by 1461.802 days at high levels of

component sharing. This implies that decision makers have a preference to provide a quick response to relevant consumer complaints involving various brands to avoid the high recall cost. Figure 3.4 supports the fact by presenting how the relationship between complaint relevance and time to recall varies depending on component sharing.

Table 3.2 Impact of Complaint Relevance on Time to Recall

Variable	(1)	(2)	(3)	(4)
Complaint relevance		-801.637***	-178.027	359.718**
		(146.817)	(260.618)	(169.586)
Complaint relevance * component sharing			-427.925***	
			(139.167)	
Complaint relevance * product age				-248.275***
				(47.067)
Component sharing	50.906**	53.494**	293.657***	43.431**
	(22.550)	(21.618)	(81.160)	(20.473)
Product age	262.137***	254.008***	252.262***	377.720***
	(8.303)	(8.293)	(8.397)	(22.675)
Complaint severity	31.095***	32.590***	32.036***	37.647***
	(9.063)	(9.064)	(8.828)	(9.121)
Voluntary recall	173.621***	136.152***	136.526***	95.679**
	(41.926)	(41.736)	(41.550)	(41.219)
Recall size	20.987**	19.938**	19.903**	15.271**
	(8.242)	(8.046)	(7.990)	(7.508)
Luxury	-15.125	-33.541	-46.979	-28.041
	(49.344)	(48.596)	(48.755)	(46.602)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.017***	0.017***	0.018***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-451.296***	57.058	-281.647*	-475.336***
	(90.829)	(126.030)	(167.354)	(123.421)
Observations	945	945	945	945
R^2	0.758	0.766	0.768	0.780
Adjusted R^2	0.756	0.764	0.766	0.778

Note. Robust standard errors in parentheses.
* p<0.10; ** p<0.05; *** p<0.01.

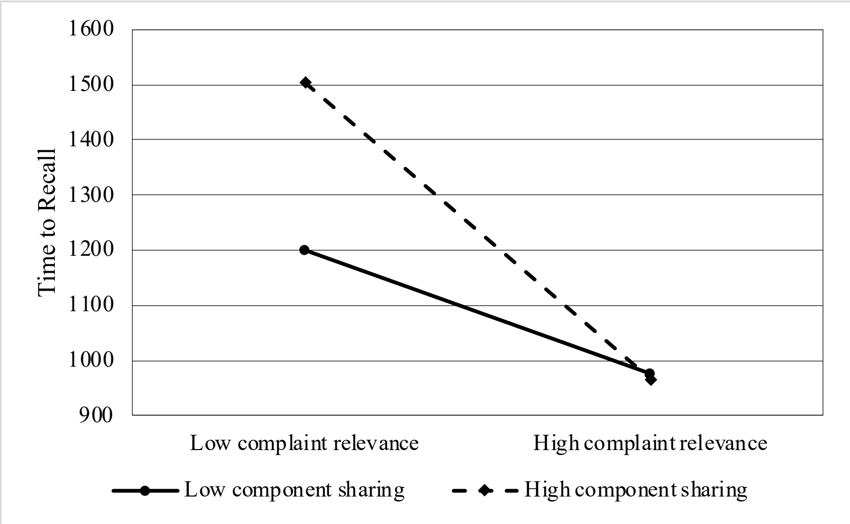

Figure 3.4 The Moderating Effect of Component Sharing on the Relationship between Complaint Relevance and Time to Recall

Column (4) in Table 3.2 investigates the role of product age in the product recall process. In line with Hypothesis 3.3, the coefficient on the interaction term between complaint relevance and product age is negative and significant. The result suggests that the level of product age negatively moderates the relationship between complaint relevance and time to recall. We compute marginal effects to gain insights into the interaction term between complaint relevance and product age. When product age is at its low level, or the product is a current-year car model, increasing complaint relevance by 1 unit will increase time to recall by 359.718 days. However, given that the product age is at its high level, a one unit increase in complaint relevance will decrease time to recall by 1874.757 days. This is in line with the fact that senior managers are more likely to identify safety issues for new car models through quality control programs. However, consumer complaints serve as an important signal of safety issues for older car model recalls. Figure 3.5 reports the moderating influence of product age on the relationship between complaint relevance and time to recall.

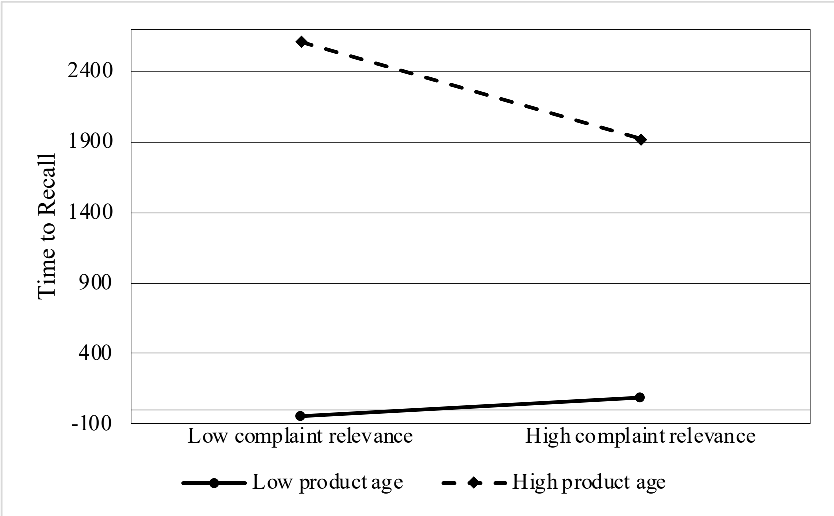

Figure 3.5 The Moderating Effect of Product Age on the Relationship between Complaint Relevance and Time to Recall

Regarding control variables, the complaint severity is consistently positive across all regressions, indicating that a one unit increase in complaint severity will increase time to recall by 31.095 - 37.647 days. This is in accordance with the findings of Eilert et al. (2017). When firms are aware of a potentially severe problem, they often turn inward and take time to determine accountability, thus leading to a longer time to recall. The positive estimates on voluntary recall show that the time to recall for a recall launched by the manufacturer is 95.679 - 173.621 days longer compared to that for a recall mandated by the regulator (Haunschild and Rhee 2004). Positive estimates on recall size suggest that increasing in recall size by one percentage will increase time to recall by 15.271 - 20.987 days. The coefficient on firm reputation is positive and significant, suggesting that one unit increase in firm reputation will increase time to recall by 0.017 - 0.019 days. This implies that firms with more media mentions are motived to avoid the negative effect of a recall, thus resulting in a recall delay.

3.5 Further Analyses and Robustness Checks

3.5.1 Firm Fixed Effects

In this section, we report alternative analyses and robustness checks to our baseline regression. Although our model does include certain firm-level variables, we assume that the unobserved effect is uncorrelated with all the independent variables (Wooldridge 2016). To control firm-specific and unobservable factors, we incorporate firm fixed effects into our regressions. Table 3.3 shows the results for the impact of complaint relevance on time to recall with firm fixed effects.

Table 3.3 presents the regression results evaluating the relationship between complaint relevance and time to recall. In column (1) and (2), we first include all control variables and then add the focal explanatory variable complaint relevance. In column (3) and (4), we examine the moderating influence of component sharing and product age on the relationship between complaint relevance and time to recall respectively. Negative coefficient on complaint relevance indicates that increasing complaint relevance by one unit is expected to decrease time to recall by 681.414 days. Column (3) shows that the coefficient on the interaction term between complaint relevance and component sharing is negative and significant. The result implies that the magnitude of the influence of complaint relevance on time to recall is greater when the level of component sharing is higher. Given that component sharing is at its low level, a one unit increase in complaint relevance will decrease time to recall by 459.425 days. However, when component sharing is at its high level, a unit increase in complaint relevance will decrease time to recall by 1385.801 days. In column (4), negative estimate on the interaction term between complaint relevance and product age suggests that the relationship between complaint relevance and time to recall is stronger for older

Table 3.3 Impact of Complaint Relevance on Time to Recall with Firm Fixed Effects

Variable	(1)	(2)	(3)	(4)
Complaint relevance		-681.414***	3.763	361.621*
		(165.103)	(273.058)	(185.494)
Complaint relevance * component sharing			-463.188***	
			(149.237)	
Complaint relevance * product age				-231.744***
				(49.969)
Component sharing	42.799*	44.221*	302.436***	32.522
	(24.879)	(24.671)	(88.183)	(24.332)
Product age	264.504***	258.032***	255.730***	372.953***
	(8.595)	(8.660)	(8.782)	(24.890)
Complaint severity	30.806***	32.426***	32.215***	36.596***
	(9.396)	(9.533)	(9.342)	(9.461)
Voluntary recall	166.119***	145.549***	145.057***	108.657**
	(45.450)	(44.836)	(44.475)	(43.533)
Recall size	11.664	12.361	12.940	11.801
	(9.308)	(9.114)	(9.097)	(8.321)
Luxury	10.315	-17.097	-31.709	-5.563
	(59.964)	(60.606)	(61.008)	(58.417)
Firm size	-0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Firm reputation	0.011**	0.014***	0.016***	0.014***
	(0.005)	(0.004)	(0.005)	(0.005)
Constant	-306.466	115.527	-265.802	-407.353
	(312.679)	(295.643)	(327.207)	(292.218)
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	945	945	945	945
R^2	0.799	0.804	0.806	0.814
Adjusted R^2	0.777	0.782	0.784	0.793

Note. Robust standard errors in parentheses.
* p<0.10; ** p<0.05; *** p<0.01.

car models. Specifically, increasing complaint relevance by one unit will increase time to recall by 361.621 days for current-year car models and decrease time to recall by 1724.075 days for 9-year-old car models. The results indicate that the unobservable firm-specific characteristics are unlikely to be creating significant bias in our study.

3.5.2 Threshold Regression

To ensure that our findings are robust to our chosen empirical strategy, we evaluate an alternative to our ordinary least square approach. We use threshold regression model to evaluate how the influence of complaint relevance on time to recall varies depending on product characteristics. Threshold regression model extends linear regression to allow coefficients to differ across the regions of a threshold variable (Hansen 1997, Hansen 2000, Gonzalo and Pitarakis 2002). We select component sharing and product age as threshold variables and obtain the number of threshold values for the variables according to the Bayesian information criterion (BIC) statistics. Table 3.4 reports the results for threshold regression.

In column (1) - (2) of Table 3.4, we fit a threshold regression model using component sharing as the threshold variable. The estimated threshold of 1 splits the sample into two regions. Column (1) corresponds to the portion of the sample in which the number of brands involved in a recall is less than or equal to 1. Column (2) corresponds to the portion of the sample in which the number of brands involved in a recall is greater than 1. In column (1), the coefficient on complaint relevance indicates that increasing complaint relevance by one unit will decrease time to recall by 657.752 days given that the component sharing takes a value that is less than or equal to 1. Column (2) shows that increasing in complaint relevance by one unit is associated with a decrease in time to recall by 1045.421 days if the level of component sharing is greater than 1. The results imply that the influence of complaint relevance on time to recall is greater given a higher level of component sharing. In column (3) - (6), we use product age as the threshold variable. We estimate three thresholds using the BIC criteria. The three thresholds split the sample into four regions. In the first region, the number of years that a car model has been on market is less than or equal to 3. In this case, the coefficient on complaint relevance in column (3) is negative, while not significant. In the second region, the estimate in column (4) suggests that a unit increase in complaint relevance will decrease time to recall by 570.089 days when the product age is between 3 and 6. In the third region, the product age is between 6 and 8. The coefficient in column (5) implies that increasing in complaint relevance is expected to decrease time to recall by 1248.825 days. In the fourth region, the product age is greater than 8. In this case, a unit increase in complaint relevance is associated with a decrease in time to recall by 2849.957 days. These results in Table 3.4 provide overall support for Hypothesis 3.1 - 3.3 and indicate that our findings of the influence of complaint relevance on time to recall are unlikely to be an artifact of using OLS as empirical strategy.

3.5.3 Alternative Measure for Time to Recall

In the main analyses, the time to recall is defined as the number of days from the date of the first consumer complaint to the date of a recall report received by NHTSA. To ensure that our results are robust to an alternative measure of dependent variable, we run a set of regressions using another time to recall measure that is the number of days from the date of the first consumer complaint to the date owner notified by manufacturer as dependent variable. Table 3.5 provides the regression results.

Table 3.4 Impact of Complaint Relevance on Time to Recall with Threshold Regression

Variable	(1) Component sharing <= 1	(2) Component sharing > 1	(3) Product age <= 3	(4) 3 < Product age <= 6	(5) 6 < Product age <= 8	(6) Product age > 8
Complaint relevance	-657.752***	-1045.421***	-134.909	-570.089*	-1248.825**	-2849.957***
	(176.858)	(263.088)	(119.977)	(312.832)	(547.569)	(788.216)
Component sharing			29.817	2.558	80.356	154.801
			(21.132)	(44.036)	(52.663)	(112.720)
Product age	236.465***	282.738***				
	(10.990)	(10.662)				
Complaint severity	34.006	27.770***	130.384*	53.144***	35.776***	91.371*
	(65.147)	(8.915)	(69.431)	(6.104)	(6.295)	(51.244)
Voluntary recall	153.273***	138.122**	-10.840	201.130***	-81.107	103.114
	(50.044)	(67.410)	(34.334)	(75.052)	(173.178)	(236.589)
Recall size	36.992***	-12.855	30.781***	55.694***	-38.484	62.249
	(9.725)	(11.275)	(6.484)	(17.196)	(34.930)	(62.607)
Luxury	-62.247	-41.947	-42.792	-108.751	-118.840	125.480
	(65.683)	(74.693)	(36.304)	(88.226)	(157.879)	(249.328)
Firm size	-0.000	-0.000	-0.000**	0.000	-0.000	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Firm reputation	0.019***	0.016***	0.004	0.029***	0.061***	0.057
	(0.005)	(0.005)	(0.003)	(0.005)	(0.016)	(0.039)
Constant	-84.017	617.178***	187.681**	690.974**	2619.995***	3742.314***
	(146.993)	(220.683)	(93.882)	(276.075)	(552.811)	(883.549)
Observations	628	317	473	243	109	120

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

Column (1) - (4) of Table 3.5 use the alternative measure of time to recall as dependent variable. Column (1) is the regression with all control variables. In column (2), we include the focal explanatory variable complaint relevance; in column (3), we add the interaction term between complaint relevance and component sharing. In column (4), we further study the moderating role of product age in the relationship between complaint relevance and time to recall. The coefficient on complaint relevance is negative and significant, indicating that a one unit increase in complaint relevance is associated with a decrease in time to recall by 872.906 days. In column (3), we find that a unit increase in complaint relevance will decrease time to recall by 703.842 days at low levels of component sharing and by 1437.796 days at high levels of component sharing. Column (4) shows that the influence of complaint relevance on time to recall is greater for older car models. The coefficient on the interaction term between complaint relevance and product age indicates that a unit increase in complaint relevance will increase the time to recall for current-year car models by 336.109 days and decrease the time to recall for 9-year-old car models by 1989.392 days. Regarding control variables, we find that increasing in complaint severity will increase time to recall. The number of days from the date of the first consumer complaint to the date of recall is longer for voluntary recalls. The firms with greater media visibility are more likely to delay recall. In aggregate, the results shown in Table 3.5 help build confidence that our main findings are robust to the alternative measure of time to recall.

Table 3.5 Complaint Relevance and Time to Recall: Alternative Time to Recall Measure

Variable	(1)	(2)	(3)	(4)
Complaint relevance		-872.906***	-336.865	336.109**
		(148.893)	(266.436)	(170.243)
Complaint relevance * component sharing			-366.977***	
			(138.556)	
Complaint relevance * product age				-258.389***
				(46.997)
Component sharing	62.451***	63.376***	265.645***	51.111**
	(21.940)	(21.079)	(81.168)	(20.208)
Product age	269.111***	260.521***	258.934***	389.302***
	(8.493)	(8.400)	(8.551)	(22.589)
Complaint severity	30.099***	31.781***	31.409***	37.170***
	(8.720)	(8.566)	(8.415)	(8.320)
Voluntary recall	167.223***	126.928***	127.712***	85.838**
	(43.014)	(42.490)	(42.336)	(41.803)
Recall size	22.387***	20.930**	21.410**	15.633**
	(8.590)	(8.342)	(8.298)	(7.800)
Luxury	1.000	-18.810	-29.280	-9.695
	(49.190)	(48.344)	(48.678)	(46.257)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.016***	0.016***	0.017***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-428.231***	129.261	-163.514	-417.597***
	(95.239)	(129.429)	(171.963)	(126.314)
Observations	916	916	916	916
R^2	0.769	0.778	0.779	0.792
Adjusted R^2	0.767	0.776	0.777	0.790

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

3.5.4 Alternative Measure for Complaint Relevance

We perform a set of robustness checks to ensure that our results are robust to alternative measure of independent variable. As mentioned, the *complaint relevance2* is the modified Jaro-Winkler similarity metric between the description of consumer complaints and defect summary by specifying the boost threshold at 7/10. Table 3.6 presents the regression results by using complaint relevance2 as explanatory variable.

Table 3.6 shows the results for time to recall as dependent variable. Negative coefficient on complaint relevance2 suggests that a one unit increase in complaint relevance2 will decrease time to recall by 1005.974 days. In column (3), the estimate on the interaction term between complaint relevance2 and component sharing is negative and significant, suggesting that the higher the level of component sharing, the stronger the relationship between complaint relevance and time to recall. If component sharing is at its low level of 1, a unit increase in complaint relevance2 will decrease time to recall by 781.131 days. Given that component sharing is at its high level of 3, a unit increase in complaint relevance2 will decrease time to recall by 1732.907 days. Column (4) shows that the relationship between complaint relevance2 and time to recall is stronger for older car models. A unit increase in complaint relevance2 will increase the time to recall for current-year car models by 389.388 days. However, when the product age is at its high level of 9, the time from the first consumer complaint to recall will decrease by 2224.815 days as complaint relevance2 increases by one unit.

Overall, the results using complaint relevance2 are in line with our main findings using complaint relevance. The negative link between complaint relevance and time to recall is robust. The level of component sharing negatively moderates the relationship between complaint relevance and time to recall. Likewise, the influence of complaint relevance on time to recall is greater for a higher level of product age.

Table 3.6 Complaint Relevance and Time to Recall: Alternative Complaint Relevance Measure

Variable	(1)	(2)	(3)	(4)
Complaint relevance2		-1005.974***	-305.243	389.388*
		(178.617)	(312.883)	(199.387)
Complaint relevance2 * component sharing			-475.888***	
			(161.613)	
Complaint relevance2 * product age				-290.467***
				(52.667)
Component sharing	50.906**	54.204**	340.342***	43.656**
	(22.550)	(21.518)	(99.886)	(20.356)
Product age	262.137***	253.020***	251.392***	411.493***
	(8.303)	(8.294)	(8.394)	(27.559)
Complaint severity	31.095***	32.835***	32.293***	38.320***
	(9.063)	(9.106)	(8.887)	(9.283)
Voluntary recall	173.621***	129.054***	130.354***	89.397**
	(41.926)	(41.931)	(41.727)	(41.186)
Recall size	20.987**	19.948**	19.955**	15.509**
	(8.242)	(8.025)	(7.978)	(7.470)
Luxury	-15.125	-33.827	-47.527	-28.547
	(49.344)	(48.431)	(48.681)	(46.445)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.017***	0.017***	0.018***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-451.296***	216.423	-194.669	-503.328***
	(90.829)	(145.699)	(205.572)	(143.284)
Observations	945	945	945	945
R^2	0.758	0.767	0.769	0.782
Adjusted R^2	0.756	0.765	0.767	0.779

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

3.5.5 Instrumental Variable Analysis

We implement an instrumental variable (IV) approach to address the potential issue of endogeneity in our models. A first concern is reverse causality: the similarity between the description of consumer complaints and the defect summary in a recall report may be determined jointly with the timing of product recall decisions. A second concern is that of omitted variables. Product recall decisions are possible to be influenced by time-varying omitted variables such as industry policy, institutional and economic changes that related to our complaint relevance measure. To alleviate the concerns, we employ IV methods to examine the relationship between complaint relevance and time to recall. Specifically, we use the complaint length as an instrument for our key independent variable complaint relevance because it is highly correlated with complaint relevance but does not have direct relation with the error term. The *complaint length* is measured as the average number of words contained in the description of consumer complaints involved in a recall. We also seek a second instrument for the interaction term of complaint relevance and moderators. Following Wooldridge (2016) and Avgerinos et al. (2020), we first run the first stage for complaint relevance using complaint length as an instrument. Then we take the interaction term of the linear prediction from that model that is *complaint relevance3* with each moderator and use it as our second instrument for the interaction term of complaint relevance and the moderating factor. Table 3.7 reports the results using instrumental variables approach.

Table 3.7 Impact of Complaint Relevance on Time to Recall with IV Approach

Variable	(1)	(2)	(3)	(4)
Complaint relevance		-1816.796***	-1028.788	285.255
		(437.777)	(647.847)	(551.174)
Complaint relevance * component sharing			-518.636*	
			(264.641)	
Complaint relevance * product age				-552.053***
				(89.671)
Component sharing	50.906**	56.772***	347.740**	35.946
	(22.550)	(21.360)	(155.179)	(21.965)
Product age	262.137***	243.713***	241.924***	513.923***
	(8.303)	(9.459)	(9.529)	(47.948)
Complaint severity	31.095***	34.482***	33.750***	46.623***
	(9.063)	(9.195)	(8.936)	(10.397)
Voluntary recall	173.621***	88.704*	90.662*	-23.739
	(41.926)	(47.325)	(46.959)	(48.658)
Recall size	20.987**	18.609**	18.609**	7.604
	(8.242)	(8.320)	(8.234)	(8.348)
Luxury	-15.125	-56.861	-72.409	-55.665
	(49.344)	(49.955)	(49.194)	(50.915)
Firm size	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.017***	0.018***	0.019***	0.021***
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	-451.296***	700.816**	269.889	-178.422
	(90.829)	(298.061)	(401.978)	(345.636)
Observations	945	945	945	945
R^2	0.758	0.753	0.756	0.731
Adjusted R^2	0.756	0.751	0.753	0.728

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

Table 3.7 shows the results of two-stage least squares (2SLS) analysis. Column (1) shows the baseline regression with moderating variables and control variables. Column (2) uses complaint length to instrument for complaint relevance. Column (3) uses complaint length as well as the interaction term between complaint relevance3 and component sharing as instruments. In column (4), the instruments include complaint length as well as the interaction term between complaint relevance3 and product age. The estimate in column (2) indicates that a one unit increase in complaint relevance is expected to decrease time to recall by 1816.796 days. In column (3), the coefficient on the interaction term between complaint relevance and component sharing is negative and significant, suggesting that the influence of complaint relevance on time to recall is greater for a higher level of component sharing. Column (4) implies that product age negatively moderates the relationship between complaint relevance and time to recall. As expected, the results of 2SLS regressions provide full support for our hypotheses.

3.5.6 Further Analyses in the Relationship between Complaint Relevance and Time to Recall

We conduct a variety of regressions to examine further explanations for the relationship between complaint relevance and time to recall. One could wonder whether the relationship between complaint relevance and time to recall is contingent on the characteristics of situations that decision makers find themselves with. In particular, the product recall decision-making process may be affected by the price tier of the brand. To address this issue, we measure the *luxury products* as the number of luxury car models involved in a recall using data from US Consumer Reports. Moreover, our data contains both vehicle and non-vehicle recalls. It's possible that the impact of complaint relevance on time to recall differs across the recall types. To deal with the concern, we use the *vehicle recall* that is an indicator variable taking the value of one if the recall type is a vehicle recall, and zero otherwise. Another issue is how component variety affects the product recall decision-making process. The *component variety* is an indicator variable that equals one if the number of unique components is larger than or equal to its median level of 6. Table 3.8 presents the results for alternative explanations.

In Table 3.8, we use time to recall as dependent variable. In column (1), we add focal explanatory variable and control variables. In column (2), we examine the moderating effect of luxury products on the relationship between complaint relevance and time to recall. Therefore, we exclude luxury from control variables and use luxury products as moderating factor. The results indicate that a one unit increase in complaint relevance will decrease time to recall by 689.053 days at the low levels of luxury products and by 1068.205 days at the high levels of luxury products. Considering that the cost of a recall that involves luxury car models is astoundingly high, decision makers who are faced with relevant consumer complaints are more likely to recall earlier to avoid higher recall costs (Ramdas and Randall 2008, Bray et al. 2019). In column (3), we include vehicle recall as moderating variable. The coefficient on the interaction term between complaint relevance and vehicle recall is negative and significant. Increasing in complaint relevance by one unit is expected to increase time to recall for non-vehicle recalls by 934.830 days and decrease time to recall for vehicle recalls by 875.899 days. In column (4), we identify how the influence of complaint relevance on time to recall varies depending on component variety. Negative coefficient on the interaction term between complaint relevance and component variety suggests that the influence of complaint relevance on time to recall is greater when the level of component variety is higher. That may be because high component variety causes the recall being broader in

Table 3.8 Further Analyses in the Relationship between Complaint Relevance and Time to Recall

Variable	(1)	(2)	(3)	(4)
Complaint relevance	-801.637***	-689.053***	934.830***	-376.034**
	(146.817)	(154.995)	(345.346)	(154.550)
Luxury products		62.967*		
		(35.463)		
Complaint relevance * luxury products		-126.384**		
		(62.765)		
Vehicle recall			1195.056***	
			(248.067)	
Complaint relevance * vehicle recall			-1810.729***	
			(376.571)	
Component variety				376.733**
				(164.809)
Complaint relevance * component variety				-823.086***
				(279.911)
Component sharing	53.494**	48.379**	52.178**	71.812***
	(21.618)	(22.222)	(21.578)	(23.672)
Product age	254.008***	253.053***	253.807***	255.136***
	(8.293)	(8.457)	(8.268)	(8.415)
Complaint severity	32.590***	33.758***	33.861***	34.251***
	(9.064)	(9.164)	(9.028)	(9.047)
Voluntary recall	136.152***	131.648***	123.722***	121.016***
	(41.736)	(41.493)	(41.734)	(41.673)
Recall size	19.938**	20.192**	19.701**	18.895**
	(8.046)	(8.043)	(8.003)	(7.985)
Luxury	-33.541		-36.018	-30.803
	(48.596)		(48.421)	(48.377)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.017***	0.018***	0.017***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	57.058	3.030	-1085.421***	-146.756
	(126.030)	(128.076)	(242.183)	(123.672)
Observations	945	945	945	945
R^2	0.766	0.767	0.769	0.770
Adjusted R^2	0.764	0.765	0.766	0.767

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

scope and leads to higher recall cost (Ball et al. 2018b). When multiple components are involved in a safety issue, firms react much quicker to consumer complaints with high relevance to product defects to avoid a more massive recall. Taken together, the results shown in Table 3.8 provide reasonable confirmation that our findings are robust to alternative explanations, models, and specifications.

3.6 Concluding Remarks

Defective products pose a threat to customer safety and firm profitability (Eilert et al. 2017, Mukherjee et al. 2022). If a product is suspected of a safety defect, consumers can report the safety issue to the regulator. The regulator analyses consumer complaints to decide whether to initiate a recall. Recalls are costly. However, leaving unsafe products on the market can endanger customer safety and lead to higher recall cost and diminished reputation (Cho et al. 2021, Gao et al. 2022, Mao et al. 2022). Therefore, understanding the recall process and the time taken to make a recall decision is of great value with important implications for both regulators and firms. This study addresses the research question by examining whether and how consumer complaint impacts the time taken to make a recall decision.

We evaluate the relationship between customer complaint and time to recall using a car recall data set from NHTSA in the US. We use text-based method to construct a novel measure of complaint relevance that is the similarity between the description of consumer complaints and the defect summary in a recall report. The result indicates that complaint relevance decreases the number of days from the date of the first consumer complaint to the date of a recall. Moreover, we find that the magnitude of the effect of complaint relevance on time to recall will be greater if the level of component sharing is higher. Likewise, the level of product age expands the influence of complaint relevance on time to recall. Our findings are robust to alternative measures, models, and specifications.

3.6.1 Theoretical Contributions

Our study makes several novel contributions. First, we propose a novel complaint relevance measure that relates consumer complaints to product defects in recalls. Specifically, we measure complaint relevance as the similarity between the description of consumer complaints and the defect summary in a recall report with Jaro-Winkler metric. Also, we calculate modified values of the complaint relevance to ensure that our results are robust to alternative measure of complaint relevance.

Second, this study provides a contribution to product recall research by examining the impact of consumer complaint on the time taken to make a recall decision. The product recall literature has examined factors that can be associated with product recall timing decisions such as recall strategy and defect type (Hora et al. 2011), plant inspections (Ball et al. 2017), problem severity (Eilert et al. 2017), female directors (Wowak et al. 2021), social media discussions (Gao et al. 2022), and CEO tenure (Mayo et al. 2022). Nevertheless, the influence of consumer complaint on time to recall has not been investigated. Specifically, we identify complaint relevance as a driver of the time taken for recall decisions. Moreover, by showing the moderating roles of product characteristics in the recall decision-making process, we provide insights on how the magnitude of the impact of complaint relevance on time to recall varies under various scenarios.

Moreover, this research contributes to the marketing research by establishing a relationship between consumer complaint and operational decision-making process. The marketing literature has investigated the financial impact of customer complaint (Luo and Homburg 2008, Luo 2009). However, very little empirical research exists with respect to explicitly quantifying the impact of consumer complaint on operational decisions. This research addresses the gap in literature by demonstrating that the attention-based view of firm may explain how consumer complaint can have an impact on manufacturers' recall timing decisions. Our results provide evidence on the role of relevant consumer complaints in decreasing the senior managers' response time to potential product defects, thus indicating a faster recall. In addition, our results confirm that the influence of consumer complaint on operational decision-making varies depending on product characteristics.

3.6.2 Practical Contributions

Our findings have several implications for both manufacturers and government agencies. Our text-based analysis can be of interest to managers to efficiently respond to safety problems. Using our approach, it is now possible to quantitatively analyse consumer complaints that were inherently qualitative. Our results evaluating the relationship between complaint relevance and time to recall show that consumer complaints that highly relate to product defects lead to a faster recall decision. This confirms the role of relevant consumer complaints in decreasing the senior managers' response time to product defects. Therefore, managers should attach importance to signals of product defects when receiving consumer complaints from customers.

Our study also provides insights to manufacturers who use component sharing strategy in new product development process. Component sharing strategy is a double-edged sword for manufacturers. On the one hand, component sharing enables manufacturers to improve responsiveness to opportunities, reduce manufacturing cost and enhance economies of scale. On the other hand, component sharing introduces complexity and uncertainty to the recall decision-making process. Consequently, managerial efforts should be focused on consumer complaints about complex products with shared components. For manufacturers, an effective quality control program should be established to periodically inspect and test vehicles with shared components. The regulator may need to be proactive to respond to consumer complaints that involve diverse brands. Also, it is conceivable that the relationship between complaint relevance and time to recall is stronger for older car models. For this reason, managers should attach importance to consumer complaints for old car models. However, managerial efforts can be focused on other sources of information when safety issues are associated with newer car models.

Our results can help guide recall timing decisions under various scenarios. This study identifies luxury products as a moderating factor in the relationship between complaint relevance and time to recall. To avoid astonishing losses from recalling luxury car models, managerial efforts should be targeted to encourage customers to report safety issues through an effective quality control program for luxury products. Also, this study finds that the relationship between the complaint relevance and the time to recall varies depending on the recall type. It implies that managers should disentangle and distinguish consumer complaints for vehicle recalls from those for non-vehicle recalls. The influence of complaint relevance on time to recall is greater when more components are involved in a recall. Consequently, managers are advised to adopt a broader perspective by considering how component variety helps them in responding to safety problems.

3.6.3 Limitations and Future Research

Although we incorporate numerous control variables in our models, and we verify our results through several robustness checks, this study still has some limitations that can be fruitful future research directions. First, consumer generated data comes in various forms, including consumer complaints, consumer ratings, product reviews, videos, and blogs (Tirunillai and Tellis 2012). Our focus has been on consumer complaints because complaints could be directly related to the product recall process. If consumer ratings data becomes available, a future research direction is to examine the effect of customer ratings on the recall process and the time taken to make a recall decision. Second, the current study focuses on examining the relationship between consumer complaint and time to recall, and how such relationship is contingent on product characteristics. The time to recall is defined as the number of days elapsed since a consumer complaint was reported to the regulator. However, we understand little about the role of consumer complaints in preventing future recalls (Chakravarty et al. 2022). Future studies can explore whether and how firms learn from consumer complaints to reduce the likelihood of future recalls (Astvansh et al. 2022a). Finally, consumer complaints are related to product recall timing decisions, but its relative importance might vary for automobile, toy, or pharmaceutical recalls, which remains important topics for continued research. In sum, this research paves the way for consumer complaint and product recall studies and hopefully inspires new research questions in this exciting domain.

Chapter 4 Impact of Complaint Variety on Time to Recall: Evidence from the Automobile Industry

4.1 Introduction

The question of whether and when to initiate a recall is one of the most challenging decisions a firm may face (Ball et al. 2018b). Firms dread product recalls because recalls have negative impact on firm profitability and reputation (Mayo et al. 2022). However, allowing defective products to remain in the market may endanger customer safety and lead to higher recall cost and reputation damage (He et al. 2020). Therefore, understanding the recall process and the time taken to make a recall decision can be of great importance to both firms and regulators (Astvansh et al. 2022a).

If a product is suspected of a safety defect, consumers can submit complaints to the regulator. The regulator analyses consumer complaints to decide whether to open an investigation. When a safety defect is identified, the firm may launch a voluntary recall or initiate a recall mandated by the regulator. Although the complaints provide signals of safety defects, the regulator clearly faces a great deal of uncertainty about the quality of the signals (Li et al. 2017). The defect signals could be highly precise and informative, or the defect signals could be ambiguous and not informative. The quality of defect signals may directly influence the recall process and the timing of recall decisions. However, little is known about how the regulator interprets and responds to the defect signals.

The goal of this research is to explore the impact of the quality of defect signals on the recall decision-making process. To address the research question, we use text-based approach to construct a novel measure of complaint variety that is defined as the diversity of defect signals contained in the consumer complaints. We then examine whether and how complaint variety can impact the recall process and the time taken for a recall decision.

We build on the literature on decision-making under information ambiguity to propose a positive relationship between complaint variety and time to recall. We argue that senior managers respond slowly to ambiguous defect signals, thus resulting in a long time to recall. We denote time to recall as the number of days from the date of the first consumer complaint to the date of a recall. We test the relationship between complaint variety and time to recall using data on 991 automotive recalls during the period from 1993 to 2019. We collect recall, product, and firm-level data from various sources: (1) National Highway Traffic Safety Administration (NHTSA) database, (2) Capital IQ database, and (3) LexisNexis database. This study finds that complaint variety increases time to recall. Moreover, the influence of complaint variety on time to recall is greater when consumer complaints describe a severer product defect or when consumer complaints are collected from diverse sources.

Our study offers a new measure of information ambiguity that is complaint variety. We combine dictionary-based approach and Blau's index to compute the diversity of defect signals contained in the consumer complaints. In addition, this research contributes to the product recall research by identifying a new antecedent of the timing of recall decisions. We find that consumer complaints with ambiguous defect signals result in a long time to recall. Moreover, our study complements the literature on decision-making under information ambiguity (Ellsberg 1961). Previous literature has documented the presence of ambiguity aversion, and its effect on individual decisions in financial and marketing settings (Sarin and Weber 1993, Li et al. 2017). To the best of our knowledge, this study is one of the first to provide empirical evidence of ambiguity-averse behaviour in an operational setting using data on product recalls.

The rest of the chapter is organised as follows. In the next section, we explain why complaint variety can impact time to recall. After we present the data, and variables, we report our results in detail. Finally, we conclude the chapter by discussing its contributions and managerial implications.

4.2 Theory and Hypotheses

We approach product recall decisions from the vantage point of the literature on decision-making under information ambiguity. The first hypothesis addresses why the level of complaint variety is positively related to time to recall. Time to recall denotes the number of days from the date of the first consumer complaint to the date of a recall. The second and third hypotheses explain how the positive relationship between complaint variety and time to recall will be contingent on the level of complaint severity and complaint diversity.

4.2.1 Complaint Variety and Time to Recall

Since Ellsberg (1961), the literature on decision making under information ambiguity has examined the presence of ambiguity aversion, that is the preference of decision makers for bets with known, rather than unknown, objective probabilities of winning (Epstein and Wang 1994, Klibanoff et al. 2005). The conditions of ambiguity are situations in which decision makers are faced with information signals of unknown quality. The quality of information depends on the amount, type, reliability, and "unanimity" of information. Sarin and Weber (1993) study the decision making in market settings and find that the individual bid prices and market price for an ambiguous asset were lower than those for an unambiguous asset. The experimental results from Muthukrishnan et al. (2009) show the correlation between ambiguity aversion and the preference for established brands. Li et al. (2017) find that mutual fund investors place a greater weight on the worst signal when faced with information signals of uncertain quality.

This study uses complaint variety as a measure of information ambiguity, that is the heterogeneity of defect signals appeared in the consumer complaints. We argue that high complaint variety is associated with a long time to recall because of the presence of ambiguity aversion. On the one hand, decision makers are potential to experience psychological discomfort when faced with ambiguous defect signals (Sarin and Weber 1993). On the other hand, senior managers may need to conduct comprehensive data collection and thorough inspections under high information ambiguity. Therefore, decision makers are more likely to respond slowly to ambiguous defect signals, thus leading to a longer time to recall. Thus, we hypothesize:

Hypothesis 4.1: *The complaint variety is positively related to time to recall.*

4.2.2 Moderating Effect of the Complaint Severity

Next, we explore how the relationship between complaint variety and time to recall is contingent on the context of product recall decisions. Specifically, one could wonder how such a relationship is moderated by complaint related factors including complaint severity and complaint diversity. We operationalize complaint severity as a confirmatory factor analysis of the number of complaints, investigations, crashes, injuries, deaths and polices aggregated by recall. This research attaches importance to complaint severity enlightened by the empirical literature that tests the role of complaint severity in product recall process (Rupp and Taylor 2002, Chen et al. 2009, Pagiavlas et al. 2022).

Research has shown that a recall involving a severe safety defect could be costlier compared to a recall involving less severe problems (Eilert et al. 2017). Senior managers are less motivated to respond to defect signals involving potential severer product defects. A signal of potential severer product defect is likely to reduce the motivation and ability of firms to respond to consumer complaints contained ambiguous defect signals. In addition, the time to recall may depend on the traceability of product defects (Hora et al. 2011). The traceability of severe safety defect under information ambiguity can be challenging. Therefore, when senior managers are faced with ambiguous defect signals involving severe problems, they will spend more time disentangling the conflicting signals to identify the safety defect, which results in a much longer time to recall. Therefore, we propose:

Hypothesis 4.2: *The impact of complaint variety on time to recall is stronger when the product defect involved in a recall is severer.*

4.2.3 Moderating Effect of the Complaint Diversity

We then explore how the effect of complaint variety on time to recall varies depending on complaint diversity. We define complaint diversity as the number of the sources of consumer complaints involved in a recall. Drawing on the literature on decision-making under ambiguity, we argue that the level of complaint diversity channels recall decision-making under complaint variety by influencing the quality of information. Given a product recall process involving multiple sources of consumer complaints, decision makers evaluate each source of information, integrate the representations made available by the evaluation process, and then map the outcome of integration into a response (Massaro and Friedman 1990). High complaint diversity may enhance the degree of information ambiguity because the reliability and value of each source of information is uncertain. Therefore, we expect that the process of recall decision-making under information ambiguity is lengthier when the consumer complaints involved in a recall are collected from different sources. Thus, we propose:

Hypothesis 4.3: *The impact of complaint variety on time to recall is stronger when consumer complaints involved in a recall are collected from diverse sources.*

4.3 Data and Variables

4.3.1 Data

This study investigates the relationship between complaint variety and time to recall as well as how such a relationship is contingent on the context of recall decision-making using data from US automobile industry. We obtained complaint and recall data from the NHTSA (National Highway Traffic Safety Administration) website, firm data from S&P Capital IQ database and LexisNexis database. The intersection of these data sources leads to a sample of 991 recalls for a period from 1993 to 2019. Table 4.1 presents the description and data sources of the variables.

To obtain complaint and recall related variables, we conducted pre-processing and cleaning on the texts of manufacturer names of the complaint, investigation, and recall data files from the NHTSA website. We matched the recall data with the investigation data by using the NHTSA recall campaign number and then merged the combined dataset with complaint data by manufacturer name, vehicle or equipment make, vehicle or equipment model, model year, and component's description.

4.3.2 Dependent Variable

The dependent variable is time to recall. *Time to recall* is defined as the number of days elapsed from the date of the first consumer complaint filed at NHTSA to the date of a recall report received by NHTSA. An alternative measure of time to recall denotes the number of days from the date of the first consumer complaint to the date owner notified by the manufacturer of a recall.

Table 4.1 Data Sources and Operationalization

Variable	Operationalization	Data sources
Time to recall	The number of days elapsed from the date of the first consumer complaint to the date of a recall	NHTSA
Complaint variety	The diversity of defect signals contained in the consumer complaints	NHTSA
Complaint severity	A confirmatory factor analysis of the number of complaints, investigations, crashes, injuries, deaths and polices aggregated by recall	NHTSA
Complaint diversity	The number of the sources of consumer complaints involved in a recall	NHTSA
Component sharing	The number of brands that are makes involved in a recall	NHTSA
Product age	The number of years that a car model has been on market	NHTSA
Voluntary recall	An indicator variable set to one if the recall was launched by a manufacturer and zero otherwise	NHTSA
Recall size	The natural log of the potential number of vehicles or equipment affected by each recall	NHTSA
Luxury	An indicator variable that takes the value of 1 if a luxury car model is involved in a recall	Consumer Reports
Firm size	The number of employees at a firm	Capital IQ database
Firm reputation	The number of mentions about the firm in the prior year of the current year	LexisNexis News and Business database

4.3.3 Independent Variable

The focal explanatory variable is *complaint variety*, which is the diversity of defect signals contained in the description of consumer complaints. We use dictionary-based analysis and Blau's index to construct complaint variety following a three-step procedure. The first step is to identify defect signals from component name with a deductive top-down, dictionary-based analysis (Humphreys and Wang 2018). Following the approach in Colak and Bray (2016) and Shou et al. (2019), we develop a key word list from component description in both recall and investigation dataset and then classify the words into 10 categories based on US Standard Industrial Classification (SIC)[6]. The categories include body, electr, signal, seat, brake, engine, fuel, suspension, transmission, accessories. Two experts who were familiar with the research questions and research methods screened the coding process. Table 4.2 presents a full list of defect signals. After identifying defect signals, we count the occurrences of defect signals in the description of the consumer complaints and then aggregate to the recall level. Complaint variety is calculated by using a conventional measure of diversity that is Blau's index (Wiersema and Bantel 1992):

$$1 - \sum_{i=1}^{10} (P_i)^2 \tag{4.1}$$

where P_i is the proportion of the occurrences of defect signals in the *ith* category. The distribution of complaint variety is illustrated in Figure 4.1.

We offer an alternative measure of complaint variety that is *complaint variety2* with a term weighting scheme. Following Manning et al. (2008), we calculate the *tf-idf* value of each defect signal *t* appeared in a description of consumer complaint *d*:

$$tf\text{-}idf_{t,d} = tf_{t,d} \times idf_t \tag{4.2}$$

[6] https://www.osha.gov/sic-manual/3714.

The term frequency $tf_{t,d}$ is the number of occurrences of defect signal t in the consumer complaint d. We denote N as the total number of consumer complaints in the complaint database and df_t as the number of consumer complaints in the collection that contain a defect signal t. The inverse document frequency of a defect signal t is thus defined as:

$$idf_t = log \frac{N}{df_t} \tag{4.3}$$

Table 4.2 List of Defect Signals

Category	**Keywords**
body	bead; bumper; pillar; rim; tailgate; tire; door; hinge; latch; lock; sun; window
electr	radio; camera; alternator; battery; breaker; circuit; controller; gauge; ignition; solenoid; start; switch; accelerator; alarm; strap
signal	concealment; flash; fog; light; signal; spot; turn; position; sens
seat	barrier; chest; child; clip; cooler; seat; tether
brake	abs; actuator; adjuster; anchor; antilock; brak; caliper; chamber; cylinder; disc; drum; governor; lining; pad; park; reservoir; rotor; vacuum
engine	inverter; train; crank; mounting; pcv; pulley; turbocharger; cooling; fan; radiator; convertor; emission; exhaust; muffler
fuel	carburetor; charging; egr; fill, filter; fuel; inject; lpg; recirculation
suspension	absorber; asc; ball; banjo; bar; bolt; bracket; coil; drag; idler; leaf; macpherson; rod; shock; spindle; stabilizer; steering; strut; suspension
transmission	bell; box; clutch; driveshaft; housing; torque; transfer; transmission
accessories	conditioner; bearing; bag; bolster; clockspring; frontal; horn; infant; label; mirror; washer

Note. The “electr” category indicates automobile components relating to electrical system and electronics, that is, audio and video devices, cameras, low voltage electrical supply system, gauges and meters, ignition system, starting system, electrical switches, and others.

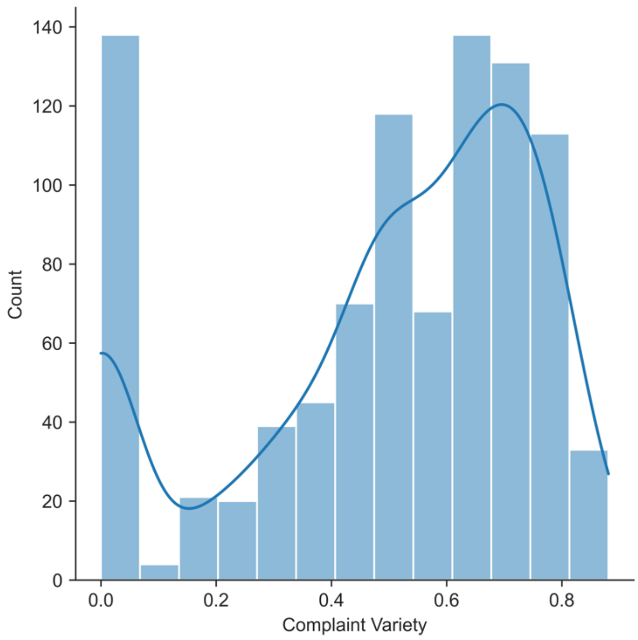

Figure 4.1 Distribution of Complaint Variety

Based on the classification of defect signals shown in Table 4.2, we add up the tf-idf weight of each defect signal in a category to obtain the tf-idf weight of each category in a description of consumer complaint. We then take the average of those tf-idf values in the consumer complaints corresponding to a recall. After that, complaint variety2 is calculated by substituting not the occurrences of defect signals, but instead the tf-idf weight into the formula of Blau's index.

4.3.4 Moderating Variables and Control Variables

We examine how the effect of complaint variety on time to recall varies depending on the context of product recall decisions such as the level of complaint severity and complaint diversity. We operationalize *complaint severity* as a confirmatory factor analysis of the number of complaints, investigations, crashes, injuries, deaths, and polices aggregated by recall. We first standardize these six items, and then perform a confirmatory factor analysis on them to create scores of complaint severity. Figure 4.2 provides the kernel density distribution curve of complaint severity. It is possible that the product recall process is affected by the number of the sources of consumer complaints (Clemen and Winkler 1993). Consumer complaints filed at NHTSA are likely to be collected from consumer action group, hotline vehicle owners questionnaire (VOQ) and so on. We define *complaint diversity* as the number of the sources of consumer complaints corresponding to a recall. Figure 4.3 shows the boxplot of complaint diversity. As reported in Table 4.1, we include a variety of control variables, which are component sharing, product age, voluntary recall, recall size, luxury, firm size, and firm reputation.

Table 4.3 lists the descriptive statistics and correlation matrix for the variables.

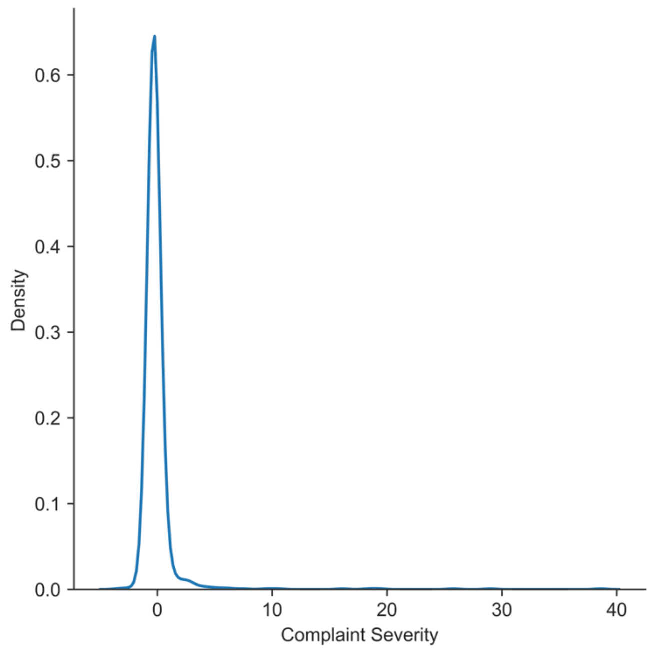

Figure 4.2 Distribution of Complaint Severity

Table 4.3 Descriptive Statistics and Correlation Matrix for the Variables

Variables	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Time to recall	991	1095.626	1168.101	0	7287	1										
(2) Complaint variety	938	0.495	0.259	0	0.881	0.229*	1									
(3) Complaint severity	991	0.000	2.175	-3.355	38.594	0.231*	0.058	1								
(4) Complaint diversity	991	2.058	1.313	1	10	0.480*	0.319*	0.405*	1							
(5) Component sharing	991	1.583	1.615	1	40	0.065*	0.001	0.066*	0.141*	1						
(6) Product age	946	4.290	3.751	-1	22	0.861*	0.177*	0.198*	0.422*	0.071*	1					
(7) Voluntary recall	991	0.572	0.495	0	1	-0.068*	-0.059	-0.114*	-0.245*	-0.010	-0.157*	1				
(8) Recall size	991	10.545	2.511	1.386	16.380	0.228*	0.169*	0.195*	0.389*	0.146*	0.237*	-0.237*	1			
(9) Luxury	991	0.211	0.408	0	1	0.074*	0.096*	0.013	0.096*	0.130*	0.068*	0.022	0.146*	1		
(10) Firm size	989	118109.200	130665.400	20	371702	-0.074*	0.014	0.110*	0.240*	0.161*	-0.134*	-0.083*	0.293*	0.054	1	
(11) Firm reputation	991	1606.355	3875.215	0	21530	0.097*	0.157*	0.088*	0.154*	0.091*	0.036	-0.043	0.070*	0.108*	0.282*	1

Note. Correlation coefficients significant with *p<0.05.

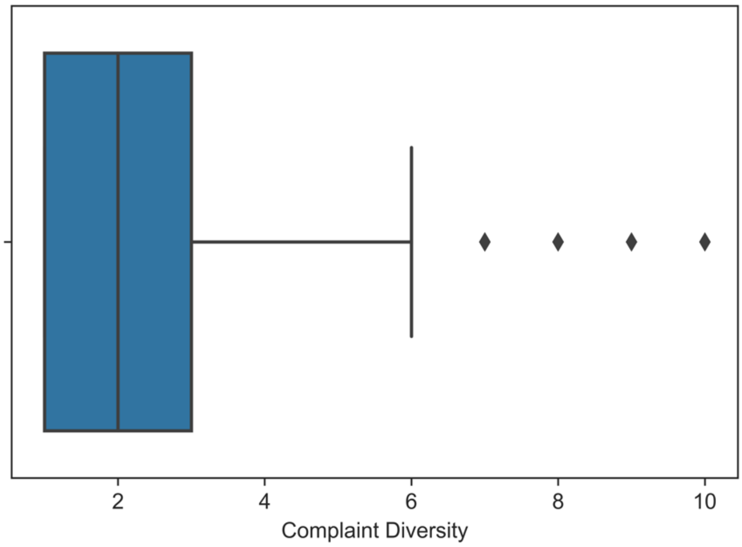

Figure 4.3 Distribution of Complaint Diversity

4.4 Complaint Variety and Time to Recall

Our study focuses on the relationship between complaint variety and time to recall as well as how such a relationship is moderated by the context of product recall decisions. For our main analysis, we estimate ordinary least squares models in which each recall is an observation. We also check for normality of residuals, multicollinearity, and heteroscedasticity. Our model evaluating the role of complaint severity in the relationship between complaint variety and time to recall is the following:

$$
\begin{aligned}
Y_i = \alpha_0 &+ \alpha_1\, complaint\ variety_i + \alpha_2\, complaint\ severity_i \\
&+ \alpha_3\, complaint\ variety_i * complaint\ severity_i \\
&+ \alpha_4\, component\ sharing_i + \alpha_5\, product\ age_i \\
&+ \alpha_6\, voluntary\ recall_i + \alpha_7\, recall\ size_i + \alpha_8\, luxury_i \\
&+ \alpha_9\, firm\ size_i + \alpha_{10}\, firm\ reputation_i + \varepsilon_i
\end{aligned}
\tag{4.4}
$$

where i indexes recall. The dependent variable Y_i is *time to recall*$_i$, or the number of days from the date of the first consumer complaint to the date of a recall. The focal independent variable is *complaint variety*$_i$, that is the diversity of defect signals contained in the consumer complaints. *Complaint severity*$_i$ is the moderating variable, which is a confirmatory factor analysis of the number of complaints, investigations, crashes, injuries, deaths, and polices aggregated by recall. We include complaint, recall and firm-related control variables, which are component sharing, product age, voluntary recall, recall size, luxury, firm size, and firm reputation.

To estimate the moderating role of complaint diversity, we include interaction between the complaint variety and the complaint diversity, using the following specification:

$$\begin{aligned} Y_i = \beta_0 &+ \beta_1\, complaint\ variety_i + \beta_2\, complaint\ diversity_i \\ &+ \beta_3\, complaint\ variety_i * complaint\ diversity_i \\ &+ \beta_4\, component\ sharing_i + \beta_5\, product\ age_i \\ &+ \beta_6\, voluntary\ recall_i + \beta_7\, recall\ size_i + \beta_8\, luxury_i \\ &+ \beta_9\, firm\ size_i + \beta_{10}\, firm\ reputation_i + u_i \end{aligned} \tag{4.5}$$

The moderating factor *complaint diversity*$_i$ represents the number of sources of consumer complaints involved in a recall.

Table 4.4 shows the regression results using time to recall as dependent variable. Column (1) is the regression with all control variables. In column (2), we add the focal independent variable complaint variety; in column (3) we explore how complaint severity moderates the relationship between complaint variety and time to recall. In column (4), we further study the moderating role of complaint diversity in the relationship between complaint variety and time to recall.

Table 4.4 Impact of Complaint Variety on Time to Recall

Variable	(1)	(2)	(3)	(4)
Complaint variety		315.371***	331.946***	-268.217*
		(76.467)	(76.887)	(138.821)
Complaint severity			-17.823	
			(24.093)	
Complaint variety * complaint severity			110.780**	
			(49.859)	
Complaint diversity				-28.350
				(48.655)
Complaint variety * complaint diversity				264.961***
				(75.693)
Component sharing	56.109**	57.505***	47.302**	37.000*
	(22.805)	(21.680)	(21.380)	(21.306)
Product age	265.189***	264.043***	258.731***	246.830***
	(8.199)	(8.571)	(8.869)	(9.461)
Voluntary recall	166.051***	159.627***	170.975***	194.190***
	(41.643)	(42.667)	(42.317)	(41.693)
Recall size	24.226***	15.488*	11.882	3.286
	(8.294)	(8.486)	(8.471)	(8.683)
Luxury	-21.767	-34.478	-29.631	-27.314
	(49.703)	(48.902)	(48.439)	(46.390)
Firm size	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.018***	0.014***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-505.351***	-546.481***	-482.959***	-266.876**
	(91.511)	(93.503)	(92.050)	(112.644)
Observations	945	893	893	893
R^2	0.755	0.762	0.767	0.780
Adjusted R^2	0.753	0.760	0.764	0.777

Note. Robust standard errors in parentheses.
* p<0.10; ** p<0.05; *** p<0.01.

In column (2), positive coefficient on complaint variety indicates that a one unit increase in complaint variety will increase time to recall by 315.371 days. This provides support for Hypothesis 4.1. When decision-makers are faced with multiple ambiguous signals, they need to conduct multiple checks to identify the potential source of defect, thus suggesting a longer time from the first consumer complaint to a recall (Li et al. 2017). Consistent with Hypothesis 4.2, the coefficient on the interaction term between complaint variety and complaint severity is positive and significant, suggesting that the number of days from the date of the first consumer complaint to the date of a recall is even longer for a recall involving severer product defect. The result shows that a one unit increase in complaint variety is expected to increase time to recall by 290.827 days at low levels of complaint severity and by 346.614 days at high levels of complaint severity. That may be because a recall involving a severe defect is costlier compared to a recall involving less severe defect (Eilert et al. 2017). Therefore, when faced with ambiguous situations, senior managers are more likely to delay a response to avoid accountability. Figure 4.4 supports the fact by presenting how the effect of complaint variety on time to recall varies depending on the level of complaint severity.

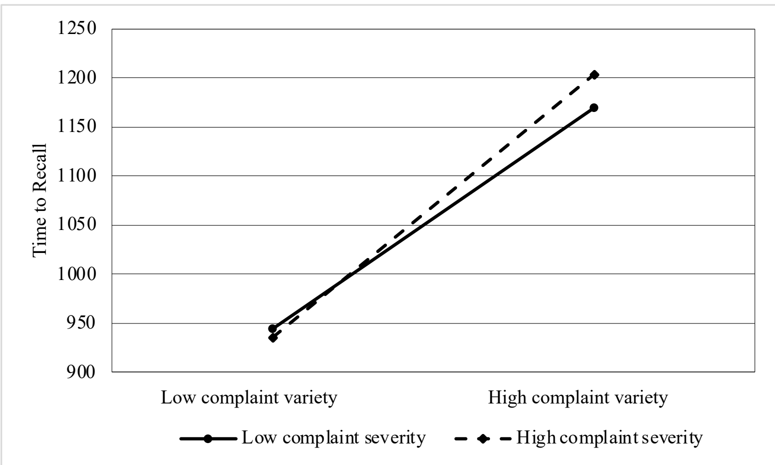

Figure 4.4 The Moderating Influence of Complaint Severity on the Relationship between Complaint Variety and Time to Recall

In column (4), the coefficient on the interaction term between complaint variety and complaint diversity is positive and significant, suggesting that the relationship between complaint variety and time to recall will be stronger when consumer complaints are collected from diverse sources. This is in line with Hypothesis 4.3. The underlying implication behind this fact is that senior managers spend more time on decision-making in situations where information of unknown quality is from different sources. The illustration of the moderating influence of complaint diversity on the relationship between complaint variety and time to recall is shown in Figure 4.5.

Regarding control variables, the results show that the coefficient on component sharing is consistently significant across all columns, suggesting that the number of days from the date of the first consumer complaint to the date of a recall is expected to increase by 37.000 - 57.505 days as one more brand is involved in a recall. A one unit increase in product age will increase time to recall by 246.830 - 265.189 days. The time to recall for a voluntary recall is 159.627 - 194.190 days longer compared to that for an involuntary recall. The estimates on firm reputation indicate that firms with higher level of media visibility are more cautious about product recall decisions, thus leading to a long time to recall.

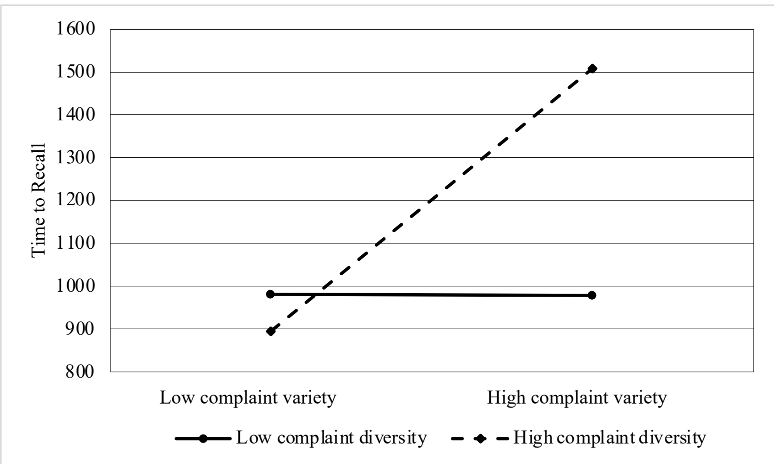

Figure 4.5 The Moderating Influence of Complaint Diversity on the Relationship between Complaint Variety and Time to Recall

4.5 Further Analyses and Robustness Checks

4.5.1 Alternative Measure for Time to Recall

In this section, we report alternative analyses and robustness checks to our baseline regression. We perform a set of robustness checks to ensure that our results are robust to alternative measure of time to recall. We use *time to recall2*, or the number of days elapsed from the date of the first consumer complaint to the date owner notified by the manufacturer of a recall, as an alternative measure of dependent variable. Table 4.5 presents the regression results.

Table 4.5 provides the results evaluating the influence of complaint variety on time to recall2. We first include all control variables and then add the focal explanatory variable complaint variety. Column (2) shows that the estimate on complaint variety is positive and significant, suggesting that a unit increase in complaint variety is expected to increase time to recall by 301.457 days. In column (3), we further investigate the moderating influence of complaint severity on the relationship between complaint variety and time to recall. The coefficient on the interaction term between complaint variety and complaint severity is positive, implying that the influence of complaint variety on time to recall is greater for a recall involving a severer defect. In column (4), we test the moderating influence of complaint diversity on the relationship between complaint variety and time to recall. The result indicates that the level of complaint diversity positively moderates the relationship between complaint variety and time to recall. Increasing complaint variety by a unit will enhance time to recall by 13.706 days at low levels of complaint diversity and by 708.287 days at high levels of complaint diversity. Overall, the results given in Table 4.5 confirm that our findings are robust to alternative measure of time to recall.

Table 4.5 Complaint Variety and Time to Recall: Alternative Time to Recall Measure

Variable	(1)	(2)	(3)	(4)
Complaint variety		301.457***	314.439***	-217.821
		(78.807)	(79.475)	(147.896)
Complaint severity			-7.397	
			(26.992)	
Complaint variety * complaint severity			85.151	
			(54.221)	
Complaint diversity				-15.975
				(53.513)
Complaint variety * complaint diversity				231.527***
				(82.260)
Component sharing	67.955***	59.228***	49.772**	39.091*
	(22.155)	(22.316)	(22.015)	(22.074)
Product age	272.148***	271.442***	266.562***	254.875***
	(8.368)	(8.764)	(9.113)	(9.698)
Voluntary recall	159.703***	154.512***	165.025***	186.368***
	(42.677)	(43.791)	(43.536)	(43.154)
Recall size	25.624***	18.347**	14.846*	6.562
	(8.649)	(8.924)	(8.889)	(9.098)
Luxury	-5.831	-13.440	-7.953	-4.993
	(49.518)	(49.002)	(48.632)	(46.959)
Firm size	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.017***	0.013***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-482.442***	-524.493***	-462.922***	-271.724**
	(96.010)	(98.304)	(97.207)	(122.592)
Observations	916	868	868	868
R^2	0.766	0.771	0.775	0.786
Adjusted R^2	0.764	0.769	0.773	0.783

Note. Robust standard errors in parentheses.
* p<0.10; ** p<0.05; *** p<0.01.

4.5.2 Alternative Measure for Complaint Variety

We conduct a series of robustness checks to examine the robustness of the results to alternative complaint variety measure. In the main analyses, we construct the complaint variety with the dictionary-based analyses and Blau's index. The potential issue of the complaint variety measure is that we regard all the defect signals in the description of consumer complaints as equally important. To deal with this issue, we assign to each category of defect signals contained in the description of consumer complaint a weight using the tf-idf term weighting scheme. We then substitute the tf-idf weight into the formula of Blau's index to obtain the measure of *complaint variety2*. Table 4.6 gives the results for evaluating the influence of complaint variety2 on time to recall.

Table 4.6 shows the results for time to recall as dependent variable. In column (1), we include all control variables in the regression. Column (2) adds the focal explanatory variable complaint variety2. Positive estimate on complaint variety2 indicates that a one unit increase in complaint variety2 is expected to enhance time to recall by 306.328 days. In column (3), we test the moderating role of complaint severity in the relationship between complaint variety2 and time to recall. The result shows that increasing complaint variety2 by one unit will increase time to recall by 281.169 days at low levels of complaint severity and by 360.881 days at high levels of complaint severity. Column (4) examines the moderating effect of complaint diversity on the relationship between complaint variety and time to recall. The coefficient on the interaction term between complaint variety2 and complaint diversity is positive and significant, suggesting that the influence of complaint variety2 on time to recall is

Table 4.6 Complaint Variety and Time to Recall: Alternative Complaint Variety Measure

Variable	(1)	(2)	(3)	(4)
Complaint variety2		306.328***	339.922***	-225.838
		(75.307)	(78.068)	(151.929)
Complaint severity			-48.952	
			(39.675)	
Complaint variety2 * complaint severity			158.289**	
			(75.650)	
Complaint diversity				-23.617
				(53.927)
Complaint variety2 * complaint diversity				254.194***
				(85.504)
Component sharing	56.109**	58.132***	47.059**	37.510*
	(22.805)	(21.638)	(21.398)	(21.294)
Product age	265.189***	264.948***	259.886***	247.998***
	(8.199)	(8.413)	(8.690)	(9.298)
Voluntary recall	166.051***	172.420***	183.011***	206.045***
	(41.643)	(42.257)	(41.904)	(41.895)
Recall size	24.226***	18.295**	14.717*	5.316
	(8.294)	(8.385)	(8.357)	(8.603)
Luxury	-21.767	-39.168	-34.815	-35.077
	(49.703)	(48.812)	(48.335)	(46.327)
Firm size	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.018***	0.014***	0.012***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-505.351***	-594.400***	-541.101***	-322.664***
	(91.511)	(92.980)	(91.367)	(120.823)
Observations	945	912	912	912
R^2	0.755	0.764	0.769	0.781
Adjusted R^2	0.753	0.762	0.766	0.778

Note. Robust standard errors in parentheses.
* p<0.10; ** p<0.05; *** p<0.01.

greater for a high level of complaint diversity. When complaint diversity is at its low levels, a unit increase in complaint variety2 will increase time to recall by 28.356 days. However, given that complaint diversity is at its high levels, increasing complaint variety2 by one unit will increase time to recall by 790.938 days.

Taken together, the results using complaint variety2 are in line with our main findings using complaint variety. The positive link between complaint variety and time to recall is robust. The level of complaint severity positively moderates the relationship between complaint variety and time to recall. Likewise, the influence of complaint variety on time to recall is greater for a higher level of complaint diversity.

4.5.3 Further Analyses in the Relationship between Complaint Variety and Time to Recall

We perform a variety of regressions to examine alternative explanations for our results. Except for the complaint related factors, product characteristics may affect the product recall process. To deal with this concern, we use product characteristics such as *component sharing, product age, and luxury* as moderators to study how the impact of complaint variety on time to recall varies depending on product characteristics. It's possible that the impact of complaint variety on time to recall differs across the recall types. To address this issue, we investigate the moderating influence of *voluntary recall* on the relationship between complaint variety and time to recall. Another issue is that there might be significant differences between US-based and other manufacturers with respect to how they respond to consumer complaints. To test this possibility, we include the *country* that is an indicator variable that takes the value of 1 if the home country of a manufacturer is in US. Table 4.7 presents the results of alternative analyses.

Column (1) tests how the component sharing strategy affects the relationship between complaint variety and time to recall. The result shows that a unit increase in complaint variety will increase time to recall by 193.240 days at low levels of component sharing and by 778.694 days at high levels of component sharing. In column (2), we study the moderating role of product age in the relationship between complaint variety and time to recall. The coefficient on the interaction term between complaint variety and product age is positive and significant, indicating that the impact of complaint variety on time to recall is greater for older car models. Column (3) examines whether the impact of complaint variety on the timing of product recall varies depending on the price tier of the car model. The estimate on the interaction term between complaint variety and luxury suggests that the increase in time to recall with a unit increase in complaint variety for a luxury brand is 524.535 days longer compared to that for a non-luxury brand. Column (4) evaluates how the impact of complaint variety on the timing of product recall differs across recall types. The result shows that the time to recall for a recall initiated by the manufacturer voluntarily is shortened by 294.619 days for a unit increase in complaint variety. Column (5) investigates whether the influence of complaint variety on time to recall differs for US-based and other manufacturers. We find that the time to recall for a US manufacturer is 412.527 days longer for a unit increase in complaint variety. In aggregate, the results shown in Table 4.7 provide reasonable confirmation that our findings are robust to alternative explanations, models, and specifications.

4.6 Concluding Remarks

Consumer complaints serve as signals to decision makers about product defects in the recall process. Clearly, decision makers face a great deal of uncertainty regarding the

Table 4.7 Further Analyses in the Relationship between Complaint Variety and Time to Recall

Variable	(1)	(2)	(3)	(4)	(5)
Complaint variety	-99.487	-24.550	218.411***	501.998***	-71.258
	(153.241)	(112.725)	(82.075)	(123.914)	(197.581)
Complaint variety * component sharing	292.727***				
	(95.585)				
Complaint variety * product age		88.761**			
		(41.000)			
Complaint variety * luxury			524.535***		
			(195.634)		
Complaint variety * voluntary recall				-294.619*	
				(150.901)	
Complaint variety * country					412.527*
					(211.120)
Country					-224.308**
					(90.132)
Component sharing	-104.273*	56.871***	53.127**	55.737**	56.388**
	(59.200)	(20.942)	(21.700)	(21.731)	(21.850)
Product age	263.527***	216.864***	262.786***	264.120***	263.988***
	(8.469)	(26.644)	(8.563)	(8.569)	(8.610)
Voluntary recall	160.173***	153.100***	156.371***	308.706***	159.891***
	(42.451)	(43.394)	(42.620)	(86.477)	(42.770)
Recall size	14.780*	14.921*	16.831**	15.261*	16.185*
	(8.465)	(8.251)	(8.538)	(8.510)	(8.565)
Luxury	-35.854	-45.864	-312.853***	-30.646	-34.921
	(48.632)	(47.445)	(115.244)	(49.007)	(48.856)
Firm size	0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm reputation	0.013***	0.013***	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-312.530***	-363.332***	-502.733***	-639.825***	-339.779***
	(120.088)	(121.238)	(93.777)	(105.637)	(113.648)
Observations	893	893	893	893	893
R^2	0.765	0.768	0.764	0.763	0.762
Adjusted R^2	0.762	0.765	0.761	0.760	0.760

Note. Robust standard errors in parentheses.

* p<0.10; ** p<0.05; *** p<0.01.

quality of the defect signals. The defect signals could be precise and informative, or vague and ambiguous. Surprisingly, very little empirical research exists with respect to explicitly quantifying the impact of the quality of defect signals on the recall decision-making process. This study fills the gap by proposing a novel measure of complaint variety that is the diversity of defect signals contained in the consumer complaints. We then study the effect of complaint variety on time to recall and how such an effect is contingent on contextual factors.

This research finds that high complaint variety results in a long time to recall, suggesting the existence of ambiguity aversion. Moreover, we find that the impact of complaint variety on time to recall is even stronger when consumer complaints describe a severer product defect. Also, the influence of complaint variety on time to recall is greater when consumer complaints are collected from diverse sources. Our further analyses show that the relationship between complaint variety and time to recall is stronger under scenarios when (1) the recall affects more brands (2) the defective products are older car models (3) the recall involves luxury brands (4) the recall is influenced by the government agency (5) the manufacturer is US-based. This study applies the decision-making under ambiguity research stream to an operations management setting by examining whether and how information quality affects the product recall timing decisions, which may be used to strengthen firm governance and regulatory policy.

4.6.1 Theoretical Contributions

Our research contributes to the existing literature in several ways. First, our study offers a new measure of information ambiguity that is complaint variety. Although the quality of defect signals is difficult to capture, researchers may consider using the heterogeneity of defect signals contained in consumer complaints to represent information quality. We first divide the defects signals into several categories via dictionary-based analysis and then calculate the ambiguity of defect signals with Blau's index of heterogeneity. We also develop an alternative measure of complaint variety with term weighting scheme and Blau's index.

Second, this study provides a contribution to product recall research by uncovering a new antecedent to product recall timing decisions. The product recall research has investigated factors that can be associated with recall timing decisions such as recall strategy and defect type (Hora et al. 2011), problem severity (Eilert et al. 2017), and female directors (Wowak et al. 2021). However, existing literature overlooks the role of complaint variety in the recall process. This study complements product recall research by evaluating how complaint variety can impact time to recall. We find that the higher the degree of diversity of defect signals contained in consumer complaints, the longer the time taken for a recall decision. We also provide insights on the theoretical mechanisms that may explain circumstances under which the long time to recall under high complaint variety is even greater.

Third, we contribute to the literature on decision-making under information ambiguity by establishing a relationship between information ambiguity and product recall timing decisions. Numerous articles have examined the presence of ambiguity aversion, and its effect on individual decisions in financial and marketing settings (Ellsberg 1961, Sarin and Weber 1993, Peysakhovich and Karmarkar 2016, Li et al. 2017, Li and Kirshner 2021). This research extends the previous literature by addressing the importance of ambiguity aversion in an operational setting. The results show that high information ambiguity enhances the time taken to make a recall decision, supporting the presence of ambiguity-averse behaviour. Moreover, the influence of ambiguity aversion on time to recall is contingent on the context of product recall decisions.

4.6.2 Practical Contributions

Our research provides several implications for product recall decision-makers. Our measure of complaint variety helps managers to efficiently deal with the issue of information ambiguity under the context of product recall decision-making. By combining text-based approach and Blau's index of diversity, senior managers are possible to quantitatively analyse the degree of ambiguity of defect signals contained in the consumer complaints. Our results of evaluating the relationship between complaint variety and product recall timing decision indicate that a higher level of complaint variety leads to a longer time to recall. This implies that decision makers are more likely to recall earlier when faced with unambiguous information. Despite that recalls are adverse events, delaying them when faced with high information ambiguity is potential to impose significant costs on firms. Therefore, manufacturers should allocate enough time and effort to analyse consumer complaints that contain ambiguous defect signals. Upon receiving the consumer complaints, senior managers may need to communicate with other stakeholders timely to figure out safety-related defects and provide effective remedies to minimise the damage from recalls.

Moreover, decision makers need to recognise that several contextual factors impede or enable a fast recall decision. The complaint database provides sufficient information for recall decision makers to identify the potential severity of a safety defect. Our findings of examining the role of complaint severity in the product recall process imply that a potential severe product defect places firms at a disadvantage when responding to the external event. In other words, when the firms face consumer complaints with ambiguous defect signals involving severe product defects, there is additional burden on them in figuring out the source of problems. Therefore, the firm should invest in quality management tools to inspect, trace, and prevent a severe product defect. Our results also suggest that the asymmetric effects of complaint diversity under ambiguous and unambiguous information persist in operational settings. When consumer complaints are collected from diverse sources, the complaints with ambiguous defect signals result in a much longer time to recall. This implies that decision makers should develop a synthesis method to integrate information on consumer complaints from different sources.

Our findings should interest decision makers who confront themselves with various scenarios. We observe that the level of component sharing positively moderates the relationship between complaint variety and time to recall. Consequently, managers are advised to exchange information on complex products with shared components with regulators and suppliers. Also, this study finds that the influence of complaint variety on time to recall is greater for older car models. The result implies that managers should allocate resources to develop sustained quality tools to trace the safety-related defect for old car models. The findings of examining the influence of luxury on the product recall process suggest that the process of recall decision-making under information ambiguity is lengthier for luxury brands. To avoid astonishing losses from recalling a luxury car model, manufacturers should prevent quality defects in the new product development process. Moreover, our findings indicate that the relationship between the complaint variety and time to recall varies depending on recall types. The result shows that the impact of information ambiguity on time to recall is stronger for a recall launched by the government agency. Therefore, the government agency may need to communicate with manufacturers frequently when inspecting a potential product defect. It's conceivable that the relationship between complaint variety and time to recall is stronger for a US-based manufacturer. For this reason, managers should attach importance to consumer complaints for a US-based firm. However, managerial efforts may be targeted at other sources of information for a non-US firm.

4.6.3 Limitations and Future Research

Several limitations of our study suggest the need for future research. One limitation to our work is that some firm-level data for private companies is not available. In this research, we use industry averages as proxies. Future research can focus on public companies to improve measurement precision. Moreover, this study focuses on the effect of complaint variety on the timing of recall decisions. It's possible that consumer complaints can affect other firm and regulator behaviours in the recall process. A future research direction is to examine how complaint variety can be predictive of the likelihood of future investigation or the likelihood of future manufacturer or government recall. Finally, the current study investigates the moderating role of component sharing in the relationship between complaint variety and time to recall. We make no claim that the component sharing strategy is the only product development strategy that can affect the recall process. If data on firm strategies becomes available, future studies can explore how other product development strategies impact the recall process. Nonetheless, this study opens new avenues for information ambiguity and product recall studies by joining these two previously disconnected streams of research and hopefully spurring new research topics linking operations management and decision theory.

Chapter 5 CEO Duality and Product Recalls in the Automobile Industry: An Empirical Investigation

5.1 Introduction

The Takata recall, the largest and most complex in US automotive history, affects 19 carmakers, more than 60 million Takata airbags, and tens of millions of US vehicles (Bushey 2020). Exploding Takata airbags have caused injuries and deaths. Takata corporation filed for bankruptcy in 2017. Takata is not alone in suffering from product recalls (Shah et al. 2017). In 2021, Philips Respironics recalled 5.2 million breathing devices because of potential health risks (Alabi 2022). After the recall, the chief executive of the company, Frans Van Houton, stepped down, and the company's market value has plunged by about 70 percent. The company has also announced plans to cut 4,000 jobs to offset losses (Jewett 2022). These examples demonstrate that product recalls can have a significant negative impact on a CEO's career, firm profitability, market reputation, and sometimes even threatening the survival of a firm (Eilert et al. 2017, Ball et al. 2018b, Mayo et al. 2022). Therefore, top executives, and especially chief executive officers (CEOs), may take steps to avoid product recalls if possible.

CEOs have long been recognized as the principal architects of organizational strategy and the extent to which CEOs affect strategy greatly depends on the power they possess (Hambrick and Mason 1984, Finkelstein 1992, Bigley and Wiersema 2002). CEO duality therefore is likely to be a salient factor that influences organizational strategy and outcome, as it represents power distributions in organizations (Boyd 1995). CEO duality is a common corporate governance phenomenon that is the practice of the CEO of a firm also serving as Chairman of the board of directors (Baliga et al. 1996, Krause et al. 2014). Despite that CEO duality is a poplar topic in management studies, scholars have rarely considered the impact of CEO duality on operational outcome (Whitler et al. 2021). This study addresses this important research question by examining the link between CEO duality and product recalls.

We build on the upper echelons theory to propose a negative relationship between CEO duality and product recalls. We argue that CEO-chairs, who hold both the CEO and board chair roles, have enhanced ability to deal with product quality issues, which results in a decrease in the number of product recalls (Bigley and Wiersema 2002). We further posit that the relationship between CEO duality and product recalls is contingent on the level of managerial discretion. Discretion is enhanced when firms have ample slack resources. We therefore predict that the existence of CEO duality more greatly influences product recalls for firms with high liquidity. Likewise, CEOs who have accumulated experience of working as CEO prior to appointment reach greater cognitive complexity, allowing them more discretions. We thus assume that the existence of CEO duality has a stronger impact on product recalls when CEOs have experience of working as CEO prior to appointment.

We test the effect of CEO duality on product recalls using data on 19 publicly traded firms during the period from 1994 to 2019. We collect CEO, recall, and firm data from diverse sources including National Highway Traffic Safety Administration (NHTSA) database, BoardEx database, LexisNexis database, Capital IQ database, and firms' annual reports. By estimating negative binomial models, we find that the existence of CEO duality decreases the number of product recalls in a firm. Interestingly, we find that there is variation in the magnitude of the effect of CEO duality on product recalls under various scenarios. For a firm using the practice of combining CEO and board chair roles, increase in firm liquidity remarkably reduces the number of product recalls.

Furthermore, our study finds that the effect of CEO duality on product recalls is greater for a firm led by a CEO with experience of working as CEO at another firm.

Our research contributes to several streams of literature: corporate governance, product recalls, and upper echelons research. First, we add to the corporate governance research by examining the influence of CEO duality on operational performance (Krause et al. 2014). We find that the existence of CEO duality decreases the frequency of product recalls. Second, this research contributes to the product recall literature by identifying CEO duality as a new antecedent to product recalls (Shah et al. 2017, Ball et al. 2018a, Astvansh et al. 2022b, Kini et al. 2022). Finally, this research complements the upper echelons research by establishing boundary conditions for the relationship between CEO duality and product recalls. Our findings indicate that the effect of CEO duality on product recalls is greater for a firm with ample slack resources or for a firm led by a CEO with prior CEO experience. In documenting the effect of CEO duality on product recalls, this study provides insights to help managers prevent product quality failures.

We organise the rest of this chapter as follows. In Section 5.2, we provide an overview of the upper echelons theory and develop the research hypotheses. We describe the data and variables used in the study in Section 5.3 and report the main results in Section 5.4. We present robustness checks to our baseline models in Section 5.5. We conclude the chapter in Section 5.6 by discussing managerial and policy implications, and suggestions for further research.

5.2 Theory and Hypotheses

We apply upper echelons theory to propose a negative relationship between CEO duality and product recalls. This leads to Hypothesis 5.1. Furthermore, we posit that the magnitude of the impact of CEO duality on product recalls varies depending on firm liquidity and prior CEO experience, leading to Hypotheses 5.2 and 5.3.

5.2.1 Effect of CEO Duality on Product Recalls

Building on bounded rationality, a central tenet of the upper echelons theory is that the manager's experiences, values, and personalities greatly influence their interpretations of the situations they face, thereby affecting their choices (Hambrick and Mason 1984). Given that the cognitive bases, values, and perceptions of top executives are not convenient to measure, the upper echelons perspective places emphasis on a host of observable managerial characteristics such as age, functional tracks, other career experiences, education, socioeconomic roots, financial positions, and group characteristics. In this vein, numerous subsequent studies have verified that top executives' background characteristics are highly related to strategy and performance outcomes (Finkelstein and Hambrick 1990, Wiersema and Bird 1993, Wasserman 2003, Mohr and Batsakis 2019).

Drawing on upper echelons theory, we assume CEO duality to be negatively associated with product recalls. CEO duality refers to the situation where the CEO also serves as the Chairman of board of directors (Lewellyn and Muller-Kahle 2012). As with other insider directors, a CEO-chair is expected to have greater knowledge of the firm and have greater commitment to the organization (Boyd 1995). From the upper echelons perspective, we argue that CEO-chairs who hold both CEO and board chair roles reflect certain personality or values that, in turn, affect organizational choices and outcomes (Dalton and Kesner 1987, Baliga et al. 1996, Blagoeva et al. 2020). Specifically, CEO-chairs may reflect similar characteristics such as charismatic and inspiring, combining a bold vision with the ability to identify the challenges and solve hard problems (Zhu and Chen 2015, Koch-Bayram and Wernicke 2018). Holding both

CEO and board chair titles implies increased CEO power (Westphal and Zajac 1995). Consequently, a CEO who also serves as a board chair may have enhanced ability to deal with potential product quality problems, thereby reducing the number of product recalls (Finkelstein and Hambrick 1988, Bigley and Wiersema 2002). Therefore, we propose:

Hypothesis 5.1: *CEO duality is negatively associated with the number of product recalls.*

5.2.2 Moderating Effect of Firm Liquidity

Recent upper echelons research proposes that managerial discretion influences the extent to which CEOs matter to organizational strategy and outcomes (Hambrick and Finkelstein 1987, Finkelstein and Hambrick 1990). Discretion defined as latitude of action exists when there is an absence of constraint and when there are multiple plausible alternatives (Hambrick 2007). A chief executive's degree of discretion can be derived from environmental conditions (e.g., product differentiability, and market growth), from organizational factors (e.g., inertial forces, and resource availability), and from individual managerial characteristics (e.g., tolerance for ambiguity, and cognitive complexity).

In this study, we examine organizational and managerial factors that influence the effect of CEO duality on product recalls (Carpenter et al. 2004). Prior literature has noticed the role of firm liquidity in predicting decision behaviours (Palmer and Wiseman 1999). Firm liquidity reflects the level of organizational slack that is the pool of resources that exceeds the minimum necessary to sustain routine operations (Baucus and Near 1991, Vanacker et al. 2017, Arena et al. 2018). We argue that the level of firm liquidity moderates the relationship between CEO duality and product recalls because slack resources provide managers with the necessary resources to tackle product quality issues (Vanacker et al. 2017). When a firm has ample slack resources, the degree of a CEO's managerial discretion will be enhanced. Enhanced discretion may strengthen the impact of CEO duality on product recalls (Finkelstein and Hambrick 1990, Li and Tang 2010). If the level of firm liquidity is relatively low, the strategic choices that CEO-chairs can adopt to deal with quality issues are limited (Smith et al. 1991). In this case, although CEO-chairs with higher power can reduce the frequency of product recalls, the reduction will be relatively small. However, when the level of firm liquidity is high, CEO-chairs can tactically allocate and utilise slack resources to avoid product safety problems, resulting in a remarkable decrease in the number of product recalls (George 2005, Kovach et al. 2015). Therefore, the influence of CEO duality on product recalls is greater for a high level of firm liquidity. Thus, we hypothesize:

Hypothesis 5.2: *Firm liquidity will moderate the negative association between CEO duality and product recalls such that the relationship will be stronger for a firm with high firm liquidity.*

5.2.3 Moderating Effect of Prior CEO Experience

We next explore the moderating influence of managerial characteristics on the relationship between CEO duality and product recalls. Upper echelons theory argues that CEO experience and expertise influence cognitive complexity, which is a salient factor that determines managerial discretion (Hambrick and Finkelstein 1987, Buyl et al. 2011, Graf-Vlachy et al. 2020). Existing literature demonstrates that individuals who were selected as CEOs may have similar characteristics such as decisive, committed, adaptable, and reliable, and individuals with experience of working as CEO can develop expertise specific to the CEO's job position, thereby engendering greater cognitive complexity (Tian et al. 2011, Crossland et al. 2014, Botelho et al. 2017, Bragaw and Misangyi 2017). Therefore, one could wonder how the impact of CEO duality on product recalls varies depending on whether the CEO has experience of working as CEO at another firm prior to appointment.

In this study, we propose that the relationship between CEO duality and product recalls will be contingent on the prior CEO experience because CEOs who have experience of working as CEO prior to appointment tend to become cognitively more complex, allowing them more discretion (Graf-Vlachy et al. 2020). If a CEO has not accumulated experience of working as CEO at another firm, the CEO's discretion is constrained by his or her ability cognitively process different alternatives simultaneously (Wong et al. 2011, Gamache et al. 2023). Under the circumstances, some quality strategies may be ruled out simply because they are beyond the CEO's cognitive bounds (Hambrick and Finkelstein 1987, Finkelstein and Hambrick 1990). Therefore, the role of CEO power in decreasing the number of product recalls will be limited for CEOs without prior experience of working as CEO. Conversely, CEOs who have experience of working as CEO at another firm are more open-minded and seek out a wide variety of information and perspectives to inform their decision making (Wong et al. 2011). CEOs with experience of serving as CEO prior to appointment gained broader perspectives about how the environment behaves, what choices are available, and how the firm could be operated differently through their involvement in strategic decision-making at other firms (Campbell et al. 2023). Consequently, we predict that CEO-chairs with prior experience of working as CEO will be better able to formulate and implement product quality strategies to avoid product safety problems, thereby indicating a significant decrease in product recalls. Thus, we hypothesize:

Hypothesis 5.3: *Prior CEO experience will moderate the negative association between CEO duality and product recalls such that the relationship will be stronger for a firm led by a CEO with prior CEO experience.*

5.3 Data and Variables

5.3.1 Data

We test the relationship between CEO duality and product recalls using data from US automobile industry. We gathered the data for the study from diverse sources. Recall-related information such as recalls, recall experience, and recall size was collected from the NHTSA (National Highway Traffic Safety Administration) website. Other data sources, particularly for the CEO and firm data, include BoardEx database, LexisNexis database, Capital IQ database, and firms' annual reports. After combining the data across these sources, we obtained a sample of 19 publicly traded firms for a period from 1994 to 2019[7]. The study period begins in 1994 because this is the first full year for which we have both CEO and firm data. Table 5.1 lists the measures and data sources for the variables.

5.3.2 Dependent Variable

Our primary dependent variable is recalls. We denote *recalls* as the number of recalls for a firm in a year. The distribution of recalls is illustrated in Figure 5.1. Figure 5.2 depicts the number of recalls by each manufacturer. There are two categories of product

[7] In our sample, 26 public traded firms have experienced recalls recorded by NHTSA. We kept observations where the listing year of a firm is no later than 1994.

recalls in the automobile industry: voluntary recall and involuntary recall. Involuntary recalls are those recalls mandated by the government agency. An alternative measure of dependent variable is *voluntary recalls* which is defined as the number of recalls voluntarily launched by the manufacturer in a year.

Table 5.1 Measures and Data Sources for the Variables

Variable	Operationalization	Data sources
Recalls	The number of recalls for each firm year	NHTSA
CEO duality	A binary variable that takes the value of 1 if the CEO was also appointed as board chair and 0 otherwise	BoardEx database, annual reports
Firm liquidity	The more liquid current assets that are quick assets divided by total current liabilities	Capital IQ database
Prior CEO experience	A dummy variable that equals to 1 if the CEO served as CEO at another stock-listed firm prior to appointment in the focal organization and 0 otherwise	BoardEx database, LexisNexis News and business database
New CEO	A binary variable that takes the value of 1 if promotion to CEO had occurred sometime during the current year	BoardEx database, annual reports
CEO age	Age of the CEO	BoardEx database, LexisNexis News and business database
Board size	The total number of board members	BoardEx database, annual reports
Recall experience	The number of recalls that a CEO has experienced over the last three years prior to the current year	NHTSA
Recall size	The average number of vehicles or equipment that are recalled by a firm in the current year	NHTSA
R&D intensity	R&D expense normalised by total revenue	Capital IQ database
Capital intensity	Capital expenditure normalised by total revenue	Capital IQ database
Firm profitability	Return on equity	Capital IQ database

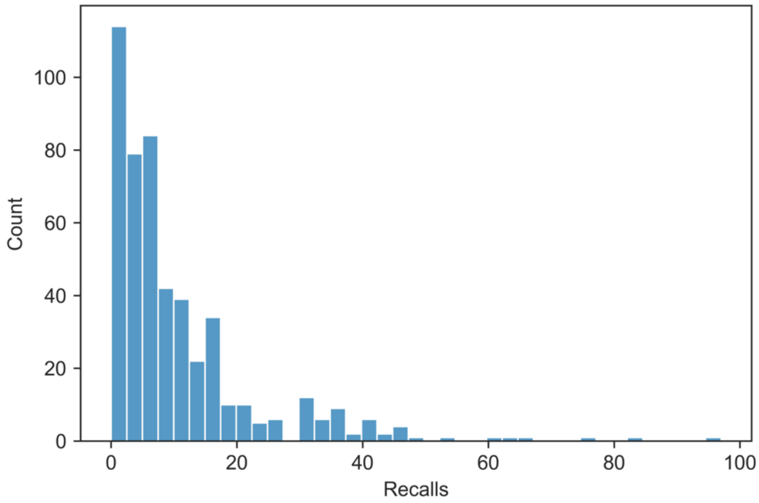

Figure 5.1 Distribution of Recalls

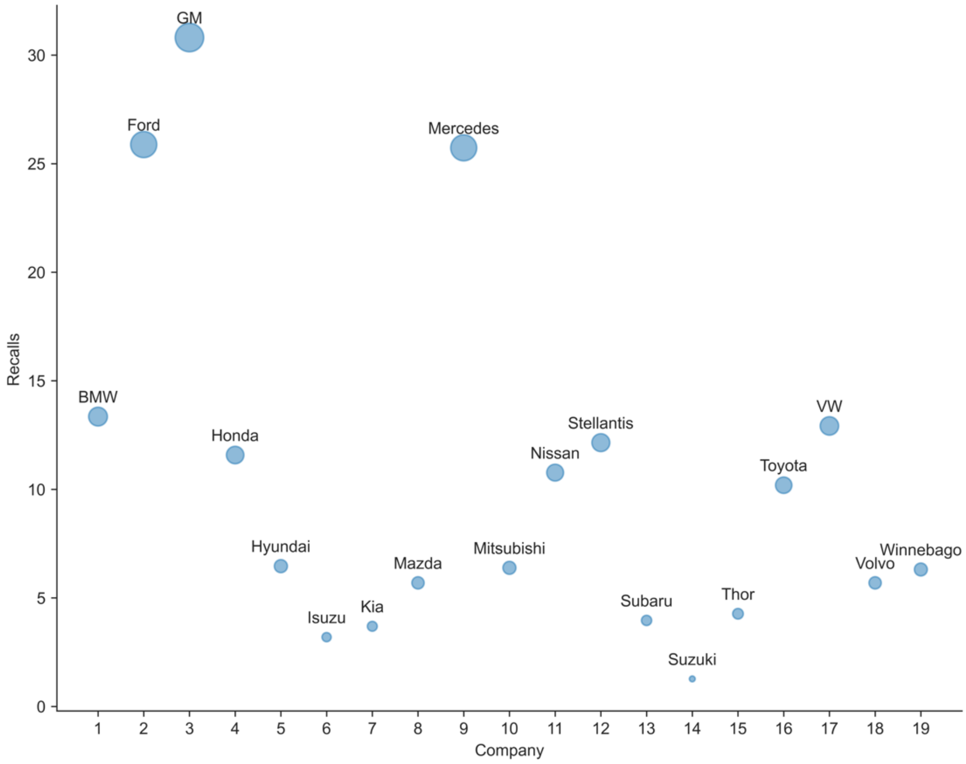

Figure 5.2 The Number of Recalls by Manufacturer

5.3.3 Independent Variable

Our focal explanatory variable is *CEO duality*, which is a binary variable that takes the value of 1 if the CEO is also appointed as board chair and 0 otherwise (Boyd 1995, Bigley and Wiersema 2002, Joseph et al. 2014). We collected the CEO power information from the BoardEx database and firms' annual reports. Of 494 firm-year observations, there are 291 cases when the CEO also holds the role of board chair.

5.3.4 Moderation Variables

We examine how the relationship between CEO duality and recalls is contingent on the level of managerial discretion (Hambrick and Finkelstein 1987, Carpenter et al. 2004). Managerial discretion can be derived from a host of organizational and managerial factors. In this study, we use firm liquidity and prior CEO experience as indicators of managerial discretion. We measure *firm liquidity* as quick ratio that is the more liquid current assets divided by total current liabilities (Smith et al. 1991, Titus et al. 2022). The distribution of firm liquidity is illustrated in Figure 5.3. Following Mueller et al. (2021), we denote *prior CEO experience* as a dummy variable that equals to 1 if a CEO has served as CEO at another stock-listed firm prior to becoming the CEO in the focal organization. We gathered the historic employment and activities for CEOs from BoardEx database. In the case when the CEO information is unavailable, we searched for the biographies of the CEOs via the LexisNexis database. The sources of the CEO biographies include *The Complete Marquis Who's who biographies*, *The Official Board Biographies*, and so on.

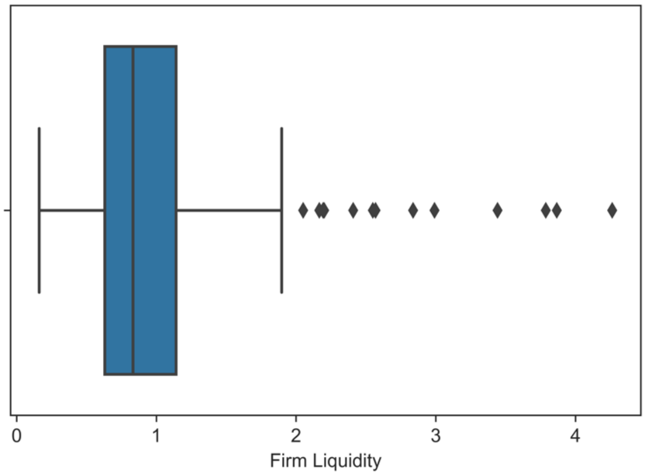

Figure 5.3 Distribution of Firm Liquidity

5.3.5 Control Variables

We control for a variety of CEO, recall, and firm related factors. If a CEO is appointed in the current year, he or she may have low levels of compensation, thus influencing product recalls (Wade et al. 2006, Graffin et al. 2008). To control for the effects of midyear promotions on product recall decisions, we create the *new CEO* that is a binary variable taking the value of 1 if promotion to CEO had occurred sometime during the current year. Evidence indicates that organizational strategies and choices may be influenced by CEO age (Li and Tang 2010, Crossland et al. 2014). We therefore control for the *CEO age* that is age of the CEO in the current year. Board members can have a direct influence on firm decisions (Joseph et al. 2014, Mayo et al. 2022). To control for the possible association, we include the *board size* that is the total number of board members. Product recall research has shown that past recalls may be associated with future recalls (Ball et al. 2017, Wowak et al. 2021, Astvansh et al. 2022b). To control for *recall experience*, we calculate the number of recalls that a CEO has experienced over the last three years prior to the current year. It's possible that the potential number of affected vehicles influences the occurrence of a recall (Kalaignanam et al. 2013, Shah et al. 2017). To control for scale effects, we define the *recall size* as the average number of vehicles or equipment that are recalled by a firm in the current year.

At the firm level, we add the R&D intensity, capital intensity, and firm profitability. Because a firm's innovation orientation may be associated with the likelihood of a product recall, we control for *R&D intensity* that is R&D expense normalised by total revenue (Thirumalai and Sinha 2011, Astvansh et al. 2022b). Capital investments involving investments in information technology are likely to increase the chances of detecting and correcting defects before products reach the market (Steven et al. 2014). We therefore include *capital intensity* that is measured as capital expenditure normalised by total revenue. Firm profitability is possible to affect a firm's motivation to respond to quality issues (Eilert et al. 2017). We measure *firm profitability* as return on equity, which is calculated by earnings from continuing operations divided by total equity (Rajagopalan and Prescott 1990).

Table 5.2 provides the descriptive statistics and correlation matrix for the variables.

5.4 CEO Duality and Product Recalls

The dependent variable in this study, the number of recalls, is a count variable that takes non-negative integer values. A Poisson process is a common approach to model count data. However, the Poisson model assumes that the variance and mean are equal. Because we find evidence of over-dispersion (rejecting the Poisson model at $p < 0.001$), we estimate a negative binomial regression for our analysis (Hausman et al. 1984, Cameron and Trivedi 2013). For the fixed-effects over-dispersion model, let y_{it} represent the number of recalls experienced by a firm i in year t and follow a Poisson

Table 5.2 Summary Statistics and Correlation Matrix

Variable	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Recalls	494	10.543	12.652	0	97	1											
(2) CEO duality	494	0.589	0.493	0	1	0.014	1										
(3) Firm liquidity	494	0.929	0.486	0.162	4.262	0.054	0.130*	1									
(4) Prior CEO experience	494	0.190	0.393	0	1	0.024	-0.130*	-0.035	1								
(5) New CEO	494	0.178	0.383	0	1	-0.004	-0.127*	-0.062	0.003	1							
(6) CEO age	494	58.904	7.089	33	85	-0.080	0.082	-0.042	-0.032	-0.149*	1						
(7) Board size	494	11.034	5.649	4	36	0.014	-0.222*	-0.014	-0.139*	-0.009	0.189*	1					
(8) Recall experience	494	19.305	27.807	0	195	0.682*	0.080	0.014	0.029	-0.265*	-0.002	0.002	1				
(9) Recall size	494	70457.170	111722.100	1	1253621	0.238*	-0.110*	-0.006	-0.029	0.031	0.010	0.166*	0.205*	1			
(10) R&D intensity	494	0.034	0.016	0.000	0.084	0.290*	0.013	-0.054	0.010	-0.041	0.066	0.231*	0.241*	0.194*	1		
(11) Capital intensity	494	0.067	0.052	0.002	0.364	0.117*	0.081	0.119*	-0.093*	-0.021	-0.152*	0.101*	0.177*	0.066	0.380*	1	
(12) Firm profitability	494	0.083	0.342	-3.022	3.075	0.042	-0.040	0.077	0.029	-0.098*	-0.021	-0.005	0.046	-0.038	-0.084	0.004	1

Note. Correlation coefficients significant with *p<0.05.

distribution with the conditional mean λ_{it}. We assume that the Poisson parameter λ_{it} follows a gamma distribution with parameters (γ_{it}, δ_i), where δ_i is the dispersion parameter, and γ_{it} is associated with the following covariates:

$$\begin{aligned}\ln(\gamma_{it}) = \alpha_0 &+ \alpha_1\, \textit{CEO duality}_{it} + \alpha_2\, \textit{firm liquidity}_{it} \\ &+ \alpha_3\, \textit{CEO duality}_{it} * \textit{firm liquidity}_{it} \\ &+ \alpha_4\, \textit{prior CEO experience}_{it} \\ &+ \alpha_5\, \textit{CEO duality}_{it} * \textit{prior CEO experience}_{it} \\ &+ \alpha_6\, \textit{new CEO}_{it} + \alpha_7\, \textit{CEO age}_{it} + \alpha_8\, \textit{board size}_{it} \\ &+ \alpha_9\, \textit{recall experience}_{it} + \alpha_{10}\, \textit{R\&D intensity}_{it} \\ &+ \alpha_{11}\, \textit{capital intensity}_{it} + \alpha_{12}\, \textit{firm profitability}_{it}\end{aligned} \tag{5.1}$$

In this equation, *CEO duality*$_{it}$ is the focal explanatory variable that is a binary variable that takes the value of 1 if the CEO was also appointed as board chair and 0 otherwise. The moderating variables are *firm liquidity*$_{it}$ and *prior CEO experience*$_{it}$. We also include a variety of control variables, which are new CEO, CEO age, board size, recall experience, R&D intensity, capital intensity, and firm profitability.

We then derive the negative binomial distribution with parameters (γ_{it}, δ_i) as follows:

$$\Pr(y_{it}) = \frac{\Gamma(\gamma_{it} + y_{it})}{\Gamma(\gamma_{it})\Gamma(y_{it} + 1)} \left(\frac{\delta_i}{1 + \delta_i}\right)^{\gamma_{it}} (1 + \delta_i)^{-y_{it}} \tag{5.2}$$

where $\Gamma(\cdot)$ is a gamma distribution. The mean and variance of y_{it} have the form $Ey_{it} = \gamma_{it} / \delta_i$ and $V(y_{it}) = \gamma_{it}(1 + \delta_i)/\delta_i^2$.

For a random-effects over-dispersion model, we allow δ_i to vary randomly across firms; namely, we assume that $\delta_i/(1 + \delta_i) \sim Beta(r, s)$. The joint probability of the number of recalls for the i_{th} firm is:

$$\Pr(y_{i1}, \ldots, y_{i26} \mid X_{i1}, \ldots, X_{i26})$$

$$= \frac{\Gamma(r+s)\Gamma(r+\sum_{t=1}^{26}\gamma_{it})\Gamma(s+\sum_{t=1}^{26}y_{it})}{\Gamma(r)\Gamma(s)\Gamma(r+s+\sum_{t=1}^{26}\gamma_{it}+\sum_{t=1}^{26}y_{it})} \prod_{t=1}^{26} \frac{\Gamma(\gamma_{it}+y_{it})}{\Gamma(\gamma_{it})\Gamma(y_{it}+1)} \tag{5.3}$$

where X_{it} is a vector of covariates as described in Equation (5.1). The over-dispersion model is estimated with a maximum likelihood approach.

Table 5.3 provides the results of conditional fixed-effects negative binomial models. Column (1) presents the base model with only the control variables included. Column (2) adds the focal explanatory variable CEO duality. Column (3) examines the moderating role of firm liquidity in the relationship between CEO duality and product recalls. Column (4) investigates how the influence of CEO duality on product recalls varies depending on the prior CEO experience. Column (5) further studies how the relationship between CEO duality and product recalls is contingent on the level of managerial discretion represented by firm liquidity and prior CEO experience.

In column (2), the coefficient on CEO duality is negative and significant, suggesting that the existence of CEO duality decreases the expected number of recalls by 31.75%. This provides support for Hypothesis 5.1. A CEO also appointed as board chair is more likely to wield power to deal with product quality issues, thus resulting in lower

Table 5.3 Estimates of Negative Binomial Model

Variable	(1)	(2)	(3)	(4)	(5)
CEO duality		-0.382**	0.049	-0.285*	0.220
		(0.153)	(0.210)	(0.163)	(0.197)
Firm liquidity			0.405*		0.485***
			(0.213)		(0.183)
CEO duality * firm liquidity			-0.478**		-0.551***
			(0.195)		(0.167)
Prior CEO experience				0.369***	0.419***
				(0.135)	(0.136)
CEO duality * prior CEO experience				-0.614**	-0.700**
				(0.298)	(0.283)
New CEO	0.123	0.061	0.093	0.055	0.088
	(0.083)	(0.087)	(0.086)	(0.077)	(0.075)
CEO age	-0.007	-0.009	-0.011*	-0.010	-0.013**
	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)
Board size	-0.011	-0.014	-0.017	-0.017	-0.021
	(0.015)	(0.014)	(0.015)	(0.015)	(0.016)
Recall experience	0.011***	0.012***	0.012***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Recall size	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	6.179	5.993	5.192	6.156	5.364
	(7.330)	(6.796)	(6.684)	(6.885)	(6.818)
Capital intensity	-1.905	-1.709	-1.555	-1.605	-1.449
	(1.775)	(1.700)	(1.615)	(1.826)	(1.730)
Firm profitability	0.097	0.090	0.077	0.080	0.066
	(0.196)	(0.183)	(0.157)	(0.184)	(0.156)
Constant	0.985*	1.377***	1.221***	1.461***	1.284***
	(0.533)	(0.463)	(0.467)	(0.469)	(0.443)
Observations	494	494	494	494	494

Note. Columns (1) – (5) estimate conditional fixed effects negative binomial models. The standard errors are obtained with bootstrap approach.
* p<0.10; ** p<0.05; *** p<0.01.

frequency of product recalls (Bigley and Wiersema 2002). Column (3) shows that the estimate on the interaction term between CEO duality and firm liquidity is negative and significant, indicating that the influence of CEO duality on product recalls is greater for a higher level of firm liquidity. To be more specific, a CEO also served as board chair in a firm with a unit higher level of firm liquidity is expected to experience 34.88% less product recalls compared to a CEO without the role of board chair. This is consistent with Hypothesis 5.2. The reason is that a high level of firm liquidity creates a context in which a CEO with greater power could tactically deploy assets to avoid product quality problems, thereby leading to a greater reduction in the number of recalls (Carpenter 2002). In column (4), negative coefficient on the interaction term between CEO duality and prior CEO experience suggests that the effect of CEO duality on product recalls is greater for a CEO who had served as CEO at another firm. This is in accordance with Hypothesis 5.3. An individual serving as both CEO and board chair who had accumulated experience as CEO at another firm is expected to experience 59.30% less product recalls compared to an individual with only the CEO role. This may be because top executives who have experience of working as CEO at other firms have broader strategic perspectives through their involvement in strategic decision-making at other firms (Zhu et al. 2020).

In column (5), the coefficient on the interaction term between CEO duality and firm liquidity is negative and significant, indicating that the number of recalls for a CEO also served as board chair in a firm with a unit higher level of firm liquidity is expected to decrease by 28.18% than that for a CEO without the role of board chair. Also, the number of recalls for an individual serving as both CEO and board chair who had prior CEO experience will decrease by 38.12% compared to that for an individual serving as

CEO only. Overall, the estimates in column (5) show that our hypotheses still hold when considering the moderating roles of both firm liquidity and prior CEO experience in the relationship between CEO duality and product recalls.

5.5 Further Analyses and Robustness Checks

5.5.1 Impact of CEO Duality on Voluntary Recalls

In this session, we report further analyses and robustness checks to our conditional fixed-effects negative binomial models. In the main analyses, the dependent variable is the number of recalls for each firm year. To ensure that our results are robust to an alternative measure of dependent variable, we run a set of conditional fixed-effects negative binomial regressions using *voluntary recalls* that is the number of recalls voluntarily launched by the manufacturer in the current year as dependent variable. Table 5.4 provides the regression results.

Column (1) of Table 5.4 is the regression with all control variables. In column (2), we add the explanatory variable CEO duality. Column (3) includes the moderating factor firm liquidity. In column (4), we test the moderating influence of prior CEO experience on the relationship between CEO duality and voluntary recalls. In column (5), we include both two moderating factors that are firm liquidity and prior CEO experience. Negative coefficient on CEO duality in column (2) indicates that CEO duality is negatively associated with the number of voluntary recalls. In column (3), negative estimate on the interaction between CEO duality and firm liquidity suggests that the relationship between CEO duality and voluntary recalls is stronger for a higher level of firm liquidity. Column (4) shows that the influence of CEO duality on voluntary recalls is greater for a CEO who accumulated CEO experience at another firm. In column (5), the estimates indicate that a CEO also served as board chair in a firm with a unit higher level of firm liquidity is expected to experience 28.75% less voluntary recalls compared to a CEO without the role of board chair. Likewise, an individual serving as both CEO and board chair who had accumulated CEO experience prior to appointment is expected to experience 48.73% fewer voluntary recalls.

Overall, the results using voluntary recalls are in line with our main findings using recalls as dependent variable. The negative link between CEO duality and recalls is robust. The level of firm liquidity negatively moderates the relationship between CEO duality and product recalls. Also, the influence of CEO duality on product recalls is greater for a firm led by a CEO with prior CEO experience.

5.5.2 Estimates of the Random Effects Negative Binomial Model

To ensure that our findings are robust to alternative model specification, we conduct a set of random-effects negative binomial regressions. In the panel negative binomial model, the random effects or fixed effects apply to the distribution of the dispersion parameter. The dispersion is the same for all observations in the same firm. In the fixed effects model, the dispersion parameter can take on any value. In the random effects model, the dispersion varies randomly from firm to firm, such that the ratio between the dispersion and one plus the dispersion follows a Beta (r, s) distribution. Table 5.5 reports the results for the random effects negative binomial model.

Table 5.5 presents the regression results using recalls as dependent variable. Column (1) is the regression with all control variables. In column (2), we add the focal explanatory variable CEO duality. In column (3), we investigate the moderating role of firm liquidity in the relationship between CEO duality and product recalls. In column (4), we examine how prior CEO experience moderates the relationship between CEO duality and recalls. In column (5), we fit a full model including the moderating roles of firm liquidity and prior CEO experience. The estimate in column (2) indicates that the number of recalls for an individual serving as both CEO and board chair is 0.696 times

Table 5.4 Effect of CEO Duality on Voluntary Recalls

Variable	(1)	(2)	(3)	(4)	(5)
CEO duality		-0.419***	0.060	-0.288*	0.296
		(0.158)	(0.245)	(0.164)	(0.222)
Firm liquidity			0.476**		0.589***
			(0.213)		(0.178)
CEO duality * firm liquidity			-0.530***		-0.635***
			(0.200)		(0.167)
Prior CEO experience				0.447***	0.513***
				(0.139)	(0.138)
CEO duality * prior CEO experience				-0.851***	-0.964***
				(0.286)	(0.275)
New CEO	0.134	0.064	0.103	0.060	0.098
	(0.095)	(0.101)	(0.101)	(0.090)	(0.089)
CEO age	-0.011	-0.013*	-0.015**	-0.014**	-0.018***
	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)
Board size	-0.013	-0.016	-0.019	-0.020	-0.025
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Recall experience	0.012***	0.012***	0.012***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Recall size	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	8.670	8.525	7.669	9.096	8.256
	(7.473)	(6.980)	(6.893)	(7.056)	(7.063)
Capital intensity	-1.863	-1.690	-1.554	-1.587	-1.451
	(1.842)	(1.764)	(1.630)	(1.883)	(1.753)
Firm profitability	0.056	0.052	0.040	0.036	0.024
	(0.221)	(0.201)	(0.167)	(0.202)	(0.165)
Constant	1.000*	1.442***	1.234***	1.560***	1.315***
	(0.552)	(0.473)	(0.474)	(0.479)	(0.449)
Observations	494	494	494	494	494

Note. The dependent variable is voluntary recalls that is the number of recalls voluntarily launched by the manufacturer for each firm year. Columns (1) – (5) estimate conditional fixed effects negative binomial models. The standard errors are obtained with bootstrap approach.

* $p<0.10$; ** $p<0.05$; *** $p<0.01$.

that for an individual serving as CEO only. In other words, the existence of CEO duality decreases the number of recalls by 30.37%. The coefficients in column (3) imply that the number of recalls for a CEO also served as board chair in a firm with a unit higher level of firm liquidity is expected to decrease by 33.70%. Column (4) shows that being a CEO also served as board chair with prior CEO experience is expected to experience 55.47% less product recalls. The estimates in column (5) suggest that the negative influence of CEO duality on product recalls will be greater for a firm with high liquidity. Also, the relationship between CEO duality and product recalls will be stronger for a firm led by a CEO with prior CEO experience. In aggregate, the results shown in Table 5.5 help build confidence that our main findings are robust to alternative model specifications.

5.5.3 Further Analyses in the Relationship between CEO Duality and Product Recalls

We perform numerous additional analyses to examine the robustness of our findings to alternative explanations. Although our empirical analyses accounted for firm-specific effects, it could be the case that many other CEO or firm factors simultaneously affect the number of recalls. Therefore, we test whether our proposed hypotheses are violated after including CEO, product, or firm level factors. Table 5.6 presents the results for further analyses in the relationship between CEO duality and product recalls.

Although we controlled for CEO level factors such as new CEO and CEO age, how long a CEO has been on the job can influence organizational outcomes (Graffin et al. 2008, Joseph et al. 2014). To test this possibility, we include the *CEO tenure* that is the number of years a CEO has been in his or her present position in the negative binomial model. The result appears in the column (1) of Table 5.6. The coefficient on CEO tenure is negative, while not significant. Moreover, the pattern of results for our hypothesized relationships is remarkably similar after including the CEO tenure. Consequently, it is

Table 5.5 Estimates of the Random Effects Negative Binomial Model

Variable	(1)	(2)	(3)	(4)	(5)
CEO duality		-0.362**	0.086	-0.274*	0.235
		(0.143)	(0.201)	(0.152)	(0.198)
Firm liquidity			0.444**		0.505***
			(0.195)		(0.176)
CEO duality * firm liquidity			-0.497***		-0.555***
			(0.180)		(0.159)
Prior CEO experience				0.336***	0.380***
				(0.115)	(0.121)
CEO duality * prior CEO experience				-0.535**	-0.615**
				(0.268)	(0.266)
New CEO	0.127	0.068	0.103	0.066	0.100
	(0.080)	(0.086)	(0.085)	(0.076)	(0.074)
CEO age	-0.010	-0.011	-0.013**	-0.012*	-0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Board size	-0.011	-0.014	-0.017	-0.016	-0.020
	(0.016)	(0.014)	(0.015)	(0.015)	(0.017)
Recall experience	0.012***	0.012***	0.012***	0.011***	0.011***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Recall size	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	7.906	7.603	7.040	7.650	7.085
	(6.119)	(6.080)	(6.109)	(6.417)	(6.323)
Capital intensity	-1.653	-1.459	-1.324	-1.376	-1.247
	(1.675)	(1.646)	(1.547)	(1.595)	(1.461)
Firm profitability	0.105	0.096	0.082	0.087	0.072
	(0.194)	(0.184)	(0.156)	(0.182)	(0.162)
Constant	1.049**	1.385***	1.193***	1.437***	1.229***
	(0.534)	(0.458)	(0.461)	(0.480)	(0.447)
ln(r)	1.729***	1.625***	1.684***	1.536***	1.568***
	(0.396)	(0.360)	(0.373)	(0.374)	(0.388)
ln(s)	2.914***	2.732***	2.785***	2.605***	2.620***
	(0.493)	(0.400)	(0.418)	(0.435)	(0.431)
Observations	494	494	494	494	494

Note. Columns (1) – (5) estimate random effects negative binomial models. The standard errors are obtained with bootstrap approach.
* $p<0.10$; ** $p<0.05$; *** $p<0.01$.

reasonable to conclude that there are no significant differences in the number of recalls for early or late tenure CEOs. As there may be gender differences in risk taking behaviours, one could wonder if the number of recalls changes after adding female directors to a firm's board of directors (Bonet et al. 2020). To address this concern, we add the *female directors* that is the percentage of board directors who are female. We collected the information on the composition of the board of directors from the BoardEx database, LexisNexis database, and the firms' annual reports. Column (2) of Table 5.6 confirms that our results hold after controlling for gender differences.

Except for CEO related factors, product characteristics may affect the number of recalls. It's possible that brand variety influences the firm's need to investigate the potential safety defect (Ball et al. 2018a). To assess this possibility, we control for *brand variety* that is the number of brands that are makes involved in recalls for a firm in a year. The results of the negative binomial model after including the brand variety variable appear in column (3) of Table 5.6. Table 5.6 shows that the estimate on brand variety is positive and significant. Nevertheless, the pattern of results is consistent with our proposed hypotheses. For the same reason, we create a *component variety* variable that is the number of components involved in recalls in a year. Column (4) of Table 5.6 indicates that the moderating influence of firm liquidity and prior CEO experience on the relationship between CEO duality and product recalls remains significant. The analysis provides additional evidence supporting our theorized effects.

The product safety problem is likely to be affected by a variety of organizational contextual variables. Specifically, we examine whether the number of product recalls varies when firms also engage in acquisition activities (Bernile et al. 2017). To evaluate the possibility, we denote *acquisition* as an indicator variable that equals 1 if a firm has

Table 5.6 Further Analyses in the Relationship between CEO Duality and Recalls

Variable	(1)	(2)	(3)	(4)	(5)	(6)
CEO duality	0.210	0.199	0.178	0.268	0.210	0.213
	(0.219)	(0.232)	(0.206)	(0.176)	(0.202)	(0.191)
Firm liquidity	0.448***	0.487**	0.371**	0.420**	0.478***	0.437**
	(0.156)	(0.208)	(0.172)	(0.188)	(0.170)	(0.173)
CEO duality * firm liquidity	-0.476***	-0.530***	-0.423**	-0.484***	-0.547***	-0.540***
	(0.153)	(0.195)	(0.167)	(0.176)	(0.162)	(0.164)
Prior CEO experience	0.442***	0.383**	0.416***	0.473***	0.426***	0.385***
	(0.158)	(0.167)	(0.118)	(0.162)	(0.140)	(0.140)
CEO duality * prior CEO experience	-0.781***	-0.632**	-0.612*	-0.681**	-0.709**	-0.641**
	(0.282)	(0.277)	(0.334)	(0.276)	(0.290)	(0.286)
New CEO	0.031	0.079	0.108	-0.040	0.090	0.081
	(0.083)	(0.073)	(0.075)	(0.074)	(0.074)	(0.073)
CEO age	-0.003	-0.013**	-0.008	-0.012*	-0.013**	-0.015***
	(0.009)	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)
Board size	-0.022	-0.021	-0.013	-0.018	-0.021	-0.021
	(0.014)	(0.020)	(0.013)	(0.018)	(0.016)	(0.016)
Recall experience	0.011***	0.010***	0.004*	0.003**	0.011***	0.011***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Recall size	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	3.372	4.386	2.084	4.951	5.424	5.185
	(6.684)	(6.881)	(5.365)	(5.509)	(6.320)	(6.899)
Capital intensity	-1.708	-1.525	0.197	0.299	-1.380	-1.393
	(1.678)	(1.743)	(1.031)	(1.785)	(1.828)	(1.601)
Firm profitability	0.065	0.070	0.059	0.033	0.071	0.009
	(0.147)	(0.157)	(0.143)	(0.143)	(0.146)	(0.143)
CEO tenure	-0.032					
	(0.020)					
Female directors		0.794				
		(1.361)				
Brand variety			0.201***			
			(0.064)			
Component variety				0.003***		
				(0.001)		
Acquisition					-0.045	
					(0.077)	
Firm solvency						-0.645
						(0.823)
Constant	0.921*	1.327***	0.854**	1.411**	1.276***	1.910**
	(0.556)	(0.445)	(0.347)	(0.640)	(0.440)	(0.859)
Observations	494	494	494	494	494	494

Note. The dependent variable is the number of recalls for a firm. Columns (1) – (6) estimate conditional fixed effects negative binomial models. The standard errors are obtained with bootstrap approach.
* p<0.10; ** p<0.05; *** p<0.01.

undertaken acquisition activities in a year. Column (5) of Table 5.6 suggests that the estimate on acquisition is negative, while not significant. Thus, we rule out the possibility of the firm's acquisition activity driving the product recall results. Moreover, the firm's ability to fulfil its long-term debt obligations is likely to influence the likelihood of product recalls. To test the possibility, we include *firm solvency* that is total liabilities divided by total assets. The results appear in column (6) of Table 5.6. The estimate on firm solvency is not statistically significant. Taken together, the results shown in Table 5.6 provide reasonable confirmation that our findings are robust to alternative explanations and specifications.

5.6 Concluding Remarks

Firms in various industries such as automobile (Astvansh et al. 2022b), pharmaceutical (Ball et al. 2018a), and medical device (Thirumalai and Sinha 2011) suffer from product recalls. Product recalls can significantly affect firm profitability, market reputation, and customer safety (Wowak et al. 2015, Ball et al. 2018b). Therefore, understanding the sources of product recalls is of great value with important implications for both regulators and firms. CEO and board members as powerful actors in a firm, are potential to influence product quality performance (Hambrick and Mason 1984). CEO duality thus may be a salient factor that relates to product recalls because it represents power distributions in firms. The practice of combining both CEO and board chair roles has long been referred to as a "double-edged sword" because of the balance between unity of command and entrenchment avoidance (Finkelstein and D'Aveni 1994). Consequently, it's unclear how CEO duality can influence the frequency of product recalls.

To address the research question, this study examines the effect of CEO duality on product recalls and how such an effect is contingent on firm liquidity and prior CEO experience. We develop and test hypotheses under the context of automobile industry in US. Our results for negative binomial models indicate that a CEO who also serves as board chair has enhanced ability to decrease the frequency of product recalls. Moreover, we find that the magnitude of the effect of CEO duality on product recalls is greater for a firm with ample slack resources. Likewise, the influence of CEO duality on product recalls is greater if the CEO has experience of working as CEO at another firm prior to appointment. Our findings are robust to alternative explanations, models, and specifications.

5.6.1 Theoretical Contributions

Our study makes several important contributions to the existing literature. First, we contribute to corporate governance research by examining the relationship between CEO duality and operational outcomes. We focus on the common corporate governance phenomenon that is the practice of an individual serving as both CEO and board chair. Prior literature conceptualized CEO duality as a double-edged sword (Finkelstein and D'Aveni 1994) and examined the effect of CEO duality on organizational outcomes such as firm performance, R&D strategy, and firm risk taking (Baysinger et al. 1991, Boyd 1995, Baliga et al. 1996, Krause et al. 2014, Zhu and Chen 2015). This study addresses the gap in literature by examining the role of CEO duality in influencing product quality performance. Our findings reveal that the consolidation of the two most senior management positions that are CEO and board chair establishes a unity of direction at the top of the firm, which leads to a decrease in the number of product recalls.

The second contribution is that we uncover a new factor that influences the frequency of product recalls. The product recall literature has tested various factors that explain the variation in the frequency of product recalls. Examples include CEO stock pay

(Wowak et al. 2015), product variety and plant utilization (Shah et al. 2017), product competition (Ball et al. 2018a), news media (Astvansh et al. 2022b), and labour unions (Kini et al. 2022). We add to the product recall literature by documenting the effect of CEO duality on product recalls. We find that CEO-chairs with higher power have enhanced abilities to reduce the frequency of product recalls.

This study also contributes to upper echelons research by establishing boundary conditions for the relationship between CEO duality and product recalls. Drawing on upper echelons theory, we argue that the relationship between CEO duality and product recalls is contingent on the level of managerial discretion. Our results indicate that a CEO-chair in a firm with ample slack resources will experience lower frequency of product recalls compared to a CEO without the role of board chair. Similarly, a CEO-chair with prior experience of working as CEO will experience a significantly lower frequency of product recalls.

5.6.2 Practical Contributions

Our findings have implications for managing product quality. Our study explores the role of corporate governance practice in influencing the frequency of product recalls. Corporate governance research refers to the practice of an individual serving as both CEO and board chair as a "double-edged sword" (Finkelstein and D'Aveni 1994). On the one hand, CEOs are potential to use the authority of the board chair role to entrench themselves at the top of an organization (Krause et al. 2014). On the other hand, combining the CEO and board chair roles establishes a unity of command at the top of the firm, which enables CEO-chairs to deal with product quality issues. Our results show that the existence of CEO duality reduces the number of product recalls. It's thus crucial for a board to establish a clear-cut leadership for purposes of strategy formulation and implementation relating to product quality.

Our results suggest that managers should recognise that financial slack is valuable for firms using the practice of combining CEO and board chair roles. We find that the relationship between CEO duality and product recalls is stronger for firms with ample slack resources. Slack resources enhance a firm's adaptability and reduce the need for communication and coordination in a firm (Baucus and Near 1991, Smith et al. 1991). Consequently, managers are advised to actively manage the diverse pool of resources in a firm that exceeds the minimum necessary to maintain routine operations. By this way, CEO-chairs in firms with ample slack resources will be better able to use power to manage product quality issues.

Moreover, our findings indicate that prior experience of working as CEO at another firm is beneficial to a CEO-chair who makes operational decisions. The results show that the relationship between CEO duality and product recalls is contingent on prior CEO experience. Top managers who have experience of working as CEO at other firms gained broader strategic perspectives by involving in strategic decision-making at other firms. Therefore, firms should place emphasis on experiences of candidates when selecting a new CEO. Similarly, experience as heir apparent that is the status of an individual was in the president or chief operating officer (COO) position may be helpful for executives to manage product quality issues.

5.6.3 Limitations and Future Research

Although we include a variety of control variables, and we verify our results through numerous robustness checks, our research still has several limitations. First, despite that our focus is on CEO duality because it is one of the most widely discussed corporate governance phenomena, we make no claim that it is the only board structure factor that can influence product quality performance. Future studies can adopt specific measures of other CEO or board characteristics to understand better their impacts on product recalls. Second, this study investigates the relationship between CEO duality and the frequency of product recalls. However, the influence of CEO duality on the recall decision-making process has not been explored. A future research direction is to evaluate the effect of CEO and board characteristics such as CEO duality on the timing of recall decisions. Third, we examine the influence of CEO duality on product recalls in the context of automotive industry, but the magnitude of such an impact might vary for automobile, pharmaceuticals, or food recalls, which suggests important topics for future research. We hope our study spurs more research on the link between top executives' characteristics and product recalls.

Chapter 6 Conclusion

Product recalls can be viewed as a manifestation of a firm's failure in delivering reliable high-quality products (Thirumalai and Sinha 2011, Kalaignanam et al. 2013). Product recalls can significantly affect firm profitability, market reputation, and customer safety (Wowak et al. 2015, Ball et al. 2018b). The objective of this thesis is to explore the sources of product recalls and the recall decision-making process. Customer complaints as signals of potential product defects can lead to product recalls (Eilert et al. 2017, Kini et al. 2022). This research proposes novel complaint relevance and complaint variety measures using text-based approaches to analyse the content of consumer complaints and the defects in the recalls. The first two studies of the thesis evaluate the impact of complaint relevance and complaint variety on the time taken for recall decisions. In addition, CEO characteristics may influence strategic choice and organizational performance (Hambrick and Mason 1984). The third study of the thesis tests the effect of CEO duality as a measure of CEO power on the number of product recalls.

The analysis addresses product recall decisions at multiple levels including the recall event level (Chapter 3 and 4), and the firm level (Chapter 5). Chapter 3 tests the effect of complaint relevance on time to recall, and the role of product characteristics in moderating this relationship. Chapter 4 examines the influence of complaint variety on time to recall, and how such an impact is contingent on complaint related factors. Chapter 3 and 4 test the hypotheses on a sample of 991 automobile recalls between 1993 and 2019. Chapter 5 investigates the relationship between CEO duality and the number of product recalls with a sample of 19 publicly traded firms between 1994 and 2019.

Chapter 3 shows that consumer complaints with high relevance to product defects are more likely to be attentional focus of decision-makers, thus resulting in a faster recall. A high level of component sharing creates a context under which decision makers intentionally and sustainedly allocate cognitive resources to relevant consumer complaints, which results in a much faster recall decision. Likewise, relevant consumer complaints for older car models suggest potential severer safety issues, thereby triggering the manufacturer to provide a quicker response to the complaints. The robustness of the findings is verified using alternative measures, econometric strategies, and explanations. Further analyses suggest that the influence of complaint relevance on time to recall is greater when (1) the recall involves more luxury brands (2) the defective products are vehicles and (3) the recall affects more components.

Chapter 4 discovers that senior managers have a preference to respond slowly to ambiguous defect signals, thus leading to a longer time to recall. Moreover, when senior managers are faced with ambiguous defect signals involving severe problems, they will spend more time disentangling the conflicting signals to identify the safety defects, thereby resulting in a much longer time to recall. Similarly, the process of recall decision-making under information ambiguity is lengthier when consumer complaints involved in a recall are collected from diverse sources. The findings are robust to alternative measurements, explanations, and specifications. Further analyses suggest that the impact of complaint variety on time to recall is greater when (1) the recall affects more brands (2) the defective products are older car models (3) the recall involves luxury brands (4) the recall is influenced by the government agency (5) the manufacturer is US-based.

Chapter 5 indicates that CEO duality is negatively associated with product recalls because CEO-chairs have enhanced ability to manage product quality issues, thereby reducing the frequency of product recalls. Moreover, the magnitude of the influence of CEO duality on product recalls varies depending on contextual factors. A high level of firm liquidity or organizational slack creates a context in which CEO-chairs can tactically allocate and utilise slack resources to avoid product safety problems, thereby indicating a remarkable reduction in the frequency of product recalls. Also, top executives who have experience of working as CEO at other firms will be better able to formulate and implement product quality strategies to prevent product safety problems. Consequently, the influence of CEO duality on product recalls is greater for a firm led by a CEO with prior experience of working as CEO at another firm. The findings still hold after including a variety of CEO, product, or firm level factors. Taken together, insights gained from this thesis can be of value for product recall decision makers.

The limitations of this research suggest the opportunities for future research. First, consumer generated data comes in various forms, including consumer complaints, consumer ratings, product reviews, videos, and blogs (Tirunillai and Tellis 2012). The focus of this research has been on consumer complaints because complaints could be directly related to the product recall process. If consumer ratings data becomes available, a future research direction is to examine the influence of customer ratings on the recall decision-making process. Second, the current research focuses on examining the relationship between consumer complaint and time to recall, and how such a relationship is contingent on contextual factors. The time to recall is defined as the time elapsed from the consumer complaint to recall. However, scholars understand little about the role of consumer complaint in preventing future recalls (Chakravarty et al. 2022). Future studies can explore whether and how firms learn from customer complaint to reduce the likelihood of future recalls (Astvansh et al. 2022a).

Third, despite that the focus of this research is on CEO duality because it is one of the most widely discussed corporate governance phenomena, I make no claim that it is the only board structure factor that can influence product quality performance. Future work can adopt specific measures of other CEO or board characteristics to understand better their impacts on operational performance. Fourth, this research examines the effect of CEO duality on the number of product recalls. However, the influence of CEO duality on the recall decision-making process has not been explored. Future research can evaluate the effect of CEO and board characteristics such as CEO duality on the timing of product recall decisions.

Finally, this research explores the sources of product recalls and the recall decision-making process in the context of automobile industry. Nevertheless, the magnitude of the hypothesized relationships might vary for automobile, pharmaceuticals, or food recalls, which suggests important topics for future research. Notwithstanding these limitations, this research opens new avenues for consumer complaint, corporate governance, and product recall studies by joining these previously disconnected streams of research and hopefully spurring new research topics linking marketing, operations management, and strategic management.

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Appendix Data Description

As described in Chapter 3, this study uses vehicle recalls data from NHTSA website. The data includes three data files. Table A.1 - A.3 list variables in the recall, investigation, and complaint data file respectively.

Table A.1 Overview of Variables in the Recall Data File

Variable name	Description
RECORD_ID	Running sequence number, which uniquely identifies the record
CAMPNO	NHTSA campaign number
MAKETXT	Vehicle/Equipment make
MODELTXT	Vehicle/Equipment model
YEARTXT	Model year, 9999 if unknown or N/A
MFGCAMPNO	MFR campaign number
COMPNAME	Component description
MFGNAME	Manufacturer that filed defect/noncompliance report
BGMAN	Begin date of manufacturing
ENDMAN	End date of manufacturing
RCLTYPECD	Vehicle, equipment, or tire report
POTAFF	Potential number of units affected
ODATE	Date owner notified by MFR
INFLUENCED_BY	Recall initiator (MFR/OVSC/ODI)
MFGTXT	Manufacturers of recalled vehicles/products
RCDATE	Report received date
DATEA	Record creation date
RPNO	Regulation part number
FMVSS	Federal motor vehicle safety standard number
DESC_DEFECT	Defect summary
CONEQUENCE_DEFECT	Consequence summary
CORRECTIVE_ACTION	Corrective summary
NOTES	Recall notes
RCL_CMPT_ID	Number that uniquely identifies a recalled component

Table A.2 Overview of Variables in the Investigation Data File

Variable name	Description
NHTSA ACTION NUMBER	NHTSA identification number
MAKE	Vehicle/Equipment make
MODEL	Vehicle/Equipment model
YEAR	Model year, 9999 if unknown or N/A
COMPNAME	Component description
MFR_NAME	Manufacturer's name
ODATE	Date opened (YYYYMMDD)
CDATE	Date closed (YYYYMMDD)
CAMPNO	Recall campaign number, if applicable
SUBJECT	Summary description
SUMMARY	Summary detail

Table A.3 Overview of Variables in the Complaint Data File

Variable name	Description
CMPLID	NHTSA's internal unique sequence number
ODINO	NHTSA's internal reference number
MFR_NAME	Manufacturer's name
MAKETXT	Vehicle/Equipment make
MODELTXT	Vehicle/Equipment model
YEARTXT	Model year, 9999 if unknown or N/A
CRASH	Was vehicle involved in a crash, 'Y' or 'N'
FAILDATE	Date of incident (YYYYMMDD)
FIRE	Was vehicle involved in a fire, 'Y' or 'N'
INJURED	Number of persons injured
DEATHS	Number of fatalities
COMPDESC	Specific component's description
CITY	Consumer's city
STATE	Consumer's state code
VIN	Vehicle's VIN#
DATEA	Date added to file (YYYYMMDD)
LDATE	Date complaint received by NHTSA (YYYYMMDD)
MILES	Vehicle mileage at failure
OCCURENCES	Number of occurrences
CDESCR	Description of the complaint

Table A.3 Overview of Variables in the Complaint Data File (continued)

Variable name	Description
CMPL_TYPE	Source of complaint code: CAG = Consumer action group CON = Forwarded from a congressional office DP = Defect petition, result of a defect petition EVOQ = Hotline VOQ EWR = Early warning reporting INS = Insurance company IVOQ = NHTSA web site LETR = Consumer letter MAVQ = NHTSA mobile app MIVQ = NHTSA mobile app MVOQ = Optical marked VOQ RC = Recall complaint, result of a recall investigation RP = Recall petition, result of a recall petition SVOQ = Portable safety complaint form (PDF) VOQ = NHTSA vehicle owners questionnaire
POLICE_RPT_YN	Was incident reported to police ‘Y’ or ‘N’
PURCH_DT	Date purchased (YYYYMMDD)
ORIG_OWNER_YN	Was original owner ‘Y’ or ‘N’
ANTI_BRAKES_YN	Anti-lock brakes ‘Y’ or ‘N’
CRUISE_CONT_YN	Cruise control ‘Y’ or ‘N’
NUM_CYLS	Number of cylinders
DRIVE_TRAIN	Drive train type [AWD, 4WD, FWD, RWD]
FUEL_SYS	Fuel system code: FI = Fuel injection TB = Turbo
FUEL_TYPE	Fuel type code: BF = BIFUEL CN = CNG/LPG DS = DIESEL GS = GAS HE = HYBRID ELECTRIC

Table A.3 Overview of Variables in the Complaint Data File (continued)

Variable name	Description
TRANS_TYPE	Vehicle transmission type [AUTO, MAN]
VEH_SPEED	Vehicle speed
DOT	Department of transportation tire identifier
TIRE_SIZE	Tire size
LOC_OF_TIRE	Location of tire code: FSW = Driver side front DSR = Driver side rear FTR = Passenger side front PSR = Passenger side rear SPR = Spare
TIRE_FAIL_TYPE	Type of tire failure code: BST = Blister BLW =Blowout TTL = Crack OFR = Out of round TSW = Puncture TTR = Road hazard TSP = Tread separation
ORIG_EQUIP_YN	Was part original equipment 'Y' or 'N'
MANUF_DT	Date of manufacture (YYYYMMDD)
SEAT_TYPE	Type of child seat code: B = Booster C = Convertible I = Infant IN = Integrated TD = Toddler
RESTRAINT_TYPE	Installation system code: A = Vehicle safety belt B = Latch system

Table A.3 Overview of Variables in the Complaint Data File (continued)

Variable name	Description
DEALER_NAME	Dealer's name
DEALER_TEL	Dealer's telephone number
DEALER_CITY	Dealer's city
DEALER_STATE	Dealer's state code
DEALER_ZIP	Dealer's zip code
PROD_TYPE	Product type code: V = Vehicle T = Tires E = Equipment C = Child restraint
REPAIRED_YN	Was defective tire repaired 'Y' or 'N'
MEDICAL_ATTN	Was medical attention required 'Y' or 'N'
VEHICLES_TOWED_YN	Was vehicle towed 'Y' or 'N'