Can Recalls be Painless? Impact of Product Recalls on the Recalling Firm and its Suppliers: New Findings from the Automotive Industry

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Certificate of Original Authorship

I, Ljubomir Pupovac declare that this thesis, is submitted in fulfilment of the requirements for the award of doctor of philosophy, in the Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

My thesis deals with the impact of product recalls on recalling firm and its suppliers, as well as possible actions that managers could undertake in order to protect firm's market value.

In my thesis essay 1 I try to address two questions: First, how does the announcement of a large-scale product recall by a firm influence the value of their suppliers?, and what are the actions that supplying firm managers could undertake in order to protect their market value? The results showed that suppliers market value drops when one of their suppliers announce large scale recall. However, suppliers could mitigate these effects by disclosing the strength of relationship with their suppliers. The study offers several contribution for suppliers firm's managers. First, it can create awareness to supplier firms' managers that external shock (e.g. product recall) that affect their customers will be spill-overed to them. Second, by publically disclosing relationship with customer, supplier firms' managers can protect firm's market value.

In my essay 2 I try to understand why managers use two different types of recalls (one where they recall all defected product at once [chunk recalls] and second where managers recall affected products by two or more announcements [slice recalls]) and what is the impact of slicing and chunking on firm's market value. The results showed that severity and size of the recall increase the probability of slicing announcements. Furthermore, on average, the stock market reacts more negatively to slicing than to chunking. However, for extremely large recalls, slicing proves less detrimental than chunking. The essay 2 offers important insight to managers: while dealing with product crisis, they should allocate resources in detecting the full scope of the problem (e.g. to detect all product affected by the same default). In that case, they could make only one recall announcement, which could protect firm's market value.

However, if the scope of the crisis is extremely large (e.g. large number of products are affected by the same defect), managers should aim to make several smaller recall announcements.

Introduction

In the last decade, there has been a sharp increase in the number of products being recalled. From 2010 to 2016, for instance, the number of automobiles recalled climbed from 20 to 53 million (Kalavar, Mohr, and Mysore 2018). Several studies published in top marketing journals (Gao et al. 2015; Liu, Shankar, and Yun 2017) show that product recalls have a negative effect on firm market value due to greater expenses associated with repair, restitution, and legal efforts, as well as decrease in revenue and reputation (Cleeren, van Heerde, and Dekimpe 2013). For example, Toyota lost an estimated USD 2 billion in output and sales when faced with a series of recalls over unintended acceleration problems (BBC 2010). Similarly, in June 2014, General Motors (GM) recalled 8.4 million automobiles with potentially faulty ignition systems, costing the company USD 3.2 billion (Spector 2017). In light of the growing challenge posed by product recalls and their detrimental impact on market value, the goal of our research is to offer firms and their suppliers new guidelines regarding how to mitigate recalls' negative performance implications.

Specifically, essay 1 deals with the impact of a product recall on suppliers' market value. The study extends considerations to the upstream impacts on the recalling firm's suppliers, focusing on those whose products were not implicated in the recall. The goal of the study is to provide novel answers to the following questions: how does the announcement of a large-scale product recall by a producer influence the market value of suppliers that are not implicated in the defective product? Is this effect stronger for suppliers with a larger power deficit? How can supplying firms' managers use customer disclosure metrics to protect shareholder value? The results of essay 1 showed that on the day of a large-scale recall announcement, the stock prices of firms that supply the recalling firm suffer a substantial drop. These losses can be mitigated though, by the extent to which the suppliers disclose their resource dependency on customers in their annual reports. These results offer several contributions for supplier firms' managers. First, when producers face negative shocks (e.g., large-scale product recalls), they can use their power over suppliers to mitigate the negative effects. Even if a supplier has a good relationship with its producer customer in a shock-free environment, this relationship can change rapidly when that producer customer faces threats to its business performance, and supplier managers need to anticipate and address those potential changes. Second, I identify a potential defense mechanism: suppliers that fully disclose their customer relationships are less affected when one of their customers announces a large-scale product recall. The manuscript has received a revision request from the Journal of Marketing for the 2nd round of review.

While working on essay 1, we noticed that in response to the same product-harm crisis (i.e., caused by the same defect of a part, or a component), producers sometimes make one large recall announcement and sometimes make several small recall announcements. The first goal of essay 2 is to see what drives firms to either make one large recall announcement (chunking) or make recall announcements piece by piece (slicing). The second goal is to determine whether chunking or slicing recall announcements is more beneficial for firm performance. The results showed that severity and size of the recall increase the probability of slicing announcements. Furthermore, on average, the stock market reacts more negatively to chunking than to slicing. However, for extremely large recalls, slicing proves less detrimental than chunking. The results of essay 2 offer several contributions to managers. First, we show that, by using the appropriate type of product recall announcement, managers can improve firm market value. Even though the decision of chunking vs slicing is not fully left to managers' discretion, the amount of resources that managers allocate to investigate complaints that eventually lead to recalls, as well as the time that elapses between the start of the investigation and the recall announcement, are under managers' control. Thus, by carefully managing product recalls, managers could even increase firm's market value. We also believe that results from essay 2 could also serve as guidance for announcing other negative news to the public—in general, if managers have to announce negative news stemming from the same problem to the public, they should deliver them all at once. However, for problems of an extremely large scale, slicing news is more appropriate. I plan to submit the manuscript to one of the premier marketing journals within the next 2 months.

References

BBC (2010), "Toyota Car Recall May Cost $2bn" (February 2) (accessed January 18, 2018), [available at http://news.bbc.co.uk/2/hi/business/8493414.stm]

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

Gao, Haibing, Jinhong Xie, Qi Wang and Kenneth C Wilbur (2015) "Should Ad Spending Increase or Decrease before a Recall Announcement? The Marketing–Finance Interface in Product-Harm Crisis Management." Journal of Marketing 79(5):80-99.

Kalavar, Sanjay, Detlev Mohr, and Mihir Mysore (2018) "Are you prepared for a corporate crisis?" pp. 19-26 in The Board Perspective A Collection of McKinsey Insights Focusing on Boards of Directors (accessed January 18, 2019) [available at: https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Leadership/The%20board%20perspective/Issue%20Number%202/2018_Board%20Perspective_Number_2.ashx]

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

Spector, Mike (2017), “GM Faces $1 Billion Reckoning in Disputed Ignition-Switch Settlement,” The Wall Street Journal (December 16), (accessed January 18, 2018), [available at https://www.wsj.com/articles/gm-faces-1-billion-day-of-reckoning-in-challenge-to-ignition-switch-settlement-1513432800]

Essay 1: Paying for Others’ Mistakes: The Influence of Product Recalls on Suppliers’ Market Value

Introduction

In June 2014, GM recalled 8.4 million automobiles with potentially defective ignition systems, costing the company $3.2 billion (Popper 2014; Spector 2017). Two similarly sized firms supplying GM at the time, Federal Mogul and Delphi—neither of which sold parts implicated in the faulty systems—experienced different effects of the recall. Federal Mogul's stock dropped by 2.63% (more formally, its abnormal stock returns dropped), but Delphi's remained stable at +.14%. But if neither firm made parts implicated in the recall, why should either of them lose market value? And furthermore, why did Federal Mogul bear the brunt of the (negative) financial impact? Notably, a striking difference between these firms appears in their annual reports, in which Delphi fully discloses its dependence on GM, whereas Federal Mogul's report does not specify any such information.[1]

To address such questions and investigate how the announcement of a large-scale product recall might affect suppliers that are not responsible for the defective product,[2] we propose a resource dependency and power imbalance framework (Pfeffer and Salancik 1978). In business-to-business channels, suppliers often serve relatively few customers (Lilien and Grewal 2012), leaving them resource dependent on their producer customers, which represent an important source of revenue. They can reach end consumers only through these producer customers, so they depend heavily on the economic health of the producer customers for their own business success. A producer's economic struggles, as might be triggered by a recall, accordingly can be detrimental for suppliers. In addition, resource dependence derives from several factors (Frazier, Gill, and Kale 1989; Scheer, Miao and Palmatier 2015), so our

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[1] Until 1998, publicly traded U.S. firms had to disclose the names of principal customers (representing more than 10% of their sales). Since 1998 though, firms only are required to disclose that they have principal customers, not their identities (Cen, Dasgupta, and Sen 2015). The Financial Accounting Standards Board (FASB) rule regarding the disclosure of relationship with customers can be found in Appendix A.

[2] We use the terms producer, customer, and producer customer interchangeably, to refer to the company issuing the recall.

proposed framework includes two likely contingency factors: (1) the extent to which suppliers disclose motivational investments in their relationships with producers and (2) suppliers' difficulty in replacing the producer with an alternative customer.

Although substantial research attention has focused on the impact of product harm crises (defined as discrete, well-publicized events in which defective or even dangerous products are subject to recalls; see Dawar and Pillutla 2000) on producers, competitors, and distributors, little attention has involved the upstream effects on producers' suppliers. Therefore, we study the impact of large-scale product recalls on suppliers, using shareholder value as a performance measure. Prior studies of channel relationships in shock-free environments cite the need to address both long-term perspectives, whereby members seek to maintain trust and positive cooperation (Doney and Cannon 1997), and short-term perspectives, whereby members exploit dependent partners for their own benefits (Hingley 2005). We extend this stream of research by examining situations in which channel members (producers) face major market disruptions (product recalls). In such cases the short-term perspective might prevail, because producers wield their power over suppliers to attenuate the negative effect of the shock, even if doing so might jeopardize longer-term relationships. For instance, to mitigate the negative impact of one of the biggest recalls in automotive history, VW renegotiated terms mid-contract with its suppliers (O'Marah 2016), putting the suppliers in difficult financial positions. If they accept the new terms, they likely will suffer diminished future performance; if they do not, they risk compromising their relationship with the producer.

To test our predictions regarding the effects of recalls on upstream suppliers, we examine large-scale recalls in the automobile industry, announced between 2010 and 2016. Our unique data set matches 28 recalls that involve more than 1 million automobiles each with 46 suppliers from the automobile industry (listed on NYSE or NASDAQ), producing a total of

980 observations. The results show that the suppliers' market value drops when one of their customers issues a large-scale recall, even if they do not supply the faulty part; thus, they pay for the mistakes of their customers. In line with predictions from our resource-dependence framework, the drop in market value is attenuated when suppliers are fully transparent about the extent of their investment with customers. However, this drop is greater when it would be more difficult for the supplier to replace the recalling producer with another customer.

Our study contributes to three research streams in marketing. First, we identify a new phenomenon: that large-scale product recalls can also be detrimental for suppliers' market value. As shown in Figure 1, previous studies have focused on the recalling firm, its competitors and distributors. Second, by examining the producer-supplier relationship when the former faces a disruptive market shock (i.e., a large-scale product recall), we shed new light on channel relationships since they have previously been studied in shock-free contexts. Finally, our study extends findings on marketing metrics' (Moorman and Day 2016) impact on firm performance. We show how customer disclosure metrics can be used by supplying firms' managers to mitigate the negative effects caused by a product recall from one of their customers.

[Insert Figure 1 about here]

The remainder of the paper is organized as follows: next, we develop our theoretical framework leading to the hypotheses. We describe our empirical methodology and data before presenting the results. Finally, we discuss the theoretical and managerial implications of our work, its limitations and opportunities for further research.

Theoretical Framework

As our fundamental research question, we ask how suppliers who are not responsible for a product harm crisis created by a customer might be negatively affected by a large-scale product recall. We also attempt to understand why this effect might be stronger for some suppliers (e.g., those with a greater power deficit) than for others. The theoretical framework we use to address these questions is grounded on three observations. First, suppliers are resource dependent on producers, so they suffer a relative power disadvantage. Second, producers that experience economic challenges have incentives to exploit their power advantage over suppliers, to recoup at least some of their losses. Third, investors seek cues of suppliers' resource dependency on recalling producers.

Suppliers' Resource Dependency on Producers

Firms are open systems that depend on contingencies in the external environment (Hillman, Withers, and Collins 2009). Accordingly, resource dependence theory stipulates that "organizational survival hinges on the ability to produce critical resources from the external environment" (Casciaro and Piskorski 2005, p.168), such that firms' survival and growth reflect their ability to acquire resources from the environment (Pfeffer and Salancik 1978). Palmatier, Dant, and Grewal (2007) in turn argue that firms use their capabilities and resources to compete. In this view, suppliers are resource-dependent on producers, which represent customers that are an essential source of revenue for the suppliers.

Resource dependency also is closely linked to concepts of power, or the capability of firm A to influence firm B to act in a way it would not otherwise (Emerson 1962). When the dependence of firm B on firm A grows, the power of firm A to influence firm B increases. Based on Emerson's (1962) framework, the marketing channel literature identifies two main determinants of the resource dependency of a channel member (Geyskens et al. 1996; Scheer, Miao, and Garrett 2010): (1) the motivational investment in the relationship with a channel partner, proportional to the value of the resource mediated by that partner (Frazier, Gill, and Kale 1989; Frazier and Rody 1991, Scheer, Miao, and Palmatier 2015), and (2) the difficulty of replacing the channel partner, which increases when fewer suitable alternatives are available (Buchanan 1992, Scheer, Miao, and Palmatier 2015).

Producers' Incentives to Exploit Suppliers' Resource Dependency

Power imbalances in marketing channels create exploitation opportunities for the more powerful partner (Geyskens et al. 1996; Hingley 2005). Dominant retailers such as Walmart thus impose sustainability mandates on their suppliers but also appropriate the value created when they implement such mandates (Gielens et al. 2018). Similarly, we argue that producers can exploit suppliers' power imbalance to compensate for the economic damage they suffer due to large-scale product recalls. The producers and their shareholders incur significant losses of wealth following product recalls, because they both reduce revenues and inflate costs (e.g., Chen, Ganesan, and Liu 2009; Eilert et al. 2017; Gao et al. 2015; Liu, Shankar, and Yun 2017; Thirumalai and Sinha 2011).

Product recalls can evoke deteriorated reputations, sales, market share, and brand equity, as well as increased expenses associated with repair, restitution, and legal efforts (Cleeren, van Heerde, and Dekimpe 2013). For example, Toyota estimated that it would lose $2 billion in output and sales when faced with a series of recalls over unintended acceleration problems (BBC 2010). Such financial strains mean that producer firms and their executives often face substantial pressure, from different stakeholders (e.g., customers, investors, government), to remedy the situation—as illustrated by the dismissal of VW CEO Matthias Müller after the 2015 emission scandal that led to the recall of 19 million automobiles worldwide (Boston 2018). Therefore, a powerful producer struggling with a recall might exploit its influence over suppliers (Geyskens et al. 1996) and give them few options other than to accept new requirements or contract terms. As we noted, VW used its power to recoup some losses associated with the 2015 emission scandal by renegotiating the terms of its contracts with suppliers (O'Marah 2016).

Investors Screen Suppliers' Resource Dependency Cues

Suppliers' resource dependency on their customers is not always evident to investors, though as information economics suggests, they search for observable cues about firms' future performance (Akerlof 1970). For example, investors seek cues about firms' intentions to hide financial information that is material to their future performance (Panagopoulos, Mullins, and Avramidis 2018). Following a large-scale recall, investors may try to determine suppliers' vulnerability to producers' potential exploitation of their power advantage. They can obtain such information by noting two main drivers of channel members' resource dependence (Geyskens et al. 1996; Scheer, Miao, and Palmatier 2015): (1) suppliers' motivational investment in their relationships with producers and (2) the level of difficulty associated with replacing the producer.

Hypotheses

We develop our hypotheses by building on the three preceding observations. Overall, we expect product recalls to influence suppliers' market value negatively, even if the suppliers are not responsible for the product harm crisis. We also expect this effect to be stronger if environmental cues suggest to investors that suppliers' resource dependence on recalling producers is greater, in that they have a greater motivational investment in the relationships and would struggle to replace the producers.

Influence of Product Recalls on Suppliers' Market Value

Producers' large-scale recalls should reverberate upstream in the value chain. The recalls clearly are detrimental to producers' market value and financial position (Chen, Ganesan, and

Liu 2009; Cleeren, van Heerde, and Dekimpe 2013; Liu, Shankar, and Yun 2017), while the suppliers' opportunities to leverage critical resources from their environment depends on the performance of their downstream channel partners (Pfeffer and Salancik 1978). Therefore, investors should anticipate that the detrimental effects of large-scale recalls on producers will spread to suppliers, negatively affecting their future business performance. Empirical evidence suggests such transmissions of value-relevant events to upstream channel members; for example, both suppliers (Hertzel et al. 2008) and alliance partners (Boone and Ivanov 2012) experience negative stock price reactions when producer firms declare bankruptcy. We thus hypothesize:

H_1: Suppliers' market values drop when a producer announces a large-scale recall.

Suppliers' Motivational Investment in Relationships with Customers

From a resource dependency perspective, the larger the revenue accounted for by a channel partner, the more dependent that channel member is (Frazier, Gill, and Kale 1989; Gielens et al. 2018). That is, if the producer accounts for a larger share of the supplier's overall sales, that supplier is more vulnerable to power exploitation attempts by the producer (Geyskens et al. 1996; Johnsen and Ford 2008; Kumar, Scheer, and Steenkamp 1995). For producers, highly dependent suppliers represent targets for renegotiation of terms, because they have few options other than to accept newly imposed business conditions (Geyskens et al. 1996; Wuyts and Geyskens 2005).

Information about the resource dependence of suppliers on their customers is not generally publicly available (Ellis, Fee, and Thomas 2012). However, investors can seek information about suppliers' motivational investments in their relationships with customers by monitoring relevant metrics, such as the strength of customer relationships (Bayer, Tuli, and Skiera 2017). Transparent information about customer relationships might appear in annual reports, but suppliers also may choose not to provide customer names and sales figures.[3] We thus identify four degrees of transparency with which firms disclose the strength of their customer relationships, reflecting the three disclosures documented by Ellis, Fee, and Thomas (2012) but also adding non-disclosure, as we outline in Table 1.

[Insert Table 1 here]

Suppliers use *full disclosure* if they provide sales figures and names of both principal and non-principal (representing less than 10% of sales) customers. Investors' risk perceptions can be assuaged by such relevant information (Bayer, Tuli, and Skiera 2017), which may be why some managers fully disclose their customer relationships. *High disclosure* entails providing the names of customers and sales figures of principal customers, responsible for more than 10% of the firm's overall sales (Cen, Dasgupta, and Sen 2015). This disclosure might be a remnant of former regulations that required disclosures of the identity of principal customers (Cen, Dasgupta, and Sen 2015). *Low disclosure* refers to suppliers that provide the names of their customers but not corresponding sales figures. Revealing the names of highly reputable customers may be advantageous, such as to facilitate the acquisition of new customers or increase future performance (Hada, Grewal, and Lilien 2014). Finally, *non-disclosure* occurs when suppliers do not report the identity of any customers. These managers may be unwilling to reveal valuable information to competitors (Wuyts and Dutta 2008).

When they lack critical information, investors often behave as if the worst-case scenario is in effect, due to their aversion to ambiguity (Easley, O'Hara, and Yang 2013; Epstein and Schneider 2008). When suppliers instead fully disclose the names and sales figures of their customers, investors have complete information and can assess suppliers' resource dependence, as well as the potential revenue losses if producers exploit their power

[3] Based on the FASB rule from Appendix A.

advantage. That is, with full disclosure, investors can confidently anticipate the economic consequences of the recall for suppliers, which are substantial only if suppliers' motivational investment is high. Low and non-disclosure conditions are more ambiguous though. Without sales figures, investors cannot determine suppliers' motivational investment precisely, so they likely assume the suppliers are strongly resource dependent, the worst-case scenario, regardless of which producer issues the recall (Easley, O'Hara, and Yang 2013; Epstein and Schneider 2008). Similarly, high disclosure might be transparent about principal customers (more than 10% of sales), but it limits information about other customers, with relationships that may account for sales ranging from less than 1% to 9.9%. In this sense, the high disclosure condition still involves ambiguity. We anticipate that investors might expect large revenue losses if the recalling producer is a principal customer (information is disclosed) but assume losses commensurate with a resource dependence level of 9.9% if the producer is not a principal customer (worst-case scenario). Consequently, full disclosure should lead to lower estimates of market value losses than any other disclosures, because it never causes investors to assume the worst-case scenario in terms of motivational investment in the relationships. We thus hypothesize:

> **H_2**: Suppliers that fully disclose customer relationships experience a smaller drop in market value than suppliers that use (a) high disclosure, (b) low disclosure, or (c) non-disclosure of their relationships with a producer that announces a large-scale recall.

Difficulty of Replacing Customers

The resource dependence of suppliers on producers is greater when the latter are harder to replace (Buchanan 1992; Ganesan 1994; Schmitz, Schweiger, and Daft 2016), a measure that often is proportional to their relative size difference with suppliers. That is, keeping its size constant, a supplier depends more on its relationships with larger customers due to the lower likelihood of finding another, similarly large customer if current sales were lost (Assael

1967; Tóth, Henneberg, and Naudé 2017). In addition to the difficulty of compensating for lost sales, if a channel relationship ends, a significant part of the potential market falls outside the supplier's realm, because the producer provides the main access to end consumers (Lilien and Grewal 2012). All else being equal, larger producers are therefore harder to replace than smaller ones, conferring them a greater power advantage in their relationships with suppliers.

On the flip side, keeping its size constant, a producer cannot replace a large supplier as easily as a small one. Imagine one recalling producer and two suppliers with similarly strong relationships (e.g., the producer represents 10% of the sales of each supplier) but different sizes (e.g., the small supplier makes 200,000 units of a component; the large supplier makes 5,000,000 units). The suppliers' motivational investments in their relationships with the producer are similar (10% of revenues), but the producer is less dependent on its relationship with the smaller than with the larger supplier, because it would normally be easier to find alternative suppliers that can make 20,000 instead of 500,000 units. Following a large-scale product recall, investors thus might use information about both channel partners' sizes to determine the extent to which producers can exert power over suppliers and leave them with no alternative other than to accept new arrangements or contract renegotiations. Thus:

> **H_3**: The larger the relative difference in size between the recalling producer and supplier, the greater the drop in the supplier's market value after a large-scale recall is announced.

Research Methodology

Event Study Approach

We sought a methodology that would permit us to isolate the impact of a specific event (product recall) on the performance of specific firms (suppliers). It also needed to support measurements with minimal confounds and permit plausible inferences of causation. Other econometric approaches might be considered, using performance measures such as sales, return on assets, and Tobin's Q, but none of those has the granularity of daily stock prices, which incorporate the latest information about a firm's expected future performance. Therefore, we selected an event study methodology, as has often been used in previous product recall studies (e.g., Cleeren, Dekimpe, and van Heerde 2017). With a specific event (product recall), we can determine the precise time of occurrence. Moreover, the event study methodology can address reverse causality concerns (Srinivasan and Hanssens 2009) by using short event windows.

We follow a common approach in marketing and finance to implement the event study methodology, such that we calculate the abnormal return of suppliers' stock price around the recall announcement as the difference between the actual stock return and expected stock return. We use a market model to calculate the expected stock return (Sorescu, Warren, and Ertekin 2017). First, we regress firms' returns on the market return, before the event, to obtain values for $\widehat{\alpha_i}$ and $\widehat{\beta_i}$:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it},$$

where R_{it} is the stock return of a firm i on day t, and R_{mt} is the base return of a value-weighted market index m on day t. We used 240 days (starting 250 days before and ending 10 before the event) to estimate the base return of the stock. This window is long enough for the estimation of $\widehat{\alpha_i}$ and $\widehat{\beta_i}$, but it ends 10 days before the recall so that we can control for the influence of the event on the parameter estimation. Second, we use $\widehat{\alpha_i}$ and $\widehat{\beta_i}$ to calculate firm i's expected return $E[R_{it}]$ on the day of the event: $E[R_{it}] = \widehat{\alpha_i} + \widehat{\beta_i} R_{mt}$. Third, we calculate the abnormal return (AR) as the difference between actual and expected returns, $AR_{it} = R_{it} - E[R_{it}]$, on the day of the event. Fourth, the cumulative abnormal return (CAR) is obtained as $CAR_i [-t_1, t_2] = \sum_{-t_1}^{t_2} AR_{it}$.

Measures

Dependent variable. A key decision in event studies is the selection of an event window (days around the event used to calculate the CAR). Our research goals include minimizing the influence of other confounding factors on the firm's stock value, minimizing the likelihood of capturing multiple recalls in a short time, and accounting for the possibility of leakage before the event and information dissemination afterward. Warren and Sorescu (2017) argue that a 3-day window best addresses these research goals, so we select that span of time. Robustness checks confirm that our results are robust to the choice of different event windows, as we detail subsequently. To deal with extreme values, we follow Rego, Morgan, and Fornell (2013) and winsorize[4] CAR at 1% on both sides of the distribution.

Independent variables. Our first independent variable is *customer disclosure*. We used the annual report available when the recall occurred (i.e., one year before the recall year), because this information would be available to investors at the time of the recall. We set full disclosure as the reference category and estimated the impact of varying from that base. We then operationalized a second independent variable, *difference in size,* as the ratio of the producer's annual sales and those of the supplier.

Control variables. In line with past research, we account for the number of automobiles recalled (Liu, Shankar, and Yun 2017) and media coverage (Gao et al. 2015). To operationalize media coverage, we determined whether the top five newspapers by circulation (*The Wall Street Journal*, *USA Today*, *The New York Times*, *The Washington Post,* and *The New York Post*; Gao et al. 2015) covered the recall. We added *The Financial Times* to this list

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[4]In a winsorized estimator, the extreme values are replaced by certain percentiles (trimmed minimum and maximum, 1% and 99% in our case). Winsorizing differs from trimming. In a trimmed estimator, the extreme values are discarded.

because it is an important source of information for investors. If two or more recalls involved the same supplier within three or fewer days, we considered them as one recall (i.e., "merged"). Robustness checks confirm that the results are stable if we remove these cases.

At the producer level (e.g., VW, Toyota), we controlled for reputation; an excellent reputation might shelter producers from negative effects of product recalls (Saboo, Kumar, and Anand 2017). For 882 of the 980 observations for which a producer appeared on *Fortune*'s list of most admired companies in the year of the recall, we used the corresponding reputation scores (Chen, Ganesan, and Liu 2009). For producers that were not listed, we assigned them the lowest score from *Fortune*'s "Motor vehicles" category.

We also included control variables at the supplier level, including size, profitability, and age (see Table 2), and controlled for the reputation of suppliers. However, 63% of the suppliers were not on *Fortune*'s most admired list, so we developed a categorical variable to reflect their reputations. The first category, high reputation, includes suppliers on *Fortune*'s list of most admired firms; medium reputation refers to those suppliers on the contenders' list; and low reputation includes suppliers not mentioned by *Fortune*. Finally, we rely on dummy variables for year, producer, recall, and standard industrial code (SIC) classification 3714, "Motor Vehicle Parts and Accessories."

[Insert table 2 here]

Data

In line with prior product recall studies, we use a single-industry approach, to increase internal validity and preclude the need to control for cross-industry factors (Liu, Shankar, and Yun 2017). We rely on three criteria to select an appropriate industry: (1) recalls are frequent and their characteristics are well-documented, (2) information about which suppliers work with the recalling firms is available, and (3) there is sufficient information regarding producers and suppliers' characteristics. The automobile industry fulfills these criteria, in that recalls are commonplace and increasing in this industry (Liu, Shankar, and Yun 2017), information about recalls is easy to access (e.g., extensive media coverage), and it is possible to identify production suppliers from available sources (e.g., Compustat SIC classification 3714 "Motor Vehicle Parts and Accessories," automobile producers' websites, media reports). Furthermore, many of the producers and suppliers in this industry are public firms, so they are legally required to provide the information we require for this research. Finally, many product harm crisis studies similarly rely on this industry as their empirical context (e.g., Eilert et al. 2017; Liu, Shankar, and Yun 2017).

We also needed to determine the minimum size of recalls for the analysis. Recalling a very small number of vehicles is unlikely to evoke much media coverage or have significant economic consequences for the producer (Liu, Shankar, and Yun 2017). Therefore, we focus on large recalls; for this initial investigation of recalls' influence on suppliers though, we could find little guidance about what constitutes a large recall. Thus, we use different inclusion thresholds: 2 million, 1 million, and 500,000. Such large recalls may be identified from two sources: the media or records from the National Highway Traffic Safety Administration (NHTSA) database. We chose the former source over the latter, for two reasons. First, a product harm crisis is a discrete, well-publicized event (Cleeren, Dekimpe, and van Heerde 2017; Dawar and Pillutla 2000), and significant media coverage confirms that the event generated the necessary publicity. Second, the NHTSA covers only U.S. recalls, which excludes some prominent cases, such as VW's recall in September 2015—the largest individual case in our database. The automobiles were recalled in Europe though, so the NHTSA database does not include it.

Accordingly, we searched Factiva, Google, *The Wall Street Journal,* and *Automotive News* magazine, using keywords such as "product recall," "automobiles recall," "car recall," “[name of 10 largest automobile producers] recalled,” and “largest recalls in the automobile/car/automotive industry.” For clarity and to avoid confounds, we only retain recalls for which the producer is responsible for the product defect, as reported by the media. We emphasized producers present in three key markets: Europe, North America, and Asia. In the 2010–2016 period, we identified 16 recalls larger than 2 million automobiles, 29 recalls larger than 1 million, and 64 recalls larger than 500,000 vehicles. We did not remove overlapping cases (i.e., two or more recalls affecting the same supplier at the same time), to retain valuable information (Warren and Sorescu 2017). Instead, we treated all recalls within three days of one another as a single event (in line with our 3-day [-1,1] event window), using the earliest recall as the event date. A robustness check confirmed our results are similar when removing overlapping cases from the analysis.

We used several sources to identify suppliers. For every company in SIC 3714 (“Motor Vehicle Parts and Accessories”), we confirmed that it was an automotive supplier; this code includes truck part suppliers as well. We also reviewed the websites of major automobile producers. Finally, we searched *The Wall Street Journal*, *Financial Times,* and *Automotive News* for additional suppliers. Through these efforts, we identified 46 industry suppliers. Next, to match these suppliers with automobile producers, we started with suppliers that use full, high, or low disclosure and checked their annual reports, websites, and producers’ websites. With a Factiva search, we also entered the combined names of the suppliers and producers in our data set (e.g., “Magna Ford,” “Magna GM,” “Magna Toyota”). For suppliers that use non-disclosure, we relied solely on the secondary sources, namely, the producer’s websites and a Factiva search. After this matching step, the final sample consists of 537 observations for recalls larger than 2 million cars, 980 for recalls larger than 1 million, and 2,133 observations for recalls larger than 500,000 vehicles.

Results

The pairwise correlations and descriptive statistics are in Table 3. More than half of the firms (58.87%) belong to SIC 3714, and the rest are dispersed across different industries, such as “Steel Works, Blast Furnaces & Rolling Mills (Coke Ovens)” or “Paints, Varnishes, Lacquers, Enamels & Allied Prods.”

[Insert Table 3 here]

Regarding customer disclosure, we find that the four disclosure levels are nearly evenly distributed in our sample: 20.61% of firms use full disclosure, 26.12% high disclosure, 22.85% low disclosure, and 30.4% non-disclosure (Table 3). Both suppliers’ age and size correlate negatively with full (r = -.37 and r = -.13, respectively) and high (r = -.23 and r = -.19, respectively) disclosure; older and larger firms are less transparent than younger, smaller firms. Furthermore, firms in SIC 3714 are more transparent than automobile suppliers from other industries (correlation with full disclosure = .43).

Impact of Product Recalls on Supplier Firms’ Value

We first test whether product recalls affect the value of supplier firms that are not responsible for the product harm crisis at the origin of the recalls. Row 1 of Table 4 shows that the average AR of suppliers on the day of the recall is negative and significant for the three recall size thresholds. The average drops in suppliers’ market value are –.47% for recalls of 2 million and above (t = -2.97, $p < .01$), –.35% for 1 million and above (t = -2.88, $p < .01$), and –.19% at the 500,000 threshold (t = -2.57, $p < .01$). These results support H_1; across all three thresholds, suppliers experience a loss of value when a producer announces a product recall. Such large-scale recalls are frequent enough to present a systematic risk for suppliers. As the annual averages in Table 4, row 3, show, there are more than 2 recalls per year that include more than 2 million automobiles, about 4 recalls larger than 1 million, and about 9 recalls larger than 500,000 vehicles. Noting that suppliers have 7.5 customers among the top 10 producers on average, over a one-year period, a supplier can expect to be hit by about 7 large recalls of at least 500,000 automobiles ($9.14 \times .75 = 6.75$).

[Insert Table 4 here]

Table 4 also provides estimates of financial significance, using the expected yearly drop in market value for a median-sized supplier in our sample (by market capitalization). For each threshold, we multiply the average AR on the day of the recall by market capitalization and the expected number of recalls involving a customer of the supplier over a one-year period. The magnitude of the average drop per recall decreases with smaller recall sizes, as shown in row 4 (i.e., $33.64 million at 2 million automobiles, $24.92 at 1 million, and $13.53 at 500,000). However, the cumulative annual financial impact is larger for small recalls, which are more frequent: losses of $77 million dollars for recalls of 2 million automobiles, $103 million for 1 million recalls, and $123.7 million for 500,000 recalls (row 5).

Moderating Influence of Resource Dependence on Negative Impacts of Product Recalls on Suppliers' Market Value

We also examine whether cues about resource dependence moderate the negative impact of product recalls on suppliers' market value. We use recalls larger than 1 million automobiles, which are both large enough to affect suppliers' market value and frequent enough to present a challenge for suppliers' managers. In a robustness test, we confirm the results at the 500,000-vehicle threshold. Accordingly, we estimate three models. In Table 5, Column I contains the results from a model in which we included all independent variables, control variables, year fixed effects and producer fixed effect. In Column II, we replace producer fixed effects with recall fixed effects.[5] In Column 3, we include producer fixed

[5] We do not use producer and recall fixed effects in the same model, because many producers in the data set issued only one recall.

effects and clustered robust standard errors, to control for within-supplier correlations (i.e., equivalent to random effects) and heteroscedasticity.[6] In all three columns, the dependent variable is the market model CAR over the [-1, +1] window; we use full disclosure as the reference category. Notably, hierarchical linear modeling would be appropriate only if the data had a strict hierarchical structure (i.e., suppliers embedded within recalls embedded within producers), which is not the case in our empirical setting (see Appendix B). Multicollinearity is not a concern; all variance inflation factors are below 10 (maximum = 5.4).

[Insert Table 5 here]

Customer disclosure. Suppliers using a full disclosure experience a smaller drop in market value than suppliers using any other disclosure level, as revealed by the negative and significant effects of high ($\beta = -.0068$, $p < .05$), low ($\beta = -.008$, $p < .05$), and non-disclosure ($\beta = -.0121$, $p < .01$) conditions, in support of $H_{2a\text{–}2c}$. Complete transparency about the strength of customer relationships can mitigate the negative effect of product recalls on market value, relative to a partial or absence of transparency. These results are robust to different model specifications: Both Columns II and III also provide support for $H_{2a\text{–}2c}$ by revealing the negative, significant effects of high, low, and non-disclosure conditions (□s range from -.0067 to -.0121, $p < .05$). When we vary the reference category, we find no significant differences among high, low, and non-disclosure (see Appendix C). That is, only fully transparent suppliers can protect their shareholders' wealth from a product recall by one of their customers. Investors lacking complete information about the strength of the relationship with the producer infer the worst-case scenario (i.e., high resource dependency).

[6] We did not use firm fixed effects, because one of our main independent variables (customer disclosure) does not vary over time. Instead, we used standard errors clustered within firms.

Producer–supplier relative size. The larger the producer relative to the supplier, the greater the drop in the latter's market value, according to the negative and significant effect of relative size (β = -.0041, $p < .05$), in support of H_3. This result is consistent with the idea that suppliers with a greater power deficit, due to their customer's larger size, appear more vulnerable to investors during a product recall. This result persists in Columns II (β = -.0041, $p < .05$) and III (β = -.0041, $p < .10$), though at α = .10 in the latter case. Some control variables also have noteworthy effects. In Column I, both media coverage (β = -.0044, $p < .01$) and the number of automobiles recalled (β = -.0063, $p < .05$) exert negative impacts on market value, in line with our theoretical framework. That is, recalls that garner more media attention put more pressure on the producer firms, spurring more compensatory tactics at the expense of weaker suppliers. The size of the recall also is negatively related to the recalling firm's market value drop (Liu, Shankar, and Yun 2017), which should bolster producers' incentives to compensate by wielding their power over suppliers.

Endogeneity Issues

Some firm actions can be endogenous in models of marketing and financial performance. However, customer disclosure should not suffer from such a threat, because none of the three possible sources of endogeneity—simultaneity, measurement error, or omitted variable—is a concern. First, we used a lagged value of disclosure levels, so the level of transparency is determined before the recall. Second, measurement error likely is inconsequential, because disclosure is directly observable in firms' annual reports. Third, any omission of factors that influence both the choice of disclosure and market value fluctuations due to recalls is unlikely to threaten our results, because managers do not choose disclosure levels as a function of the resource dependence of their firms on customers, nor do they adjust disclosure levels to protect firm value from customer recalls.

If disclosure were endogenous, firms' disclosure would change regularly over time; for example, managers would decrease their transparency level when firms' revenue depends on fewer customers (as might occur due to the increasing concentration of automobile producers in recent years; Shepardson 2017) or as the frequency of recalls increases (and 2016 witnessed the most automobiles recalled in the United States, at 53.2 million, breaking previous records set in 2014 and 2015; Shepardson 2017). Instead, the disclosure levels are remarkably stable in our data set, such that we observe only 1 of 322 possible changes between 2010 and 2016. In addition, suppliers' transparency in disclosing their motivational investments with customers is negatively correlated with their size (see Table 3). Larger suppliers, which tend to be less resource dependent on customers than small suppliers (Saboo, Kumar, and Anand 2017), disclose less information about the structure of their customer portfolio, which is contrary to an endogeneity argument that firms would become less transparent as they grow more resource dependent.

These points are not meant to suggest that customer disclosure decisions are random; rather, we contend that they are not based on recalls by the firm's customers. Instead, the strong correlation between the automotive industry dummy variable and the four disclosure options (Table 3), coupled with the lack of change in the type of disclosure used over time, suggest that supplier firms may choose a level of disclosure early on, perhaps by mimicking others in the industry, signaling reflexive imitation due to uncertain environments (McFarland, Bloodgood, and Payan 2008).

Robustness Checks

We perform several analyses to assess the robustness of our results, with (1) 500,000 automobiles as a threshold for recall size rather than 1 million, (2) different event windows,

(3) AR calculations that use an alternative to the market model, (4) the removal of overlapping cases (5) by controlling for possible self-selection bias.

Alternative recall size threshold (Table 6, Column I). When we use 500,000 automobiles as a threshold, our results replicate the effects of the resource dependency cues with the 1 million car threshold (customer disclosure levels: high $\beta < -.0042$, $p < .05$; low $\beta < -.0046$, $p < .05$; non-disclosure $\beta < -.0089$, $p < .01$; relative size $\beta = -.0053$, $p < .05$). These findings provide further support for $H_{2a\text{-}2c}$ and H_3. We had already confirmed the robustness of H_1 to the 500,000 threshold (see Table 4).

Different event windows (Table 6, Columns II and III). We test our hypothesis with alternative event windows for calculating the CARs. To allow for the possibility that information dissemination extends further than one day after the recall, we use a [-1,2] window instead of [-1,1]. We also use a [-2,2] window, to capture possible information leakage two days before the announcement (Warren and Sorescu 2017). The results in both cases are consistent with $H_{2a\text{–}2c}$ and H_3. Only the results for size difference vary somewhat, such that it is marginally significant for the [-1,2] window in Column II ($\beta = -.0048$, $p < .10$) and non-significant for the [-2,2] window in Column III ($\beta = -.0029$, $p > .10$). These results are to be expected; longer windows are more likely to include noise from extraneous events (Sorescu, Warren, and Ertekin 2017).

Alternative to the market model to calculate ARs (Table 6, Column IV). With a Fama-French model, we calculate the CAR using an alternative measure.[7] According to this operationalization, the average AR at the 1 million automobile threshold (980 cases) is negative and significant (-.32%, $t = -2.72$, $p < .01$), which confirms H_1. In addition, this

[7] The Fama-French model controls for two more factors than the market model (difference in returns between small and large stocks and difference between high and low book-to-market ratio stocks; Eilert et al. 2017), but it is more appropriate for a long- than a short-term event study (Sorescu, Warren, and Ertekin 2017), which is why we chose to conduct our main analyses with the market model.

model is consistent with our previous results, in that both power imbalance variables are negative and significant (customer disclosure: high $\beta = -.006$, $p < .01$; low $\beta = -.0071$, $p < .05$; non-disclosure $\beta = -.0111$, $p < .01$; relative size: $\beta = -.0045$, $p < .05$), in support of $H_{2a–2c}$ and H_3.

Removing overlapping cases (Table 6, Column V). We excluded 127 cases for which a supplier was connected to two or more recalls within three days of the event window. The average AR for the 853 remaining observations is negative and significant (-.30%, $t = -2.39$, $p < .01$), confirming H_1. Both customer disclosure (high $\beta = -.0076$, $p < .05$; low $\beta = -.0108$, $p < .01$; non-disclosure $\beta = -.0154$, $p < .01$) and relative size (□ = -.0051, $p < .05$) have negative, significant effects, again supporting $H_{2a–2c}$ and H_3.

Controlling for self-selection bias. Producers could use power difference as one of the criteria when choosing their suppliers since relatively less powerful suppliers will be susceptible to potential pressure imposed on them. To account for potential selection bias, we applied a two-stage Heckman selection model (Heckman 1976). Appendix D provides the details: the results show that there is no selection bias and confirm previous findings in support of the hypotheses.

Discussion

Product harm crises are a concern for managers of producer firms but also for managers of supplier firms. As Gao et al. (2015) show, large-scale product recalls inflict significant economic damage on recalling firms. But these firms are often powerful players in the supply chain who can exploit their power advantage to blunt the financial blow of large recalls on their outcomes, at the expense of their suppliers. Such compensatory tactics are consistent with the negative and significant AR we find among suppliers when one of their customers announces a large-scale recall. Crucially, these suppliers did not cause the recalls we study; instead, these firms are paying for others' mistakes.

Resource dependence provides information that investors use to identify suppliers that are the most likely targets of recalling producers. We find that suppliers that fully disclose the strength of their customer relationships fare better than those that leave investors in a state of uncertainty regarding the extent to which they depend economically on the recalling producer, seemingly because investors assume the worst when diagnostic information is unavailable (Bayer, Tuli, and Skiera 2017; Chen, Ganesan, and Liu 2009). Furthermore, investors expect suppliers with a greater size deficit, relative to the recalling producer, to perform worse in the future.

Theoretical Contributions

Prior research documents detrimental financial consequences of product recalls on the recalling firm, its competitors, and distributors; no study has investigated whether such crises also affect upstream channel members. By addressing this issue, we make three contributions. First, we assess the effect of a recall on suppliers, a previously overlooked marketplace outcome, and thereby document that the total economic impact of a recall far outweighs that associated with the recalling firm. In addition, a recall is more likely to affect a supplier than the producer, due to frequency considerations. In a given year, there are about 4 recalls of more than 1 million vehicles, but an average supplier supplies 7.5 of the top 10 automobile producers susceptible to such a recall. The recall also exerts a multiplicative effect in the supply chain: For each recalling firm, numerous supplier firms might be affected. For instance, Eilert et al. (2017) estimate that recalls lead to shareholder losses of $14–$156 million; our findings instead suggest that the total economic losses across all suppliers amount to $859 million per large-scale recall.[8]

Second, prior research on channel relationships often considers suppliers and producers (e.g., Palmatier, Gopalakrishna, and Houston 2006), but rarely addresses power considerations, despite its importance in supply chains (Boyd, Chandy, and Cunha 2010; Gielens et al. 2018). Studies in shock-free contexts affirm that more powerful partners can extract more value from the relationship than can the weaker party (Hingley 2005). Our findings show that in a shock period, following a product recall, resource dependence also can be detrimental to the weaker partner, even if the reason for the negative effect is not related to any action by that partner. The producer's ability to renegotiate or cancel agreements is enough to cause concern for investors about suppliers' future performance.

Third, this research addresses a call from Moorman and Day (2016) for more studies of customer metrics. A few studies document the performance benefits of relying on a larger set of marketing metrics (Bayer, Tuli, and Skiera 2017; Mintz and Currim 2013), as well as appropriate uses of specific metrics (Moorman and Day 2016). Our findings show that the effective usage of one specific marketing metric, customer disclosure, can mitigate the negative market value implications of recalls by producer customers on suppliers.

Managerial Implications

Managers of suppliers must recognize that their firms' market value may suffer from their producer customers' product recalls. Our findings point to detrimental effects on the market value of suppliers even if they did not sell the faulty parts causing the recall. As Table 4 shows, the average impact depends on the size of the recall, ranging from -.19% to -.47% of

[8] We calculated overall economic losses by multiplying the loss per recall per supplier from Table 4 by the number of publicly traded suppliers and the probability that they count the recalling producer as their customer (.75). We based our calculation on results obtained for recalls of more than 1 million automobiles.

the suppliers' market value. Smaller recalls are less damaging, but they are also more frequent, such that their total expected negative financial impact is greater.

It is not straightforward whether managers should adopt fully transparent customer disclosure though. On the one hand, the strength of the relationship is important information that helps investors estimate the impact. On the other hand, such information might reveal the strong dependence of the supplier on the recalling producer. To illuminate the consequences of this dilemma, we consider two scenarios. First, if a supplier depends heavily on the recalling producer, investors could react negatively to the vast power imbalance, which they learn about because the supplier is fully transparent. However, if this information is not disclosed, investors will assume the worst anyway and react as if the relationship were strong.

Second, if the supplier is not overly dependent on the recalling producer, a full disclosure should not lead to negative reactions from investors. However, with any other type of disclosure, investors will assume strong dependence, leading them to downgrade their performance forecast. Therefore, in comparison with the other degrees of transparency, at worst, full disclosure has the same effect on suppliers' market value; at best, it can improve it. Notably though, only 20% of firms use full disclosure, and they almost never change their level of disclosure. Thus, greater customer disclosure could be a useful defense mechanism against major economic setbacks, as well as a controllable risk factor that most firms appear to have overlooked.

Limitations and Further Research

We conducted this study in the automobile industry and included only suppliers listed on major U.S. stock exchanges. A possible extension thus would be to review other industries, to make the conclusions more generalizable. We also consider only two indicators of resource dependence: motivational investments and size differences of channel partners. It would be interesting to investigate if other factors that influence resource dependence affect product recall outcomes. For example, does product complexity influence a recall's detrimental impact on suppliers? Might suppliers selling complex products be spared the aggressive tactics of producers, because such products would be harder to substitute? Finally, we define a product recall as a market shock that transfers to a firm's suppliers. More studies could examine if similar effects arise for other shocks, such as corporate scandals, and if the negative effects spread to other collaborators, such as alliance partners.

In summary, we hope our study of the influence of product recalls on suppliers' market value inspires further research into the upstream effects of both positive and negative market disruptions and provides guidance for managers, regarding what to expect and how to navigate such unpredictable, but inevitable, disruptions.

References

Akerlof, George A. (1970), "The Market for Lemons: Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, 84(3), 488–500.

Assael, Henry (1967), "The Political Role of Trade Associations in Distributive Conflict Resolution," *Journal of Marketing*, 31 (April), 21-28.

Bayer, Emanuel, Kapil R. Tuli, and Bernd Skiera (2017), "Do Disclosures of Customer Metrics Lower Investors' and Analysts' Uncertainty but Hurt Firm Performance?" *Journal of Marketing Research*, 54 (2), 239-59.

BBC (2010), "Toyota Car Recall May Cost $2bn" (February 2) (accessed January 18, 2018), [available at http://news.bbc.co.uk/2/hi/business/8493414.stm]

Boone, Audre L., and Vladimir I. Ivanov (2012), "Bankruptcy Spillover Effects on Strategic Alliance Partners," *Journal of Financial Economics*, 103(3), 551-569.

Boston, William (2018), "Volkswagen Ousts CEO Matthias Müller, Promotes Herbert Diess to Top Role," *The Wall Street Journal* (April 12), (accessed May 11, 2018), [available at https://www.wsj.com/articles/volkswagen-set-to-elevate-new-ceo-roll-out-broad-restructuring-1523538272]

Boyd, Eric D., Rajesh K. Chandy, and Marcus Cunha Jr. (2010), "When Do Chief Marketing Officers Affect Firm Value? A Customer Power Explanation," *Journal of Marketing Research*, 47 (6), 1162-76.

Buchanan, Lauranne (1992), "Vertical Trade Relationships: The Role of Dependence and Symmetry in Attaining Organizational Goals," *Journal of Marketing Research*, 29 (February), 65-75.

Casciaro, Tiziana and Mikolaj J. Piskorski (2005), "Power Imbalance, Mutual Dependence, and Constraint Absorption: A Closer Look at Resource Dependence Theory," *Administrative Science Quarterly*, 50 (2), 167-99.

Cen, Ling, Sudipto Dasgupta, and Rik Sen (2015), "Discipline or Disruption? Stakeholder Relationships and the Effect of Takeover Threat," *Management Science*, 62 (10), 2820-41.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product-recall Strategy Affect its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises," *Journal of Marketing*, 73 (6), 214-26.

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

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

Dawar, Niraj, and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (2), 215-26.

Doney, Patricia M., and Joseph P Cannon (1997), "An Examination of the Nature of Trust in Buyer-Seller Relationships," *Journal of Marketing*, 61 (2), 35-51.

Easley, David, Maureen O'Hara, and Liyan Yang (2014), "Opaque Trading, Disclosure, and Asset Prices: Implications for Hedge Fund Regulation," *Review of Financial Studies* 27 (4), 1190–1237.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), "Does it Pay to Recall your Product Early? An Empirical Investigation in the Automobile Industry," *Journal of Marketing*, 81 (3), 111-29.

Ellis, Jesse A., C. Edward Fee, and Shawn E Thomas (2012), "Proprietary Costs and the Disclosure of Information About Customers," *Journal of Accounting Research*, 50 (3), 685-727.

Emerson, Richard M. (1962), "Power-Dependence Relations," *American Sociological Review*, 27(1), 31-41.

Epstein, Larry G. and Martin Schneider (2008), “Ambiguity, Information Quality, and Asset Pricing,” *Journal of Finance*, 63 (1), 197–228.

Frazier, Gary, James Gill, and Sudhir Kale (1989), “Dealer Dependence Levels and Reciprocal Actions in a Channel of Distribution in a Developing Country,” *Journal of Marketing*, 53 (January), 50–69.

——— and Raymond Rody (1991), “The Use of Influence Strategies in Interfirm Relationships in Industrial Product Channels,” *Journal of Marketing*, 55 (January), 52–69.

FASB (n.d.), “Financial Reporting for Segments of a Business Enterprise (Issued 12/76),” (accessed September 25, 2017), [available at https://www.fasb.org/summary/stsum14.shtml]

Ganesan, Shankar (1994), “Determinants of Long-Term Orientation in Buyer–Seller Relationships,” *Journal of Marketing*, 58(April), 1–19.

Gao, Haibing, Jinhong Xie, Qi Wang, and Kenneth C. Wilbur (2015), "Should Ad Spending Increase or Decrease Before a Recall Announcement? The Marketing–Finance Interface in Product-harm Crisis Management," *Journal of Marketing*, 79 (5), 80-99.

Geyskens, Inge, Jan-Benedict E.M. Steenkamp, Lisa K. Scheer, and Nirmalaya Kumar (1996), “The Effects of Trust and Interdependence on Relationship Commitment: A Trans-Atlantic Study,” *International Journal of Research in Marketing*, 13 (4), 303–17.

Gielens, Katrijn, Inge Geyskens, Barbara Deleersnyder, and Max Nohe (2018), "The New Regulator in Town: The Effect of Walmart's Sustainability Mandate on Supplier Shareholder Value," *Journal of Marketing*, 82 (2), 124-41.

Gruca, Thomas S. and Lopo L. Rego (2005), "Customer Satisfaction, Cash Flow, and Shareholder Value," *Journal of Marketing*, 69 (3), 115-30.

Hada, Mahima, Rajdeep Grewal, and Gary L. Lilien (2014), "Supplier-Selected Referrals," *Journal of Marketing*, 78 (2), 34-51.

Heckman, James J. (1976), "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement*, 5 (4), 475–92.

Hertzel, Michael G., Zhi Li, Micah S. Officer, and Kimberly J. Rodgers (2008), "Inter-Firm Linkages and the Wealth Effects of Financial Distress Along the Supply Chain," *Journal of Financial Economics*, 87 (2), 374 – 387.

Hillman, A. J., Withers, M. C., and Collins, B. J. (2009), "Resource Dependence Theory: A Review," *Journal of Management*, 35(6), 1404–1427.

Hingley, Martin K. (2005), "Power to All our Friends? Living with Imbalance in Supplier–Retailer Relationships," *Industrial Marketing Management*, 34 (8), 848-58.

Johnsen, Rhone E., and David Ford (2008), "Exploring the Concept of Asymmetry: A Typology for Analysing Customer-Supplier Relationships," *Industrial Marketing Management*, 37(4), 471–483.

Kumar, Nirmalya, Lisa K. Scheer, and Jan-Benedict E.M. Steenkamp (1995), "The Effects of Perceived Interdependence on Dealer Attitudes," *Journal of Marketing Research*, 32 (August), 348–56.

Lilien, Gary L., and Rajdeep Grewal (2012), *Handbook on Business to Business Marketing.* Chichester: Edward Elgar Publishing.

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

McFarland, Richard G., James M. Bloodgood, and Janice M. Payan (2008), “Supply Chain Contagion,” *Journal of Marketing*, 72 (2), 63–79.

Mintz, Ofer, and Imran S. Currim (2013), "What Drives Managerial Use of Marketing and Financial Metrics and Does Metric Use Affect Performance of Marketing-Mix Activities?" *Journal of Marketing*, 77 (2), 17-40.

Moorman, Christine, and George S. Day (2016), "Organizing for Marketing Excellence," *Journal of Marketing*, 80 (6), 6-35.

Ni, John Z., Barbara B. Flynn, and F. Robert Jacobs (2014), "Impact of Product Recall Announcements on Retailers’ Financial Value," *International Journal of Production Economics*, 153, 309-22.

O’Marah, Kevin (2016), “VW Plays Chicken with Supply Chain and Loses” *Forbes* (August 25), (accessed January 25, 2018), [available at https://www.forbes.com/sites/kevinomarah/2016/08/25/vw-plays-chicken-with-supply-chain-and-loses/#29d265121d89]

Palmatier, Robert W., Rajiv P. Dant, and Dhruv Grewal (2007), “A Comparative Longitudinal Analysis of Theoretical Perspectives of Interorganizational Relationship Performance,” *Journal of Marketing*, 71 (October), 172–94.

Palmatier, Robert W., Srinath Gopalakrishna, and Mark B. Houston (2006), "Returns on Business-to-Business Relationship Marketing Investments: Strategies for Leveraging Profits," *Marketing Science*, 25 (5), 477-93.

Panagopoulos, Nikolaos G., Ryan Mullins, and Panagiotis Avramidis (2018), "Sales Force Downsizing and Firm-Idiosyncratic Risk: The Contingent Role of Investors' Screening and Firm's Signaling Processes," *Journal of Marketing,* 82(6), 71-88

Pfeffer, Jeffrey, and Gerald R. Salancik (1978), *The External Control of Organizations: A Resource Dependence Perspective*. New York: Harper & Row.

Popper, Ben (2014), "GM's Latest Recall of 8.4 Million Cars is one of the Largest in History" *The Verge* (June 30), (accessed January 19, 2018), [available at https://www.theverge.com/2014/6/30/5858108/gm-announces-it-will-recall-another-7-6-million-cars]

Rego, Lopo L., Neil A. Morgan, and Claes Fornell (2013), "Reexamining the Market Share–Customer Satisfaction Relationship," *Journal of Marketing*, 77 (5), 1-20.

Saboo, Alok R., V. Kumar, and Ankit Anand (2017), "Assessing the Impact of Customer Concentration on Initial Public Offering and Balance Sheet–Based Outcomes," *Journal of Marketing*, 81 (6), 42-61.

Scheer, L. K., C. Fred Miao, and Jason Garrett (2010), "The Effects of Supplier Capabilities on Industrial Customers' Loyalty: The Role of Dependence," *Journal of the Academy of Marketing Science*, 38(1), 90–104.

———, C. Fred Miao, and Robert Palmatier (2015), "Dependence and Interdependence in Marketing Relationships: Meta-Analytic Insights," *Journal of the Academy of Marketing Science*, 43 (6), 694–712

Schmitz, Tobias, Bastian Schweiger, and Jost Daft (2016), "The Emergence of Dependence and Lockin Effects in Buyer–Supplier Relationships: A Buyer Perspective," *Industrial Marketing Management*, 55 (May), 22-34.

Shepardson, David (2017), “Auto Recalls Hit Record 53.2 Million in 2016,” *Automotive News* (March 10), (accessed August 10, 2017), [available at http://www.autonews.com/article/20170310/RETAIL05/170319989/auto-recalls-hit-record-53.2-million-in-2016]

Sorescu, Alina, Nooshin L. Warren, and Larisa Ertekin (2017), "Event Study Methodology in the Marketing Literature: An Overview," *Journal of the Academy of Marketing Science*, 45 (2), 186-207.

Spector, Mike (2017), “GM Faces $1 Billion Reckoning in Disputed Ignition-Switch Settlement,” *The Wall Street Journal* (December 16), (accessed January 18, 2018), [available at https://www.wsj.com/articles/gm-faces-1-billion-day-of-reckoning-in-challenge-to-ignition-switch-settlement-1513432800]

Srinivasan, Shuba, and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46 (3), 293-312.

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

Tóth, Zsófia, Stephan C. Henneberg, and Peter Naude (2017), “Addressing the ‘Qualitative’ in Fuzzy Set Qualitative Comparative Analysis: The Generic Membership Evaluation Template,” *Industrial Marketing Management*, 63 (4), 192–204.

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), “The Impact of a Product-Harm Crisis on Marketing Effectiveness,” *Marketing Science*, 26 (2), 230–48.

Warren, Nooshin L., and Alina Sorescu (2017), "When 1 + 1 > 2: How Investors React to New Product Releases Announced Concurrently with Other Corporate News," *Journal of Marketing*, 81 (2), 64-82.

Wuyts, Stefan, and Shantanu Dutta (2008), "Licensing Exchange—Insights From the Biopharmaceutical Industry," *International Journal of Research in Marketing*, 25 (4), 273-81.

——— and Inge Geyskens (2005), "The Formation of Buyer–Supplier Relationships: Detailed Contract Drafting and Close Partner Selection," *Journal of Marketing*, 69 (4), 103–117.

TABLE 1
Customer Disclosure Metrics

Name	Explanation
Full disclosure	Sales figures and names of principal and non-principal customers (responsible for less than 10% of their sales)
High disclosure	Sales figures of principal customers (≥10% of sales)
Low disclosure	Only name of customers, with no sales figures attached
Non-disclosure	No information about the identity of customers

TABLE 2
Variable Descriptions

Dependent variable	Description	Source
CAR: [t_1,t_2]	Cumulative abnormal return, with event window of t_1 as the beginning of the observed period and t_2 as the end of the observed period.	CRSP
Independent variables		
Customer disclosure	Full if the supplier provides information about sales volume from principal (≥10% of sales) and non-principal (≤10% of sales) customers High if the supplier only indicates sales to principal customers Low if the supplier only indicates the names of customers Non-disclosure if the supplier does not give any information about the identity of customers	Annual report
Size difference	Producer annual sales divided by supplier sales (both during the year of the recall)	Compustat
Control variables		
Recall size	Natural logarithm of number of automobiles recalled	Media reports
Media coverage	How many of the following media outlets covered the recall: *WSJ, USA Today, The New York Times, The Washington Post, New York Post, Financial Times*	Factiva
Merged	1 = if two recalls hit the same supplier within the 3-day window; 0 = otherwise	Study database
Producer's reputation	Reputation scores from *Forbes*'s list of most admired companies	Fortune
Supplier's size	Natural logarithm of number of employees	Compustat
Supplier's profitability	Suppliers net income divided by assets	Compustat
Supplier's age	Difference between year of initial public offering and the year of the recall	CRSP
Supplier's reputation	1 = on *Forbes*'s most admired list; 2 = on contender list; 3 = not listed	Fortune
Supplier's SIC	1 = if supplier belongs to SIC 3714, 0 = otherwise	Annual report/ Edgar
Year	Dummy for each year, minus 1	Study database
Producer	Dummy for each producer, minus 1	Study database
Recall	Dummy for each recall, minus 1	Study database

TABLE 3
Descriptive Statistics and Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	MM[-11]	1																	
2	FF[-11]	.974	1																
3	Full Disclosure	.066	.058	1															
4	High Disclosure	-.038	-.034	-.303	1														
5	Low Disclosure	-.032	-.033	-.277	-.324	1													
6	Non-Disclosure	.008	.011	-.337	-.393	-.36	1												
7	Size difference	-.084	-.094	-.091	.135	.190	-.223	1											
8	Ln automobile recalls	-.047	-.065	.023	-.031	.008	.002	.043	1										
9	Media coverage	-.02	-.02	.011	-.026	-.006	.021	.026	.233	1									
10	Supplier's age	.044	.04	-.367	-.231	.077	.473	-.172	.035	.047	1								
11	Supplier's size	.048	.049	-.134	-.193	-.08	.376	-.234	-.009	.002	.377	1							
12	Supplier's profitability	.055	.055	.166	.082	-.281	.033	-.458	.012	-.031	.154	.141	1						
13	Merged	-.002	-.008	.014	-.015	-.015	.009	-.027	.386	.382	.021	-.024	-.007	1					
14	Producer's reputation	-.02	-.049	.02	.037	.037	-.006	.053	.555	.165	.029	-.01	-.032	.091	1				
15	Supplier SIC	.0054	.009	.426	-.074	-.074	-.66	-.244	-.002	-.021	-.444	-.301	.287	.001	-.007	1			
16	Supplier reputation - high	.04	.045	-.351	-.109	-.109	.685	-.195	.009	.035	.624	.547	.091	.014	-.000	-.646	1		
17	Supplier reputation - medium	.036	.036	-.105	-.112	-.112	.077	-.073	-.039	-.03	.07	.07	.051	-.018	-.037	-.027	-.142	1	
18	Supplier reputation - medium	-.055	-.058	.384	.152	.152	-.697	.219	.007	-.021	-.635	-.56	-.109	-.006	.015	.639	-.913	-.274	1
	M	-.002	-.003	.206	.261	.229	.304	263.08	14.82	2.97	31.08	52.41	.043	.13	5.63	.589	.321	.041	.638
	SD	.03	.029	.404	.439	.42	.46	701.34	.75	1.76	23.08	79.64	.099	.336	1.27	.492	.467	.198	.481

Correlations above .065 significant at $p < .05$

TABLE 4
Influence of Product Recalls on Suppliers' Stock Market Value

Row	Description	Recall Size		
		More than 2 million automobiles recalled	More than 1 million automobiles recalled	More than 500,000 automobiles recalled
1	Supplier's abnormal return (AR) on the day of a recall (H_1)[a]	-.47% (t = -2.968; *p* < .01)	-.35% (t = -2.876; *p* < .01)	-.19% (t = -2.568; *p* < .05)
2	Sample size	537	980	2133
3	Average number of recalls per year	2.29	4.14	9.14
4	Financial effect per recall on suppliers' market value (in millions)[b]	-$33.64	-$24.92	-$13.53
5	Annual financial effect on suppliers' market value (in millions)[c]	-$77.03	-$103.17	-$123.67
6	Number of automobiles recalled per year (in millions)	11.87	14.49	18.63
7	Average media coverage during the event window[d]	54%	46%	31.5%

[a]In all models, the ARs for the day before and the day after the recalls were not significant (*p*s > .1). Portfolio time-based t-tests are reported; results from Patell Z test yield similar results.
[b] Calculated as mean AR multiplied by (1) median size firms' market capitalization (in our case, Alcoa Corporation) and (2) the probability that a supplier will be affected (.75, because supplying firms have on average 7.5 of the top 10 automobile producers as customers),
[c] Calculated as the average number of recalls per year (row 3) multiplied by the financial effects per recall (row 4)
[d] Number of media outlets that covered the recall divided by 6 and multiplied by 100.

TABLE 5
Impact of Customer Disclosure and Size Difference between the Recalling Producer and Suppliers

Dependent/Independent Variables		CAR: MM [-1,1]				
		Column I		Column II		Column III	
		Estimates	SE	Estimates	SE	Estimates	SE
Customer disclosure (Reference category: Full)							
High	H2a	-.0068**	.0028	-.0067**	.0028	-.0068***	.0024
Low	H2b	-.008**	.0033	-.008**	.0032	-.008***	.0029
Non	H2c	-.0121***	.0042	-.0121***	.0042	-.0121***	.0034
Size difference	H3	-.0041**	.002	-.0041 **	.002	-.0041 *	.0021
Control variables							
Ln automobile recalled		-.0063**	.0025	.026	.0295	-.0063**	.0024
Media coverage		-.0044***	.001	-.0057	.0048	-.0045***	.0009
Producer's reputation		4.98 E-05	5.57 E-05	-.0016	.0017	-.0007	.0014
Supplier's age		.0008	.0114	5.04E-05	5.48E-05	4.98E-05	4.66E-05
Supplier's profitability		-3.3 E-04	9.46E-04	3.85E-04	1.13E-02	8.73E-04	1.35E-02
Supplier's size		-.0007	.0016	-.0003	.0009	-.0003	.0007
Supplier's reputation (Reference category: High)							
Medium		.0031	.005	.0035	.0049	.0031	.0025
Low		-.0037	.0044	-.0036	.0043	-.0037	.0035
Merged		.0063	.0064	-.0199	.0132	.0063	.0059
Supplier's SIC		-.0038	.0039	-.0038	.0039	-.0038	.004
Intercept		.1040***	.0367	-.3546	.4177	.1040***	.0334
Year fixed effect		YES		YES		YES	
Producer fixed effect		YES		NO		YES	
Recall fixed effect		NO		YES		NO	
Unobserved firm effects		NO		NO		Clustered standard errors	
Sample size		980		980		980	
R-squared		.065		.094		.096	

*** $p < .01$, ** $p < .05$, * $p < .1$.

Notes: The dependent variable is market model CAR [-1,1]. In Column I, we used year and producer fixed effects. In Column II, we used year and recall fixed effects. In Column III, we used year and producer fixed effects, as well as supplier-level clustered standard errors. For ease of exposition, the value of the size difference variable is multiplied by 1,000.

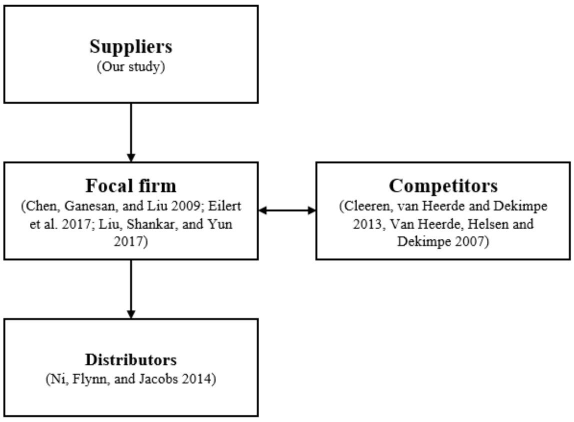
TABLE 6
Robustness Checks

Dependent/Independent Variables		CAR: MM [-1,1]		CAR: MM [-1,2]		CAR: MM [-2,2]		CAR: FF[-1,1]		CAR: MM [-1,1]	
		Column I		Column II		Column III		Column IV		Column V	
		Estimates	SE	Estimates	SE	Estimates	SE	Estimates	SE	Estimates	SE
Customer disclosure (Reference category: Full)											
High	H2a	-.0042**	.002	-.0063**	.0023	-.0077***	.0026	-.006***	.0022	-.0076***	.0028
Low	H2b	-.0046**	.002	-.00687**	.0032	-.0079**	.0035	-.0071**	.0027	-.0108***	.0033
Non	H2c	-.0089***	.0021	-.0124***	.0035	-.0115**	.0043	-.0111***	.0033	-.0154***	.0036
Size difference	H3	-.0053***	.0014	-.0048*	.0024	-0.0029	.0023	-.0045**	.0021	-.0051**	.0019
Control variables											
Ln automobile recalls		-.0014	.0013	-.0044*	.0023	-.0059***	.0021	-.0058**	.0024	-.0069***	.0025
Media coverage		.0011	.0007	-.0032***	.001	-.0065***	.001	-.0045***	.0009	-.0043***	.0009
Producer's reputation		-.0016	.0019	-.002	0.00159	-.0017	.0021	-.0011	.0013	-.0016	.0171
Supplier's age		3.63E-06	3.41E-05	3.94 E-05	4.56 E-05	6.03 E-05	5.35 E-05	3.56 E-05	4.41 E-05	9.2* E-05	5.09 E-05
Supplier's profitability		-.012	.009	.0008	.0118	.0019	.0162	-2.64 E-05	1.39 E-02	9.36 E-05	1.38 E-02
Supplier's size		-.0018**	.0008	-.0002	.0008	-.001	.0021	-.0003	.0006	-.0007	.0006
Supplier's reputation (Reference category: High)											
Medium		.0013	.0016	.0029	.0022	.0013	.0021	.0025	.0023	.0042	.0027
Low		-.0043	.003	-.0039	.0039	-.0058	.0044	-.0042	.0032	-.0038	.0035
Merged		-.0095***	.0031	.007	.007	.0062	.0079	.0042	.0054		
SIC dummy		-.004	.0025	-.0044	.0041	-.0045	.0045	-.0032	.0036	-.0053	.0034
Intercept		.0436**	.0174	.0806**	.0366	.1013**	.0381	.0978***	.0341	.1192	.1225
Year fixed effects		YES		YES		YES		YES		YES	
Producer fixed effects		YES		YES		YES		YES		YES	
Unobserved firm effect		Clustered standard errors		Clustered standard errors		Clustered standard errors		Clustered standard errors		Clustered standard errors	
Sample size		2190		980		980		980		853	
R-squared		.03		.08		.10		.10		.10	

*** $p < .01$, ** $p < .05$, * $p < .1$.

Notes: Dependent variable is market model [-1,1] in Columns I and V, market model CAR [-1,2] in Column II, market model CAR [-2,2] in Column III, and Fama-French [-1,1] in Column IV. We used year and producer fixed effects, as well as supplier-level clustered standard errors. For ease of exposition, we multiply the value of the size difference variable by 1,000.

FIGURE 1
Focus and Selected Studies of Product Recalls



Appendix A
Financial Reporting for Segments of a Business Enterprise[9] (Issued on 12/76)

Summary

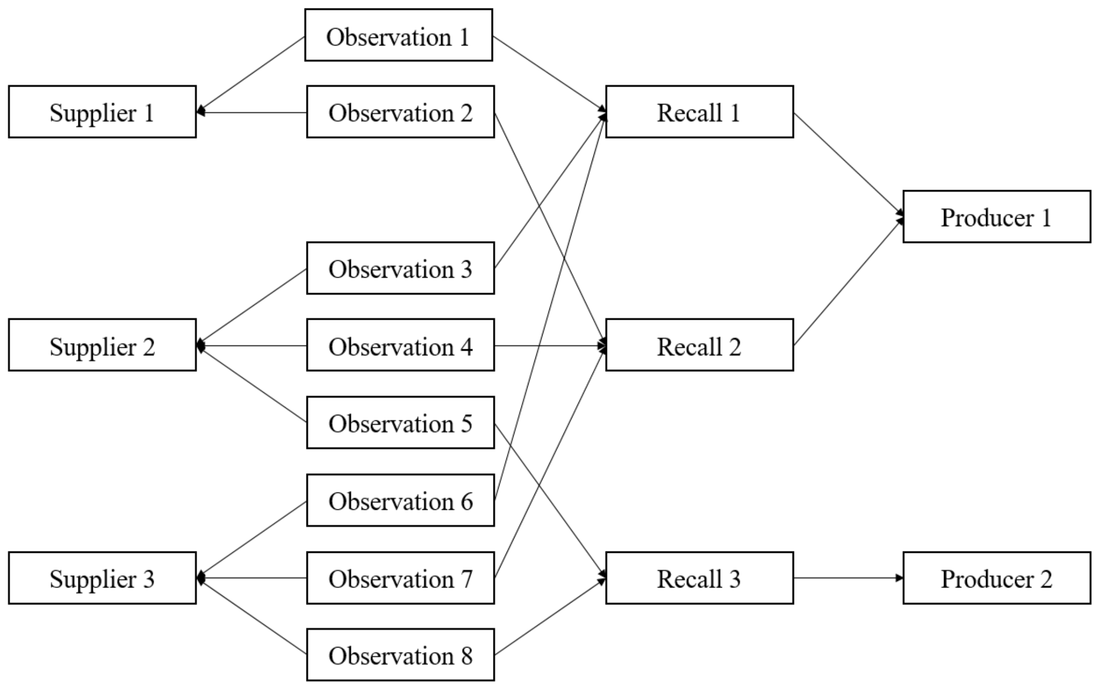
This Statement requires a publicly held business company to present, for each segment of its operations qualifying as a reportable segment, information on revenues, profitability, identifiable assets, and other related disclosures (such as the aggregate amount of a segment's depreciation, depletion, and amortization expense). Similar information is required to be reported on a geographic basis for those companies having foreign operations and export sales. If 10 percent or more of the revenue of a company is derived from sales to any single customer, that fact and the amount of revenue from each customer must also be disclosed. Finally, this Statement requires that a company operating predominately or exclusively in a single industry identify that industry.

[9] Available at: https://www.fasb.org/summary/stsum14.shtml

Appendix B
Data Structure

In Figure A1, observations are nested at the recall (or producer) and supplier levels. However, we used fixed effects instead of hierarchical linear models (HLM), because the observations are cross-classified (clustered on the recall and supplier levels independently from one another). That is, HLM models are appropriate mostly if there is a hierarchy of observation (Gruca and Rego 2005) (level 1 is clustered within level 2, which is clustered within level 3), so they do not fit well with our empirical setting. Instead, we relied on producer fixed effects and robust standard errors clustered around suppliers (one of our main independent variables, suppliers' disclosure of motivational investment with customers, does not vary over time for a given supplier).

Figure A1. Nested Structure of Observations



Notes: All three suppliers supply producer 1; however, supplier 1 does not supply producer 2 (i.e., supplier 1 has only two observations).

Appendix C
Impact of Customer Disclosure on Suppliers' Market Value by Using Different Reference Category for Customer Disclosure

Dependent/Independent Variables	CAR: MM [-1,1]					
	Column I		Column II		Column III	
	Estimates	SE	Estimates	SE	Estimates	SE
Customer disclosure						
Full	.0068***	.0024	.008***	.0029	.0121***	.0034
High	Referent category		.0012	.0028	.0053	.0033
Medium	-.0012	.0028	Referent category		.0041	.003
Low	-.0053	.0033	-.0041	.003	Referent category	
Control variables	YES		YES		YES	
Year fixed effect	YES		YES		YES	
Producer fixed effect	YES		YES		YES	
Unobserved firm effects	Clustered standard errors		Clustered standard errors		Clustered standard errors	
Sample size	980		980		980	
R-squared	.096		.096		.096	

*** $p < .01$, ** $p < .05$, * $p < .1$.

Notes: In all columns, we use market model CAR [-1,1], year and producer fixed effects, and clustered standard errors. The model specifications are the same as in Table 5, Column III, yielding the same value for the estimates and SE for the control variables and the size difference.

Appendix D
Heckman Two-Stage Selection Model

In the first stage of the two-stage Heckman selection model, we estimated a probit selection equation with the probability that suppliers have a relationship with recalling producers as a dependent variable. We then used the probit estimates to obtain the inverse Mills' ratios that we included in the second stage equation.

To satisfy the exclusion restrictions, we did not include the variables SIC dummy, suppliers' size and suppliers' profitability in the second stage. These exclusion restrictions are relevant because they should influence producers' choice of suppliers. If a firm belongs to the 3714 SIC classification, it should focus more on automobile producers than on other customers. We thus expect that suppliers from the automobile industry have more customers from that industry than suppliers that belong to other industry classifications. Larger suppliers should also have more customers. Since they have more resources to acquire and retain customers, they are more likely than smaller suppliers to count a given producer as one of their customers. Finally, if the assumption that producers prefer less powerful suppliers hold we expect less profitable suppliers–who lacks the financial security to resist exploitation attempts by producers–to have more customers from the automobile industry.

Apart from having a significant influence on the inclusion of suppliers in the sample, we expect the exclusion restrictions to be valid since they should not be correlated with the residual of the dependent variable from the main analysis (CAR). Regarding the SIC dummy, industry classification is stable and managers cannot change it frequently. In addition, industry classification should not have diagnostic value for investors trying to estimate the influence of recalls on suppliers. Some firms from the 3714 classification are more focused on truck producers; hence, they do not depend on automobile producers. At the same time, others firms outside of the 3714 classification are highly dependent on the automobile industry. Furthermore, suppliers' size and profitability should already be reflected in the value of firms' shares, thus these indicators should not influence investors' assessment of recalls' impact on suppliers. Finally, our previous analysis showed that neither SCI dummy, suppliers' size and profitability have a significant impact on suppliers' CAR when one of their customers makes a large-scale recall (see Tables 3 and 5).

The results in Table A2 confirm the previous findings and support the hypotheses. The results also show that all three instruments are good predictors of the inclusion of suppliers in the sample. Importantly, the inverse Mill's ratio parameter is not significant regardless of the combinations of instruments used: SIC dummy and supplier's size (Column I), SIC dummy and supplier's profitability (Column II), or SIC dummy, supplier's size and supplier's profitability (Column III). Therefore, self-selection bias should not be a concern for our analyses.

Table A2: Heckman Two-Stage Selection Model Results

Dependent/Independent Variables	CAR: MM [-1,1]		CAR: MM [-1,1]		CAR: MM [-1,1]	
	Column I		Column II		Column II	
	Estimates	SE	Estimates	SE	Estimates	SE
Customer disclosure (Reference category: Full)						
High H2a	-.0069**	.0028	-.0069**	.0028	-.0068**	.0028
Low H2b	-.008**	.0033	-.0071**	.003	-.0069**	.003
Non H2c	-.0118***	.004	-.0107***	.0037	-.0103***	.0036
Size difference H3	-.0043**	.002	-.0035*	.0019	-.0032**	.0016
Control variables						
Ln automobile recalled	-.0063**	.0025	-.0063**	.0025	-.0063**	.0025
Media coverage	-.0044***	.001	-.0045***	.001	-.0045***	.001
Producer's reputation	-.00007	.0016	-.0007	.0017	-.0007	.0017
Supplier's age	4.95 E-05	5.43 E-05	4.24 E-05	5.38 E-05	4.41 E-05	5.38 E-05
Supplier's profitability	.0006	.011	-	-	-	-
Supplier's size	-	-	-.0005	.0009	-	-
Supplier's reputation (Reference category: High)						
Medium	.0029	.005	.0028	.0049	.0028	.0049
Low	-.0044	.0033	-.0048	.0041	-.0045	.0032
Merged	.0063	.0063	.0064	.0063	.0065	.0063
Intercept	.0923**	.0364	.0971***	.0372	.0968***	.036
Inverse Mills' ratio	.0256	.0222	.0143	.0223	.0096	.0096
Year fixed effect	YES		YES		YES	
Producer fixed effect	YES		YES		YES	
Selection model (First stage model)						
SIC dummy	.3029***	.0842	.3267***	.0859	.385***	.0885
Supplier's size	.0508**	.024	-	-	.0797***	.0257
Supplier's profitability	-	-	-1.016**	.469	-1.521***	.4897
Intercept	.5775***	.0916	.7508***	.0618	.5268***	.0939
Sample size (Selected)	1210 (980)		1210 (980)		1210 (980)	

*** $p < .01$, ** $p < .05$, * $p < .1$.

Notes: We use market model CAR [-1,1], year and producer fixed effects in the second stage model. For the reader's ease, we multiply the value of the size difference by 1,000. In Column I we excluded SIC dummy and supplier's size, in Column II we excluded SIC dummy and supplier's profitability and in Column III we excluded SIC dummy, supplier's size and supplier's profitability from the second stage analysis.

Essay 2: When the Whole Is (Not) Greater Than the Sum of Its Parts: Chunking Versus Slicing Product Recalls

Introduction

In response to the same product-harm crisis, where recalls are triggered by the same defective part or component, producers sometimes make one large recall announcement and sometimes several small recall announcements related to each other. For instance, in 2004, General Motors (GM) recalled more than 3 million automobiles due to problems with tailgate support tables. That was the only recall related to this product-harm crisis. However, in 2014, GM announced a large number of recalls—all related to faulty ignition switches—that affected 30 million automobiles in total. These examples raise two important questions: (1) what drives firms to either make one large recall announcement (chunking) or make recall announcements piece by piece (slicing), and (2) is it more beneficial for firm performance to chunk or slice recall announcements? Our research aims to address these questions.[10]

Our study builds on research that investigates the effect of a product-harm crisis on firm value. Due to a steadfast growth in the number of products being recalled, there is an increasing need for studies examining if how recalls are announced matters for firm's performance. For example, 2016 was the year with the highest number of automobiles recalled; including almost 53 million in the US alone, while in 2010 there were only 20 million automobiles recalled (Kalavar, Mohr and Mysore 2018). However, among 25 studies in premier marketing journals focusing on product-harm crisis (Cleeren, Dekimpe and van Heerde 2017), few of them pay attention to the behavior of the firm during the recall (Eilert et al. 2017). The few existing studies on this matter mostly cover the level of advertisement expenditure (Cleeren, Van Heerde and Dekimpe 2013; Liu and Shankar 2015; Borah and Tellis 2016; Liu, Shankar and Yun 2017), whether the firm or a third-party initiated the recall

[10] Our study focuses on the announcements of the recall but not the implementation of the recall itself. Namely, when the recall is announced, producers have to develop a "recall remedy" and inform NHTSA about their remedial activities (what they plan to do). Thus, even if the recall is announced on a certain date, the actual recall of the product happens sometime in the future (Craig and Thomas 1996). However, our focus is only on the different announcements of the number of products that the firm will recall due to the same reason.

(Liu and Shankar 2015; Chen, Ganesan and Liu 2009; Liu, Shankar and Yun 2017), and how long firms take to execute recalls (Eilert et al. 2017). However, based on our literature review, no study appears to look at different types of recall announcements policy and their influence on a firm's performance. Thus, our goal is to fill this gap by offering new insights into the chunking versus slicing of recall announcements and their impact on firm market value.

To answer our research question, we use product recall data from the US automobile industry for the period 2006 to 2017. By relying on the behavioral theory of the firm (Cyert and March 1963), we posit that, due to managers' limited capacity to gather all relevant facts before making a decision (Cyert and March 1963), managers are more likely to rely on a slicing recall strategy as severity (defined as the number of injury, fire or death) and recall size increase. When product-harm crises are more harmful and affect more customers, managers may recall products without knowing the full extent of the problem, leading them to make additional related recalls later—this is manifest as the slicing strategy. Furthermore, drawing on signalling theory, we also find that on average the stock market reacts negatively to slicing compared to chunking announcements. However, our results also suggest that for extremely large recalls, this result reverses and it is more advantageous to use a slicing strategy.

Our study offers several contributions (see Figure 1). From a theoretical perspective, we contribute to the ongoing discussion about managers' resource allocations through the lens of the behavior theory of the firm (Cyert and March 1963). Our results show that early product complaints should receive a significant amount of managers' attention. Even though they are often due to benign and harmless defects, there is always the possibility that early complaints are the precursors of a severe and/or a large scale product-harm crisis that will require additional recalls later on, negatively affecting the firm's performance. We also extend existing research on firm behavior during product recalls (Eilert et al. 2017), showing that chunking or slicing announcements can have varying effects on capital markets. Our study also contributes to the literature examining firm's communication with the public and its impact on firm performance. Our research differs from existing studies in this field as we investigate the disaggregation of related negative news. Existing literature looks at investors' apologies following negative news (Borah and Tellis 2016), pre-release buzz prior to the release of a new product (Houston et al. 2018), or the coupling of positive news, such as the launch of a new product coupled with another unrelated positive news (Warren and Sorescu 2017).

Finally, from a managerial point of view, we provide practical guidance regarding product recall announcements. We show that if recalls are smaller than 2.6 million automobiles, managers should make one recall announcement (i.e. use a chunking strategy). However, if the recall is extremely large, managers should aim for more than one recall (i.e. use a slicing strategy). We also believe that managers could use our results for the announcement of other negative news to the public.

[Insert Figure 1 here]

The reminder of the paper is organised as follows: first, we develop our theoretical framework leading to the hypotheses. We then present our data and describe our empirical methodology before presenting the results, including the testing of some of the assumptions. Finally, we discuss the theoretical and managerial implications of our work, the limitations of this study and opportunities for further research.

Theoretical Framework

Our study seeks answers to two questions: what factors are influencing managers to slice or chunk recalls, and how do investors react to these two types of recall announcement? To answer these questions, we draw from the behavioural theory of the firm to explain why managers sometimes slice and other times chunk recalls, and use signalling theory to explain why investors react differently to these two types of recall announcements.

RQ 1: Why do managers use different types recall announcements?

The behavioural theory of the firm explicates how managers make key decisions within the organisation (Cyert and March 1963). One of the main pillars of the theory is the bounded rationality of decision-makers (Cyert and March 1963; Argote and Greve 2007). As Gavetti et al. (2012, p 4.) highlights "…decision makers lack perfect knowledge and must search for information, their actions are usually inconsistent with maximization postulate of the rational agent". Thus, it can not be expected that managers always make the most advantageous decisions regarding the firm's future performance.

Gavetti et al. (2012) also argue that there are three central postulates of the behavioral theory of the firm that further explain how managers make decissions. First, the satisficing postulate implies that managers often look for an option that is "good enough"; they may take a decision as soon as they believe that they have sufficient rather than complete information. Second, the search postulate stipulates that managers have to search for information to make decisions. The search postulates apply to both processes and outcomes of decision-making. In terms of processes, managers search for information until a satisficing decision is deemed feasible. In addition, the search process is also problemistic, hence, managers might resume the search process if a decision they made results in an outcome that is not satisficing. Finally, the third postulate relates to the rules and standard operating procedures that managers rely on when much uncertainty surrounds the consequences of decisions and there is limited available information to reduce this uncertainty. In these situations, managers tend to disregard decisions' future consequences and use simple automatic rules. Such rules often imply that problems that surface are only investigated partially, due to the lack of cognitive and time resources, leading to search for information "in the neighbourhood of the current symptoms…" (Cyert and March 1963, p. 170), for instance, by applying decisions made in prior similar situations. In the following section, we build upon these three postulates in order to understand factors that drive managers to either slice or chunk recalls.

The severity of the product defect and the number of defective products

We argue that severe defects affecting a large number of products are more likely to result in the slicing than in the chunking of recall announcements. Existing literature on the influence of product recalls on a firm's market value defines the size of the recall (Liu, Shankar and Yun 2017), and recall severity (Eilert et al. 2017) as the two most important characteristics of product recalls. Furthermore, studies show that recall severity has a detrimental effect on a firm's market value. For example, recall severity has a negative impact on investors' reaction to the recall announcement (Chen, Ganesan and Liu 2009). Furthermore, severity also has a negative impact on the distributors' financial value during product recalls (Ni, Flynn and Jacobs 2014). A second important factor is the number of defective products being recalled from the market (Eilert et al. 2017). As Liu, Shankar and Yun (2017) identify, recall size is one of the most informative characteristics for investors. The size of the recall has multiple negative consequences as well, such as an increase in the firm's expenditures, as well as increased lawsuits and fines (Govindaraj, Jaggi and Lin 2004). Several studies look at the impact of recall size on a firm's performance. For example, recall size has a negative impact on brand uptake by consumers (Liu and Shankar 2015) and lead to negative word of mouth that product owners spread about the recalling firm (Borah and Tellis

2016). Finally, Liu, Shankar, and Yun (2017) show that recall size has negative effects on a firm's performance both in the short and long-term.

Every recall, regardless of its ultimate size and severity, starts from a complaint or an internal investigation (NHTSA, n.d.). Importantly, the large majority of complaints received reveal benign product issues and only a small fraction are potentially hazardous. For example, in the 2006 to 2017 period, there were about 80,000 complaints recorded in the NHTSA database (NHTSA Complaints, n.d.) with fewer than 1000 (< 1.25%) ending up in recalls (NHTSA Recalls, n.d.). In addition, managers face many complaints daily but they cannot know ex-ante which ones will ultimately culminate in a large number of products being recalled. Thus, as per the behaviour theory of the firm, when facing a new complaint tracking precisely the problem in the early stage would require a significant amount of resources due to the numerous relevant factors informing the ultimate size and scope of the problem, leading managers to look for satisficing solutions (Gavetti 2012).

The severity of the product defect as a driver of slicing versus chunking

There are numerous reasons why products are defective, such as design flaws, production and packaging errors, material and functional defects, as well as software glitches (Thirumalai and Sinha 2011). Some of these defects could be benign and not directly dangerous to consumers. For example, in 2006 Honda made a recall due to incorrect content in the owner manual (NHTSA Recalls, n.d.), an issue which did not cause any injuries, fire or fatal cases (NHTSA Recalls, n.d.). However, other types of defects can have a negative effect on consumers, resulting in injury, fire or even death. For example, media reported that GM's faulty ignition switch led to a large number of fatalities (Shepardson 2015).

We argue that more severe product defects increase the probability of slicing rather than chunking recalls. In situations where early information—from consumer complaints for instance—indicates that some firm products pose serious threats to consumers' safety (e.g., GM's ignition switch), managers will be under strong pressure to react quickly since delays could lead to additional injuries or fatalities. The behavioral theory of the firm indicates that because managers do not have time to collect the necessary information to identify all the defective products in such a decision context, that they will look for satisficing solutions (Giavetti et al. 2012). Consequently, managers might opt to recall products for which they have direct evidence of safety threat while at the same time continuing to gauge the full scope of the problem—e.g., investigating what other models or product lines might also be of concerns. By contrast, when the product defect is not severe (e.g., the owner's manual of Honda), removing hazards from the market is not as crucial and managers should experience less market pressure to recall products quickly. Hence, managers should have more time to fully investigate and identify all products affected before making a recall. Consequently, when product defects are more severe, managers are more likely to make recall announcements before all the defective products have been identified, increasing the chances of slicing over chunking—as exemplified by GM making several distinct recalls related to the same ignition switch issue. This. Thus:

H1 A more severe product-harm crisis increases the probability of slicing recalls

The total number of defective products as a driver of slicing versus chunking

We argue that the number of defective products increases the probability of implementing a slicing strategy. The main reason is that managers do not know ex-ante the total number of defective products there is to identify—early warning signs are similar (e.g., consumer complaints) whether that number will ultimately be very large or very small. As per the behavioral theory of the firm (Giavetti et al., 2012), managers' reliance on rule-based decision making at the onset of the crisis should have different consequences regarding slicing versus chunking as a function of the total number of defective products on the market. Hence, even if managers only investigate products that are similar to those featured in early customer complaints (Giavetti et al., 2012), when the actual number of defective products is small, the ensuing recall is more likely to capture all such products. Consequently, the effective removal of product safety hazards from the market should be a satisficing outcome for managers, lowering their motivation to search for more information about additional defective products (Giavetti et al. 2012). This will, in turn, prevent the need for subsequent recalls, leading to chunking rather than slicing.

By contrast, when the number of defective products is large, rule-based procedures (Cyert and March 1963) are unlikely to reveal to managers the full information about the products that need to be recalled. In this case, it becomes harder to identify all the different sources of defective products; hence, the types, models, production facilities involved, diversity of the geographic locations of operation affected, etc. are likely to be numerous and a full investigation resource intensive. As a consequence, the standard rule consisting in recalling products based on the first information obtained is likely to result in only partially removing the hazard from the market. Since such outcome is unlikely to be considered satisficing by managers (Giavetti et al. 2012), they should engage in further information search until they identify additional defective products, resulting in the slicing of recalls. Importantly, however, the additional search for information is still unlikely to be sufficient for identifying all defective products, hence potentially multiple subsequent slices are possible. Therefore:

H2 Increase in recall size leads to an increase in the probability of slicing recalls

RQ 2: Do investors react differently to slicing versus chunking?

There is information asymmetry when different agents in the market have different information regarding a specific phenomenon — this influences the decision-making process of the less informed party (Stiglitz 2002). In particular, Connelly et al. (2011) argue that managers are fully informed about their resources and assets while outsiders (e.g. investors) do not have all information since some of the firm's characteristics are unobservable to outsiders. This asymmetry between two sides has a negative impact on the less informed side in the case of perceived uncertainty (Panagopoulos, Mullins and Avramidis 2018).

To remedy the lack of appropriate information, investors rely on other sources of information that managers signal with their actions and behaviour. It is not straightforward how the impact of unfavourable news affects market value depending on whether recalls are chunked or sliced. We develop our hypotheses by building on a signalling framework. Accordingly, slicing provides more information to the market than chunking about the future performance of the recalling firm as it signals there may be further recalls due to the same faulty product or part. Since investors can only rely on publicly available information (Connelly et al. 2011), they rely on signals sent from the more informed side (the recalling firm) to update their beliefs about the market value of the firm.

Influence of different types of recall announcements on firm market value

As per the efficient market hypothesis, if slicing rather than chunking represents diagnostic information regarding the future value of the firm, it should be reflected in its stock price. The main idea behind the efficient market hypothesis is that the price of a security follows a "random walk" (Malkiel 2003), implying that changes in value occur randomly. Nonetheless, security prices fully reflect all available information (Malkiel and Fama 1970)—the value changes without delay when new information is available. Future security prices thus depend on forward-looking information only rather than on previous stock value fluctuations. Prior research shows that when a product recall is announced, investors immediately react to its information content, such as the reasons for the recall, the number of automobiles recalled, how long it took the firm to announce the recall, or the recalling firms' advertising expenses (Eilert et al. 2017; Gao et al. 2015).

Even though a significant amount of information is available about recalls and safety issues, there is still a possibility that managers have access to private information such as internal reports that are not shared with the public based on discussions with some of the firm's employees (e.g. the firm's engineers). In the case of slicing, there is new information that is not present with chunking: the safety problems caused by the faulty part were not fully resolved by the first recall, the first "slice". In that case, investors could see as a second slice as a signal that new, additional recalls, might still occur. Thus, while adjusting their estimate of the firm's future performance, they might assume that future "slices" of this recall (related to the same problem) are probable (asking themselves, how many more related recalls are coming and when will it stop). It is therefore expected that investors react more negatively to sliced than to chunked recalls as they will adjust their evaluation of the stock based on the risk of more related recalls in the future:

H3 The stock market will react more unfavorably to slicing than to chunking recalls

As the number of products being recalled is increasing, the slicing strategy should become relatively more advantageous than chunking. The main reason why slicing large recalls might be a more appropriate option is investors' susceptibility to extreme values. Namely, a recall described as "the worst" or "the largest" could have a strong impact on investors' future performance expectations. Individuals tend to focus on extreme results — being the second largest if often not salient enough. Some studies in marketing and finance show that a third-party recognition for design excellence increases the firm's market value (Boyd and Kannan 2018). In the same vein, Barber et al. (2001) argue that returns for the least favorable firms yield 130% less return in comparison to the second least favorable group of firms. The largest difference between the other groups was 13%.

Chunking large recalls could make some of them the largest within a certain period. This could lead investors to anticipate a decline in the firm's future performance. Furthermore, large recalls send a signal that the firm is dealing with a large systematic problem that is not easily resolved. Sliced recalls circumvent these issues as they prevent the aggravating factors of "extreme values" from worsening the effect of chunking. Therefore:

H4 As the recall size is larger, the stock market reacts more unfavorably to chunking rather than slicing recall announcements

Method

Data

Following other studies on product recall, we adopt a single industry approach to increase internal validity and control for cross-industry factors (Eilert et al. 2017, Liu, Shankar and Yun 2017). We used two criteria to select an appropriate industry: (i) recalls have to be well-documented and information should be publicly available; and (ii) there should be sufficient details available regarding the defective parts or components at the origin of the recalls to distinguish between chunking and slicing cases. We thus chose the automobile industry since recall information is detailed and publically available. A description of every recall is also available, making it possible to identify chunking and slicing cases.

Data is sourced from the US National Highway Traffic Safety Administration (NHTSA), the federal government agency responsible for monitoring highways and motor vehicle safety (Kalaignanam, Kushwaha and Eilert 2013). Our observation period begins in

2006 and ends in 2017. Following Gao et al. (2015), we include in our analysis five firms (GM, Ford, Toyota, Honda, and Nissan) listed on the NYSE.[11]

One of the challenges when studying product recalls, is to define a recall size threshold for inclusion in the analysis. Recall size varies from only several automobiles to millions of automobiles being recalled. The only study that reports the size of the recall as a selection criterion is Gao et al. (2015) in which the threshold for inclusion varies from 20,000 for Nissan to 50,000 for Toyota. We use a 10.000 recall size threshold; this is lower than Gao et al. (2015) since slicing recalls could deflate the apparent recall size. For example, if the number of defected products is 40,000 and managers make two recalls of 20,000, these cases would not be included in the study using Gao et al.'s (2015) criteria.

Based on the criteria described above, we identify 469 recalls recorded in the NHTSA database between 2006 and 2017. However, some of the recalls were made by the same firm on the same day. They create an additional challenge since our dependent variable (abnormal returns) is based on daily observations. Therefore, it is impossible to identify the effect of different recalls that happened on the same day. As a consequence, if such cases only included chunking recalls, we kept them in the database and summed the overall characteristics of the recall (for example, number of automobiles recalled). However, if different recalls happened on the same day and they consist of both chunking and slicing cases they were removed from the database since it is impossible to separate whether the market reacted to the sliced or chunked announcement. Finally, if the removed slicing case is

[11] We did not include Chrysler since during our observation period the firm changed ownership several times and during most of the observation period was not listed at any major US stock exchange. Even though Chrysler was listed on NYSE as a part of FCA group from late 2014, we did not use that period of observation since many cases that were sliced but happened before 2015 would not be visible. Thus, we would miscode them as chunked cases. For example, let us assume that the firm used slicing strategy with two recalls, one at the beginning of 2014 and second in 2016. Since the beginning of 2014 for Chrysler is outside our data range (dependent variable value is not available since the firm was not listed), the 2016 recall would look like the standalone case and thus we would classify it as chunked. Consequently, we believe that by adding two years of observation for Chrysler (2015-2017) would be more harmful than beneficial.

composed of only two 'slices' we would remove the second slice as well, even if it takes place at a later point in time since otherwise, it would be a 'stand-alone' slice. After removing overlapping cases, our dataset consists of 379 unique recalls. Finally, after merging sliced cases (details in the variable section), our final dataset consists of 315 recall cases, which is larger than the sample size of comparable studies.[12]

Variables Description

The main variable of interest (also dependent variable in the first model and independent in the second model) is the different type of announcements: chunking and slicing.

In order to code for this new variable, we use information provided by NHTSA. However, the information regarding the relatedness of different recalls is not directly provided, in spite of the detailed description of every event in the NHTSA database. We therefore establish three conditions that define a recall as sliced: (1) same firm, (2) same part or component, and (3) same defect. In order to define if the recalls are sliced or chunked, two independent experts coded the data. One has a long consulting history in the automobile industry, and the other has a long academic history of research focused on the automobile industry. The experts read defect summaries provided by the NHTSA in its original database and coded if the recalls were related or not. There was a 90% level of agreement between the experts and divergences were resolved through discussion (see examples of chunking and slicing cases in Appendix B).[13]

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[12] Studies that use the same data source (NHTSA database) and same methodology (Event study). For example, Gao et al. (2015) include 110 recalls, Chen, Ganesan and Liu 2009 study 153 recalls, Liu, Shankar and Yun (2017) use 280 recalls in their analysis, and Eilert et al. (2017) provide an event study analysis based on 73 recalls.

[13] While merging slicing cases, we define how to manage independent and control variables. For the recall level variables, we use sum for continuous variables (abnormal returns, size and severity) and mean value for categorical variables (recall initiator). For the firm and macro-level variables, we use mean values. For example, for recall size, we sum the effect, since it best captures the full effect of the sliced recall. However, we take the mean value of firm age, since summing would artificially inflate the value of the age variable.

Our dependent variable in the second model is the cumulative abnormal returns around the recall (details in the model section). We calculate abnormal return (AR) as the difference between the actual stock return and expected stock return on the day of the event.

(1) $$AR_{it} = R_{it} – E[R_{it}],$$

where R_{it} is the stock return of firm *i* on day *t*. In order to estimate $E[R_{it}]$ we use the market model. First, we used 240 days before the event (starting 250 days before the event, ending 10 before the event) to estimate the base return of the stock:

(2) $$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} ,$$

where R_{mt} is the base return of a value-weighted market index *m* on day *t*. Second, we use $\widehat{\alpha_i}$ and $\widehat{\beta_i}$ from (3) to calculate firm *i*'s expected return $E[R_{it}]$ on the day of the event:

(3) $$E[R_{it}] = \widehat{\alpha_i} + \widehat{\beta_i} R_{mt}.$$

Finally, the cumulative abnormal return (CAR) is calculated as:

(4) $$CAR_i [-t_1, t_2] = \sum_{-t_1}^{t_2} AR_{it}.$$

We use two days before and after the event [–2, 2] to account for possible leakage and delays in dissemination of news. In the robustness check, we also use a shorter event window [–1,1] and the Fama–French model for calculating the abnormal return.

Our independent variables in the slicing versus chunking model are the recall size, defined as the number of automobiles recalls with the announcement (Eilert et al. 2017), and recall severity, measured as the principal component score of the number of complaints, fires, injuries, and fatalities within the same recall (Eilert et al. 2017). We also use several control variables. On the recall level, we control for the initiator of the recall: government agency or producer (Gao et al. 2015). Furthermore, we control for the number of production facilities the recalling firm uses, as more production facilities could lead to higher challenges in detecting defective products, which could lead to more related recalls (slicing recalls).

Finally, we control for the number of days between the focal event and the nearest previous recall, since a smaller number of days might lead investors to wrongly believe that recalls might be related, based on the same faulty part (Jarrell and Peltzman 1985).

On the firm level, we control for the firm's age, financial leverage (Liu, Shankar and Yun 2017), R&D intensity (Liu, Shankar and Yun 2017), total assets (as a proxy of firm's size), and reputation (Chen, Ganesan and Liu 2009), since stronger firms could have more resources to detect the full scope of the problem early, leading to less slicing. We also control for the overall number of automobiles recalled per firm in a year, since more faulty products will require more attention from managers, increasing their tendency to slice recalls due to a greater motivation to satisfice when resources are stretched (Gavetti et al. 2012). Finally, since the automobile industry is highly sensitive to macro-economic factors (Majeed and Manivachagam 2013), we control for the GDP growth and whether the recall happened during the GFC or not. All variables, with full description and merging criteria, are presented in Table 1.

[Insert Table 1 around here]

Models

Testing H1 and H2

To test the first two hypotheses, we run a probit model to estimate the probability that managers will make slicing recalls. Thus:

$$(6) \quad Pr\ (SLvsCHi = 1) = \Phi\ (\beta 0 + \beta 1\ RSi + \beta 2\ SVi + \beta 3\ INi + \beta 4\ DBi + \beta 5\ LEpt + \beta 6\ RDpt + \beta 7\ PFpt + \beta 8\ ATpt + \beta 9\ RPpt + \beta 10\ OARpt + \beta 11 YEt + \beta 12\ GDPt + \beta 13\ CRt + \theta i)$$

where RS_i is size of recall *i*, SV_i is recall severity, IN_i is recall initiator, DB_i is the number of days between the recall and closest previous recall, LE_{pt} is leverage for firm *p* in the year of the recall *t*, RD_{pt} is R&D intensity, PF_{pt} is the number of production facilities, AT_{pt} is total assets, RP_{pt} is reputation, OAR_{pt} is the overall number of automobiles recalled by the recalling firm in the calendar year of the recall, YE_t is the year of the recall, GDP_t is the GDP growth in the US in the year of the recall, CR_t is the crisis period, and θ_i is random error. The parameters of interest in our analysis are β_1 (expected positive sign) and β_2 (expected positive sign).

Since sliced recalls have multiple observations, we follow Warren and Sorescu (2017), were we first sum up CARs of all related slices from the same product-harm crisis to form one (sliced) recall. Using our examples from Appendix B, we would sum up the effect of recalls ID 16V643000 and 15V246000 and create one sliced recall. All such cases would receive value 1 for the variable *SLvsCH*. All the cases that were chunked (did not have any related recall), would receive the value 0 for this same variable.

Testing H3 and H4

To test H3 and H4, we run the ordinary least squares (OLS) model with abnormal returns (*AR*) as the dependent variable, slicing versus chunking (*SLvsCH*) and its interaction with recall size (*RS*) as independent variables. We also include a set of control variables. We thus specify the model as follows:

$$(7) \qquad CAR_{i[t1,t2]} = \pi_0 + \pi_1\, SLvsCH_i + \pi_2 RS + \pi_3\, SLvsCH_i{*}RS_i + \pi_4\, IN_i + \pi_5\, DB_i + \pi_6\, LE_{pt} + \pi_7\, D_{pt} + \pi_8\, PF_{pt} + \pi_9\, AT_{pt} + \pi_{10}\, RP_{pt} + \pi_{11}\, OAR_{pt} + \pi_{12} YE_t + \pi_{13}\, GDP_t + \pi_{14}\, CR_t + \varepsilon_i$$

where the estimate of interest are π_1 (expected negative sign if slicing leads to inferior market value than chunking) and π_3 (expected positive sign if slicing is relatively more advantageous than chunking as recall size increases).

Results

Model-free evidence

The correlation of key variables are represented in Appendix A. Further, for the first step of our analysis, descriptive results about the two recalling strategies are provided in Table 2

[Insert Table 2 here]

First, we notice that the slicing strategy is less frequent than the chunking strategy since there are only 40 slicing cases in comparison to more than 275 cases of chunking strategy used in this period. The average abnormal return for slicing is –2.2%. Surprisingly, the average abnormal return for chunked recalls is positive, and relatively strong (.56%). In absolute terms, the change in market capitalization from a chunked recall announcement, for the five automobile companies from our sample, on average, from USD 202 million for Nissan to almost a billion USD for Toyota. To the best of our knowledge, this is the first study to empirically detect a positive effect of product recalls on a firm's market value. Up until now, there was only anecdotal evidence that product recalls can have a positive impact on a firm's performance (Craig and Thomas 1996). A possible explanation is that chunked recalls are usually benign (smaller number of automobiles being recalled and less harmful consequences to customers; Craig and Thomas 1996), thus investors could see them as a signal that producers care about their customers and will recall products even if no real safety threat exists. Also, investors might interpret such recalls as cautious, preventing potentially more harmful cases. Another point worth mentioning is that the negative abnormal return for slicing is very large, on average –2.2%. If we look at the change in the market capitalization of companies from our samples caused by this type of recall announcement, they range from almost USD 800 million for Nissan to almost USD 4 billion for Toyota.

Slicing cases are composed of 2.7 slices on average with a mean time period of just under 3 years between the first and the last slice (results not presented in the table). Slicing is also used for larger recalls; such recalls include more than 2 million automobiles, on average, in comparison with only a quarter of a million automobiles for chunking. Finally, sliced recalls are more harmful, since they include more complaints (349 on average in comparison with 28 for chunked recalls), a larger number of injuries (close to 15 on average but less than 1for chunking), and fire (around 15 cases compared to less than 1 for chunking). These preliminary results suggest that there is a large difference between slicing and chunking regarding the impact on firm market value. However, we cannot be certain if this effect is caused by the nature of slicing (multiple related recalls) versus that of chunking (not related recalls) or by their respective degrees of severity and size. The tests of our hypotheses below will more formally address this questions.

Test of Hypotheses

Results for H1 and H2

We first test how the recall size and severity influences two different strategies. Table 3 show that recall size estimation is positive and significant (β =.6338, p <.05), supporting H1. Hence, as the number of automobiles recalled increases, there is a higher probability that the recalling firm uses slicing relative to chunking. Further, the coefficient for recall severity is also positive and significant (β =.7163, p <.01), in support of H2. Thus, more severe recalls also increase the chances of slicing. The results supports our assumption that larger and more severe recalls increase probabilities of slicing recalls.

[Insert Table 3 here]

Although not hypothesized, some control variables have noticeable effects. If the firm initiates the recall, there are higher chances of slicing than chunking (β =.4466, p <.10). These results are to be expected since recalls initiated by producers are not as scrutinized as those initiated by a government agency. When the recall is voluntary (firm initiated), the firm can choose the number of automobiles to recall, thus increasing the possibility to recall only a fraction of the defective automobiles. Furthermore, larger firms (–3.4E-06, p <.01) are less likely to rely on slicing than on chunking. This effect could be explained by the larger amount of resources held by these firms, as they can more easily investigate the issue fully before announcing the recall. It is also interesting to notice that the negative year trend is marginally significant (–.0931, p <.10) even after controlling for other macroeconomic factors, such as GPD growth (–.0395, p >.10) and whether the recall is made during a period of economic crisis (.5706, p >.10). Managers may suspect that slicing sends negative signals to investors and thus minimize it when they can. We next turn to testing H3 and H4.

Results for H3 and H4

Table 4 Column I, displays results for the main explanatory variables, the set of control variables when using the Market model (–2;2) to obtain the dependent variable. In Column II we add the interaction effect to test H4 (both models include firm-level clustered standard errors).

[Insert Table 4 here]

Results from Table 4 Column I show that slicing has a negative influence on firms abnormal returns (–.0239, p <.05). This result is consistent with H3. The value of the parameter shows that the effect is not only statistically significant but also economically significant since the mean difference in abnormal returns between slicing and chunking is around 2.4%. In addition, in support of H4, as the number of products being recalled increases, slicing becomes more advantageous in comparison with chunking (.0075, p <.05). We also noticed that the value of the beta coefficient for the main effect of slicing versus chunking remains negative and significant (–.0266, p <.05). Together, these results support our contention that, on average, chunking is superior to slicing in terms of firm value; however, as the number of products is larger, slicing becomes a more desirable option.

Other results worth noting are that firm age (Column I, .0002, p <.01) and research intensity (Column I, .9540, p <.01) soften the detrimental effects of product recalls on the firm's market value. Investors might expect innovative firms to be more prone to product malfunctions since the early stage of product development is often fraught with technical issues (Rogers 1962), limiting stock price movement when making recall announcements. Older firms are more experienced with product recalls, so investors might expect that they can handle crises better than young firms (Dutton, Fahey and Narayanan 1983). Finally, the number of production facilities has a negative marginal influence on investors (–.0002, p < .10); the higher complexity of orchestrating a recall when more production sites are involved can increase anticipated costs from the investors' point of view

In order to better understand how the support of H3 and H4 could shape managerial decisions, following Spiller et al. (2013) we conduct a spotlight analysis. The objective of this analysis is to show how different types of recall announcements can influence market reactions conditionally on recall size (see Figure 2)

[Insert Figure 2, here]

The analysis shows that the crossover point for slicing versus chunking is 2.6 million automobiles recalled. Thus, if the recall is lower than 2.6 million automobiles, managers should aim for chunking; above this threshold, managers can slice the recall. Importantly, slicing and chunking yield similar results between 1.5 and 9 million automobiles recalled. We note that the large majority of recalls are smaller than 1.5 million automobiles (95% of recalls in our database), thus, in most of the cases, chunking is more advantageous than slicing. Nevertheless, recalls larger than 1.5 million automobiles are more damaging to the firm's market value, hence the crossover effect should not be neglected.

Based on the results of the spotlight analysis, we create two scenarios to show how different recall announcements impact firms market value. In the first, we measure the market reaction in cases managers have to recall one million automobiles. Based on our results, if managers slice the recall, they would lose 1.97% of market value. However, if they chunk the recall, the firm would lose only.42% of market value. Thus, an appropriate type of recall announcement, in this case, could protect 1.5% of the firm's value. In the second, we compare two different recall announcements if the recall is extremely large: 9 million automobiles. In this case, chunking will lead to 11.34% in market losses, while slicing will lead to a decrease of 5.38% in the firm's market value. Thus, in this case, managers could save around 6% of the firm's market value.

Testing the theory

In our conceptual framework, we assume that investors will react negatively to slicing since they will assume that the problem is still not resolved and that more recalls are coming. We conduct two further analyses to test our assumption (Table 5).

[Insert Table 5 here]

When the first slice of a recall is announced, investors do not know if it is the first of a series of related recalls or if it is also the last (chunked). Only after the second slice can investors conclude that the firm is recalling products in slices. If the posited mechanism is true, later slices (second, third, etc.) should be more damaging to the firm than chunked recalls and the first slice. Hence, we compare the first slice and the chunked recalls together (referent category = 1) against the second, third, etc. slices (value 0). The results, shown in Table 5, support our assumption since "First sliced and chunked vs. other sliced" has a positive and significant impact (0.0099, $p < 0.05$).

Endogeneity test

To test the validity of the findings related to the effect of the different types of recall announcements, we test whether slicing versus chunking is strategic, which would make this regressor endogenous. In other words, there might be unobserved factors that influence managers in selecting one type of announcement over the other as a function of its anticipated effect on firm performance. These factors could create an omitted variable bias that would threaten the conclusion drawn from the firm performance level. If, on the other hand, the type of recall announcement is not a strategic decision, slicing or chunking is exogenous, suggesting that it is driven by factors that do not also influence firm performance; hence, it is unlikely to be the result of managers' discretionary choice since they presumably make profit-maximizing decisions.

Before testing for endogeneity, we first try to understand what the level of discretion is regarding the announcement of recalls. There are strict rules that NHTSA prescribe for automobile producers on how to conduct recalls (NHTSA, n.d.). First, when faced with new product defects, manufacturers have five working days to inform NHTSA about the existence of safety issues or non-compliance. Further, manufacturers are almost always responsible for the malfunction of the product, even in situations where original equipment was produced by one of their suppliers. Second, manufacturers have to send a detailed "defect report" where they should provide information regarding the vehicle that will be recalled, description of the problem, a summary of events that caused the problem, among other things. Importantly, producers have to define the recall population and how it differs from similar vehicles not included in the recall. Producers also have to asses if the scope of the recall is appropriate and if the issues can affect other vehicles or not. After the report is received, NHTSA may ask for further information from the producer. Finally, when the report if received and potential ambiguity resolved, NHTSA will create the unique recall identification number. Based on NHTSA rules, it could be concluded that managers have little discretion to decide the number of products they plan to recall. However, since some recalls are voluntary and since firms self-report how many products are affected, we decided to empirically test this chunking versus slicing decision.

Since slicing versus chunking is categorical, we use the control function (CF) approach to assess endogeneity. In the first step, we regress the potentially endogenous variable, chunking versus slicing, on a set of exogenous variables (results presented in Table 3). We include all variables from the table 3: recall size, severity, initiator, year trend, leverage, number of production facilities, total assets, reputation, overall automobile recalled, days between recalls, GDP and GFC. In the second step, we compute the residuals obtained from the regression. Then, we run the second stage estimation, where we regress abnormal returns on all variables from Table 4 and the correction term $\widehat{\theta_i}$ from the stage one regression. In order to meet the exclusion restriction criteria, in the second stage regression we do not include the variables total number of automobiles recalled within the previous year, firm total assets, and the initiator of the recall. We believe that these variables are both relevant (correlated with potentially endogenous variables) and exogenous (not correlated with the error term of the abnormal returns). If the total number of automobiles recalled in a year is large, managers will have fewer resources to focus on each recall, limiting their ability to examine if more automobiles affected by the defective part or component should also be recalled (leading to subsequent related recalls). Our justification regarding relevance is supported both in Table 4 and Appendix A, which show that as the number of recalled automobiles per year grows, managers are more likely to use slicing. Annual information (such as the number of recalls per year) should be already reflected in investors' expectations. Namely, since recalls are happening frequently, investors might expect and predict recall size based on the previous period. In a similar vein, Liu, Shankar and Yun (2017) show that the recall frequency does not have an impact on the abnormal returns when a new recall is announced.

As stated earlier, firms with more assets will have more resources to detect all products that are covered by the same problem and are therefore less likely to make additional recalls due to the same problem. On the other hand, information about the firm's total assets should be already incorporated in the firm value as well. Finally, when firms are making voluntary recalls, they might have more discretions about whether they will make the recall only after they are confident to have detected all affected products. This discretion could explain why recalls initiated by the producer are more likely to end up with additional recalls (slicing). The initiator of the recall should not affect investors; if the recall is damaging (e.g. severe and large), it will have a large negative impact on the customers and thus on firm performance regardless of who initiates the recall.

To test if the slicing decision is strategic or not, and if endogeneity correction is necessary, we examine if the correction term from stage one is significant in the stage two model. Following Papies, Ebbes and van Heerde (2017), parameter estimates are based on 500 bootstraps; in addition, since we used a first-stage probit model, we use generalized residuals from the first stage (Petrin and Train 2010). The significance test for $\widehat{\theta_\iota}$ is equivalent to the Hausman test for the presence of endogeneity (Papies, Ebbes and Van Heerde 2017). As shown in Table 6, the correction term is not significant (0.0361, p >

0.10)[14], which means that slicing is mostly the result of non-strategic decisions in the sense that managers recall when they have only partial knowledge about the scope of the issue; hence, an endogeneity correction is not necessary, confirming our findings from Table 4.

Robustness check

To confirm our results, we conduct several robustness checks: (1) by using different event windows, (2) by calculating the ARs with an alternative to the market model, (3) by removing cases from 2017 (last year of over observation period), and (4) removing cases with fatal consequences.

Using different event windows

Even though most of the studies in the product recall field use –2/+2 day event windows, some authors (Warren and Sorescu 2017) argue that a shorter event window is more appropriate. Thus, we have conducted the analysis with a shorter event window – 1/+1 day. As Table 7, Column I, reveals, the results are consistent with our main analysis. It can be noted that only results for the main effect of chunking versus slicing vary somewhat from the main analysis and other checks. The value of the *CHvsSL* variable is marginally significant (–.02, p <.10); however, the value for interaction remains highly significant and positive (.0083, p <.01).

Using an alternative to the market model to calculate Ars

We use the Fama-French model to calculate the dependent variable. There is an ongoing discussion in marketing literature if the Fama-French model is an appropriate method for calculating abnormal returns. On the one hand, some authors argue that the Fama-French

[14] We repeated the analysis with a) only overall automobile recalled and initiator and b) only overall automobile recalled and total assets as instruments. In both cases, correction term in the second stage was positive but not significant (.0212, p>.10 and .0289, p>0.1, respectively.)

model should only be used for long-term but not for short-term event studies (Sorescu, Warren and Ertekin 2017). However, other authors (Eilert et al. 2017) use the Fama-French model as it controls for two more factors compared with the market model: the difference in returns between small as well as large stocks, and the difference between high and low book-to-market ratios. By using this approach we estimate abnormal returns (*AR*) as $AR_{it}=R_{it}-E(R_{it})$, where R_{it} is the observed rate of return of the stock of the firm *i* on day *t*, and $E(R_{it})$ is the expected rate of return of the stock of the firm *i* on day *t* had the event not occurred. $E(R_{it})$ is estimated with the Fama-French three-factor model (Fama and French 1993). Accordingly:

(8) $$E(R_{it}) = R_{ft} + \beta_1(R_{mt} - R_{ft}) + \beta_2(SMB_t) + \beta_3\,(HML_t),$$

where R_{ft} is the risk-free rate of return on the US Treasury bonds on day *t*; R_{mt} is the average return on market-based on the equally weighted market index of the Chicago Center for Research in Security Prices; SMB_t is the difference between the rate of returns of small and large stocks; and HML_t is the difference between the rate of returns of high and low book-to-market ratio stocks. The results of the analysis are consistent (Table 7, Column II) with previous findings since both the main effect of chunking versus slicing (–.0244, $p < .05$) and the interaction term (.0082, $p < .05$) are significant with the expected sign of beta coefficients.

Removing cases from 2017

We noticed in our database that in 2017 there were no observations of a slicing strategy being used. It could be that cases related to 2017 related recalls (subsequent slices) will occur in the future. Thus, we repeated our analysis using only observations from 2006 to 2016. As can be seen in Table 7 Column III, results remain unchanged (Chunking versus slicing: –.0268, $p < .05$ and for interaction.0082, $p < .05$).

Removing cases with fatal consequences

Cases that have fatal consequences are extremely rare, but they could also have a strong impact on market reaction and more likely to be sliced. We repeat our analysis with only recalls where no fatal consequences are reported. As shown in Table 7 Column IV, the results are consistent with previous findings; however, the effects are in both cases marginally significant (chunking versus slicing: –.0216, $p < .10$ and for interaction.01, $p < .10$).

Discussion

Our analysis of US-based product recalls in the automobile industry shows that around 13% of product recalls are sliced into several smaller recalls, which is almost twice as frequent as announcements of new product developments made concurrently with other corporate news (Warren and Sorescu 2017). To our best knowledge, this is the first study that looks at the effect of different announcement strategies about negative corporate news to the public. The potential financial consequences of different types of recall announcements were previously neglected in the literature, where prior product-harm crisis studies focus on recalls as separate events. The goal of our study was to fill this gap by comparing the underlying reasons and effects of multiple related recall announcements (i.e., slicing) with recalls that were conducted only once (i.e., chunking).

Theoretical contribution

While previous studies that investigate how product recalls affect firm's value argue that these events, in general, have a negative influence on firm's stock price (Gao et al. 2015, Liu, Shankar and Yun 2017), we find no evidence that capital markets will react negatively to product recalls.[15] We argue that since recalls are very frequent and affect all automobile

[15] The main CAR for recalls in our dataset is 0.00 (see table from appendix for details)

producers, the market already expects that firms will have new recalls in the future. As Jarrell and Peltzman (1985, p.378) explain:

> The stock market does not react to every event which entails a cost to shareholders, only to those which are not entirely expected. So, if product recalls occurred with the same regularity as, say, wage payments we would no more expect stock prices to fall when a recall occurs than on payday, even though both events impose real costs on stockholders. The market can be expected to respond to news of recalls only if the news resolves some uncertainty.

The market will not react to the recall; however, it will react to other signals that managers send regarding the way they are communicating details of the crisis. If managers slice recalls, they are signalling to investors that they are not in full control of the crisis. Thus, they need to take corrective actions by announcing additional recalls caused by the same problem. The McKinsey study made a similar conclusion regarding the managers' ability to detect all defective products. The authors of the study argue that a lot of time and resources are needed for the magnitude, scope and facts behind technical or operational issues to be really clear; hence, many of them end up as a “black box” for decision-makers (Kalavar, Mohr and Mysore 2018), since they fail to understand the scope and severity of a problem. Thus slicing the recalls could be a signal that the problem is a “black box” for managers and that investors could expect new consequences to arise from the same crisis.

Since there is information asymmetry between managers and investors (Luo 2008), investors often carefully analyze the decisions made by the former while estimating the impact of certain events on the firm’s future performance. While dealing with slicing announcements, investors might assume that even after the second recalls there is a probability of a new announcement arising from the same problem. Thus, they adjust their expectations regarding the firm's performance by incorporating a probability that new recalls will follow. The results of our study showed that ceteris paribus, slicing recall has a detrimental impact on a firm's market value in comparison to chunking recalls. Our assumption is confirmed by additional empirical analysis where we compare first sliced and chunked recalls with other (second, third and so on) sliced recalls. The results showed that other sliced recalls have a stronger negative impact on firm's performance than first sliced and chunked recalls.

We also investigate the boundary effect of different recall announcement decisions. Namely, the results of our study show that using a slicing strategy is more advantageous for recalls that are smaller than 2.6 million automobiles. However, if managers have to recall more 2.6 million automobiles, it is more appropriate to make several smaller announcements. Since investors could perceive large recalls as the "the biggest/largest" in the recent period, they may see them as a signal of a large systematic problem that the firm is facing. Thus, they might react negatively to extremely negative news if delivered once. Even though such large recalls are very rare, their impact on a firm's performance is very strong, thus these results should not be neglected.

Finally, our results show that the size and severity of a crisis increases the probability of using a slicing strategy. These results support our assumption that larger and more severe problems will require more resources. While dealing with severe and large issues, managers tend to make recall decisions even before they have all the facts available. As soon as they make the announcement, managers will continue to collect more information regarding the problem, which could lead to new related recalls.

Our results also contribute to the literature that deals with different corporate announcement strategies on firm's performance. While the focus of prior studies is on the disaggregation of positive news (Houston et al. 2018, Warren and Sorescu 2017) or managers reactions to negative news (Borah and Tellis 2016), we look at the (dis)aggregation of related negative news. We show that aggregating (chunking) of negative news is on average more advantageous than disaggregating (slicing) of related negative news. Interestingly, the same conclusion was made by the study that was dealing with new product announcement done concurrently with other corporate news (Warren and Sorescu 2017). However, our study goes one step further by looking at the boundary conditions of different announcement strategies. The results of our analysis show that for extremely negative news it is more appropriate to make announcements piece-by-piece (to slice the news).

Managerial implications

In recent years, we have witnessed a large increase of product recalls. In the US alone, the number of automobiles recalled climbed from 20 million in 2010 to 53 million in 2016 (Kalavar, Mohr and Mysore 2018). Managers are under pressure from stakeholders (e.g. customers, investors and government) since they have to deal with the many adverse consequences of recalls (Cleeren, van Heerde and Dekimp 2013) that lead to a decrease in firm's market value (Liu, Shankar and Yun 2017). Consequently, there is an increasing need for studies dealing with firm's behavior during the product recall announcement (Eilert et al. 2017).

The results of our study show that managers can use recall announcements to mitigate negative effects of product recalls on a firm's market value. The most surprising finding is that, on average, chunking announcements have a positive impact on a firm's performance. Thus, by making a single announcement regarding the specific product harm crisis, managers could make a positive impact on investors expectations. The difference between the two strategies is not only statistically significant but also economically significant. Namely, we show that the difference between these two strategies is around 2%, the effect that could be measured in billions of dollars for most of the sample firm's market capitalization.

There are three possible activities that managers could undertake while dealing with a product-harm crisis. First, as soon as information about the problem becomes available managers should put a large amount of resources into understanding the size of the problem (how many products are affected by the problem). Eilert et al. (2017) show that managers have around one year between the date of opening the investigation and the date of recall. As most of the complaints that could lead to recall are benign and harmless, it might happen that managers will not take information about new problems seriously. However, there is always a probability that the next product harm crisis is serious and potentially damaging. Therefore, as soon as the new problem is discovered managers should allocate a significant amount of resources on solving the problem. If the case ends up as being benign, a large amount of resources invested in the discovery of the problem will decrease the time of the recall, which will have a positive effect on the stock market (Eilert et al. 2017). However, if the problem is serious, a large amount of resources will allow managers to understand the problem fully and thus prevent recall slicing.

Another managerial contribution might lie in deciding about the size of the recall when managers are not certain about all the products that are affected. This is especially important since industry reports show that managers are often not fully aware of the size and the scope of the problem (Kalavar, Mohr, and Mysore 2018). If managers are not certain that the entire batch of products is affected, it might be more advantageous to recall these products then to leave them on the market. Even though these products might end up as not being faulty and thus create unnecessarily expenditures, failing to recall faulty products could lead to a significant decrease in firm market value. However, managers should also be aware that if there are signals that the potential number of affected products is extremely large, they might announce the recall as soon as the first batch of product is detected.

Finally, even though decisions to chunk or slice recalls might not be strategic and, thereofore, not endogenous, the time to recall is left to managers' discretion (Eilert et al. 2017). Thus, in a certain situation (when product harm crisis is not severe), managers might consider to postpone the recall until they collect sufficient information regarding the specific nature of the product-harm crisis. Even though more time between investigation and recall decreases firm's market value (Eilert et al. 2017), the possible of related recalls will also have a strong detrimental effect on investors. Managers should, therefore decide if they want to make quick decisions based on incomplete information, or wait for more complete information and decrease the probability of later having to announce a subsequent related recall.

We also believe that our study could also serve as guidance for announcing other negative news to the public. For example, our results show that if managers have to announce negative news to the public, they should deliver it all at once. However, for extremely large cases (in our case, more than 2.5 million automobiles), the slicing strategy proved more appropriate. When dealing with large negative news, managers should deliver information to the public piece-by-piece. In that way, firms will avoid creating the largest or the most negative news of the year, which could signal serious and systematic problems that the firm is facing.

Limitations and Further Research

The study was conducted on the US automobile industry and relied on the NHTSA dataset. A possible extension would be to review other industries, to see whether the conclusions are generalizable. Additional light should be shed on other boundary effects, such as product characteristics, which were not included in our study due to its nature (single industry study). Further, it would be also interesting to see if the (dis)aggregation of other types of negative news has the same impact on investors. Finally, another possible extension of our study could be in managing unrelated negative news.

In summary, we hope our study of the influence of the (dis)aggregation of related product recalls on investors' reactions inspires further research into the announcement of negative news to the public and its effects on investors.

References

Argote, Linda and Henrich R Greve (2007) "A Behavioral Theory of the Firm—40 Years and Counting: Introduction and Impact." *Organisation Science* 18(3):337-49.

Barber, Brad, Reuven Lehavy, Maureen McNichols and Brett Trueman (2001) "Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns." *The journal of Finance* 56(2):531-63.

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

Boyd, D Eric and PK Kannan (2018) "(When) Does Third-Party Recognition for Design Excellence Affect Financial Performance in Business-to-Business Markets?". *Journal of Marketing* 82(3):108-23.

Chen, Yubo, Shankar Ganesan and Yong Liu (2009) "Does a Firm's Product-Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises." *Journal of Marketing* 73(6):214-26.

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

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

Connelly, Brian L, S Trevis Certo, R Duane Ireland and Christopher R Reutzel (2011) "Signaling Theory: A Review and Assessment." *Journal of Management* 37(1):39-67.

Craig, Smith N and Robert J Thomas (1996) "A Strategic Approach to Managing Product Recalls." *Harvard Business Review* 74(5):102-12.

Cyert, Richard M and James G March (1963) "A Behavioral Theory of the Firm." *Englewood Cliffs, NJ* 2(4):169-87.

Dutton, Jane E, Liam Fahey and Vijay K Narayanan (1983) "Toward Understanding Strategic Issue Diagnosis." *Strategic Management Journal* 4(4):307-23.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam and Tracey A Swartz (2017) "Does It Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry." *Journal of Marketing* 81(3):111-29.

Fama, Eugene F and Kenneth R French (1993) "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of financial economics* 33(1):3-56.

Gao, Haibing, Jinhong Xie, Qi Wang and Kenneth C Wilbur (2015) "Should Ad Spending Increase or Decrease before a Recall Announcement? The Marketing–Finance Interface in Product-Harm Crisis Management." *Journal of Marketing* 79(5):80-99.

Gavetti, Giovanni, Henrich R Greve, Daniel A Levinthal and William Ocasio (2012) "The Behavioral Theory of the Firm: Assessment and Prospects." *The Academy of Management Annals* 6(1):1-40.

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

Houston, Mark B, Ann-Kristin Kupfer, Thorsten Hennig-Thurau and Martin Spann (2018) "Pre-Release Consumer Buzz." *Journal of the Academy of Marketing Science* 46(2):338-60.

Jarrell, Gregg and Sam Peltzman (1985) "The Impact of Product Recalls on the Wealth of Sellers." *Journal of Political Economy* 93(3):512-36.

Kalaignanam, Kartik, Tarun Kushwaha and Meike Eilert (2013) "The Impact of Product Recalls on Future Product Reliability and Future Accidents: Evidence from the Automobile Industry." *Journal of Marketing* 77(2):41-57.

Kalavar, Sanjay, Detlev Mohr, and Mihir Mysore (2018) “Are you prepared for a corporate crisis?” pp. 19-26 in *The Board Perspective A Collection of McKinsey Insights*

Focusing on Boards of Directors (accessed January 18, 2019) [available at: https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Leadership/The%20board%20perspective/Issue%20Number%202/2018_Board%20Perspective_Number_2.ashx]

Liu, Yan and Venkatesh Shankar (2015) "The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry." *Management Science* 61(10):2514-35.

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

Luo, Xueming (2008) "When Marketing Strategy First Meets Wall Street: Marketing Spendings and Firms' Initial Public Offerings." *Journal of Marketing* 72(5):98-109.

Majeed, Abdul, and Karthik Manivachagam (2013), "Automobiles: The economic outlook and employment situation" Pricewaterhouse Coopers (August 2013) (accessed December 11), [available at https://www.pwc.in/assets/pdfs/publications/2013/automobiles-the-economic-outlook-and-employment-situation.pdf]

Malkiel, Burton G and Eugene F Fama (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work." *The Journal of Finance* 25(2):383-417.

Malkiel, Burton G (2003) "The Efficient Market Hypothesis and Its Critics." *Journal of Economic Perspectives* 17(1):59-82.

NHTSA (n.d.), "Safety Recall Compendium" *Recall Management Division, Office of Defects Investigation, National Highway Traffic Safety Administration, U.S. Department of*

Transportation, (accessed February 05, 2019), [available at https://www-odi.nhtsa.dot.gov/recalls/documents/recompendium.pdf]

NHTSA Complains (n.d.), "Complains," National Highway Traffic Safety Administration, (accessed March 10, 2019), [available at https://www-odi.nhtsa.dot.gov/downloads/]

NHTSA Recalls (n.d.), "Recalls," National Highway Traffic Safety Administration, (accessed March 10, 2019), [available at https://www-odi.nhtsa.dot.gov/downloads/]

Ni, John Z, Barbara B Flynn and F Robert Jacobs (2014) "Impact of Product Recall Announcements on Retailers′ Financial Value." *International Journal of Production Economics* 153:309-22.

Panagopoulos, Nikolaos G, Ryan Mullins and Panagiotis Avramidis (2018) "Sales Force Downsizing and Firm-Idiosyncratic Risk: The Contingent Role of Investors' Screening and Firm's Signaling Processes." *Journal of Marketing* 82(6):71-88.

Papies, Dominik, Peter Ebbes and Harald J van Heerde (2017) "Addressing Endogeneity in Marketing Models." Pp. 581-627 in *Advanced Methods for Modeling Markets*: Springer.

Petrin, Amil and Kenneth Train (2010) "A Control Function Approach to Endogeneity in Consumer Choice Models." *Journal of Marketing Research* 47(1):3-13.

Rogers, Everett M. (1962). "Diffusion of innovations" New York: Free Press of Glencoe.

Shepardson, David, (2015), "GM compensation fund completes review with 124 deaths" The Detroit News (August 24 2015) (accessed December 11) [available at https://www.detroitnews.com/story/business/autos/general-motors/2015/08/24/gm-ignition-fund-completes-review/32287697/]

Sorescu, Alina, Nooshin L Warren and Larisa Ertekin (2017) "Event Study Methodology in the Marketing Literature: An Overview." *Journal of the Academy of Marketing Science* 45(2):186-207.

Stiglitz, Joseph E. (2002) "Information and the Change in the Paradigm in Economics." *American Economic Review* 92(3):460-501.

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

Warren, Nooshin L and Alina Sorescu (2017) "When 1+ 1> 2: How Investors React to New Product Releases Announced Concurrently with Other Corporate News." *Journal of Marketing* 81(2):64-82.

Figure 1. Relation of focal study and related studies

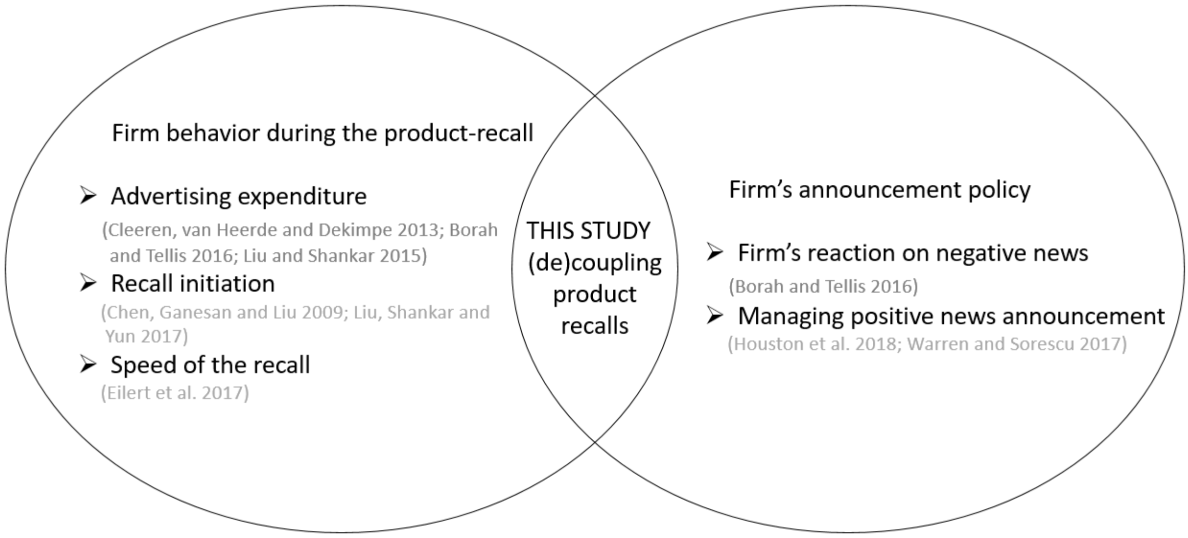

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Table 1. Variables description

Name of the Variable	Description	Merging criteria	Source
CAR: (t_1= -2, t_2=2)	Cumulative abnormal return, with event window of t_1 as the beginning of the period and t_2 as the end of the period	Sum of abnormal returns	CRSP
SLvsCH	1 – Slicing 0 – Chunking	Expert coding	NHTSA
Independent Variables			
Recall size	Number of automobiles recalled (in million)	Sum of the recall size	NHTSA
Recall severity	Principal component analysis of 1. Complains 2. Fires 3. Injuries 4. Fatalities	Sum of 1. Complains 2. Fires 3. Injuries 4. Fatalities follow by the principal component analysis	NHTSA
Initiator	0 – Government 1 – Manufacturer	0 – Government 1 – Manufacturer 2 – Both	NHTSA
Days	Days between the recall and nearest previous recall	Mean days between the recall and nearest previous recall	NHTSA
Year	Year of the recall	Median year of the recall	NHTSA
Size	Natural logarithm of total assets	Mean	Compustat
R&D	R&D expenditure divided by total assets	Mean	Compustat
Leverage	Long term debt plus Debt in Current Liabilities divided by Stockholders' Equity	Mean	Compustat
Age	Year of recall minus year of firm foundation	Mean	NHTSA/Firms websites
Production	Number of production facilities	Mean	Firms websites
Reputation	Fortune list most admired companies overall score	Mean	Fortune most admired companies
GDP	GDP growth in the year of the recall	Mean	World Bank
Crisis	One if the recall was in 2008-2010, 0 otherwise	Based on the median year of the recall	NHTSA
Overall automobiles recalled	Overall number of automobiles recalled by the same producer in the year of the recall	Based on the median year of the recall	NHTSA

Table 2. Model free evidence

	Slicing	Chunking
Number of cases	40	275
Mean CAR (MM–22)	–2.2%	+0.56%
Influence on market capitalization of GM (millions USD)[16]	–962	+270
Influence on market capitalization of Ford (millions USD)	–800	+204
Influence on market capitalization of Toyota (millions USD)	–3.898	+992
Influence on market capitalization of Honda (millions USD)	–1.152	+293
Influence on market capitalization of Nissan (millions USD)	–793	+202
Average number of automobiles recalled (millions)	2.09	.25
Average number of complaints	348.62	28
Average number of injuries	14.65	.76
Average number of fire cases	15.33	.65

[16] Calculated by multiplying abnormal returns on the day of recall and market capitalization of the firm on 08.10.2018.

Table 3. Drivers of Slicing vs Chunking

	Estimates	SE
Severity	.7163***	.2247
Recall size	.6338**	.3139
Initiator (Government referent category)		
Producer	.4466*	.2674
Both	.7216	.5375
Year	–.0931*	.0507
Leverage	.0262***	.0083
R&D	–15.9512	12.1736
Age	–.0042	.0042
Production facilities	–.0009	.0094
Total assets	–3.4E-06***	1.07E-06
Reputation	.1906**	.0782
Overall automobiles recalled	5.36E-08***	2.06E-08
Days between recalls	–.0045	.0029
GDP	–.0395	.1330
Crisis	.5706	.5008
Intercept	186.0645	101.8325
Unobserved firm effects	Clustered st. errors	
Sample size	315	
Pseudo R^2	.34	

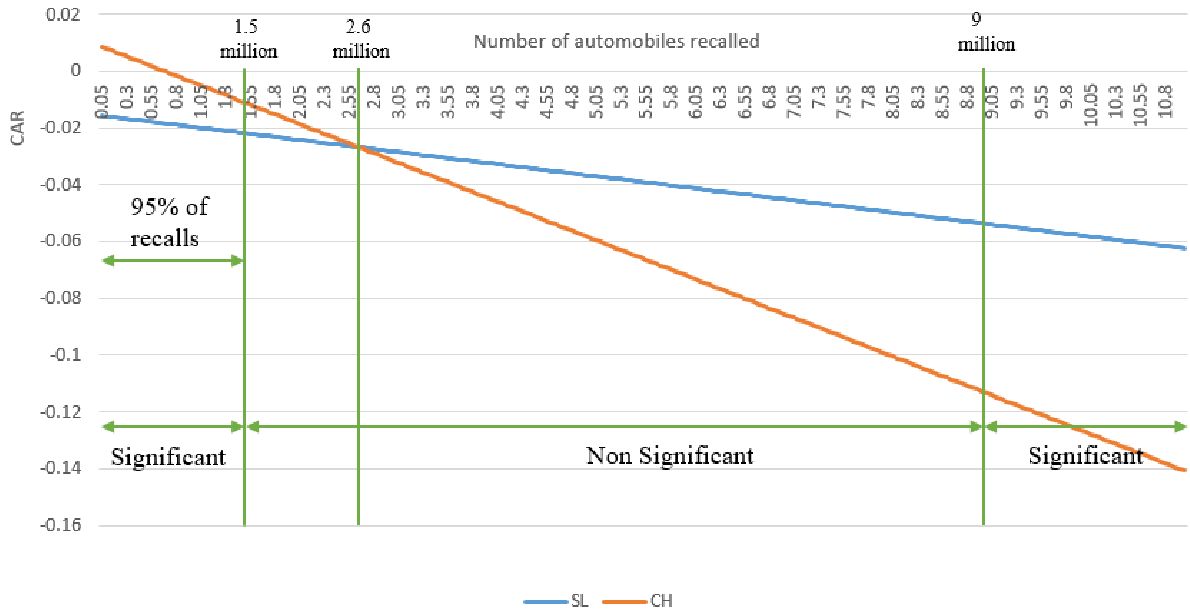
*** p<.01, ** p<.05, * p<.1.

Table 4. Influence of Slicing vs Chunking on Firm Value

Dependent/Independent Variable	Column I		Column II	
	MM [–2;2]		MM [–2;2]	
	Estimates	SE	Estimates	SE
SLvsCH (chunking referent category)	–.0239**	.0058	–.0266**	.0063
Recall size	–.0041*	.0016	–.0109***	.0021
SLvsCH*Recall size			.0075**	.0026
Severity	.0006	.0005	.0002	.0007
Initiator (Government referent category)				
Producer	–.0020	.0057	–.0027	.0055
Both	–.0397	.0529	–.0401	.0533
Year	–.0007	.0008	–.0006	.0008
Leverage	2.9E-05	5.79E-05	.0000	.0001
R&D	.9540***	.1714	.9434***	.1656
Age	.0002***	.0000	.0002***	.0000
Production facilities	–.0002*	.0001	–.0002**	.0001
Total assets	2.56E-08	3.21E-08	2.71E-08	3.10E-08
Reputation	.0058	.0029	.0057	.0028
Overall automobiles recalled	3.59E-10	4.13E-10	3.65E-10	4.20E-10
Days between recalls	–3.2E-05	2.7E-05	-3.30E-05	2.63E-05
GDP	.0010	.0022	.0012	.0022
Crisis	.0090	.0064	.009	.0065
Intercept	1.2468	1.6816	1.1207	1.6579
Unobserved firm effects	Clustered st. errors		Clustered st. errors	
Sample size	315		315	
R^2	.1067		.1089	

*** p<.01, ** p<.05, * p<.1.

Figure 2. Spotlight Analysis



* Significant at 0.05%

Table 5. Testing the Mechanism

Dependent/Independent Variable	Column I	
	MM [–2;2]	
	Estimates	SE
First sliced and chunked vs other sliced	.0099**	.0030
First sliced vs chunked		
Recall size	–.0001	.0023
Severity	–.0015**	.0006
Initiator (Government referent category)		
Producer	–.0008	.0043
Both	–.0075	.0243
Year	–.0007	.0011
Leverage	–1.9E-05	4.04E-05
R&D	.8441**	.2618
Age	17.4 E-05**	5.44E-05
Production facilities	–.00014	.000114
Total assets	3.03E-08	2.96E-08
Reputation	.0044	.0033
Overall automobiles recalled	–2.7E-10	6.18E-10
Days between recalls	–1.4E-05	3.62E-05
GDP	.0025	.0028
Crisis	.0010	.0062
Intercept	1.3400	2.2299
Unobserved firm effects	Clustered st. errors	
Sample size	377	
R^2	.05	

*** p<.01, ** p<.05, * p<.1.

Table 6. Endogeneity correction

Dependent/Independent Variable	MM[–2;2]	
	Estimates	SE
SLvsCH	–.0856*	.0449
Recall size	–.002	.0055
Severity	.0031	.0129
Year	–.0014	.0009
Leverage	.0001	.0001
R&D	.6497	.7749
Age	.0001	.0001
Production facilities	–.0002	.0002
Reputation	.0064	.005
Days between recalls	–5E-05	5.21E-05
GDP	.0010	.0046
Crisis	.0212	.0143
$\widehat{\theta_i}$	**–.0361**	**.0241**
Intercept	2.8	1.9836
Unobserved firm effects	Clustered st. errors	
Sample size	314	
R^2	.144	

*** p<.01, ** p<.05, * p<.1.

Table 7. Robustness Check

Dependent/Independent Variable	Column I		Column II		Column III		Column IV	
	MM[–1;1]		FF[–2;2]		MM[–2;2]		MM[–2;2]	
	Estimates	SE	Estimates	SE	Estimates	SE	Estimates	SE
SLvsCH (chunking category)	–.02*	.0088	–.0244**	.0077	–.0268**	.0065	–.0216*	.0085
Recall size	–.0107***	.0021	–.0104***	.0022	–.0115***	.0022	–.0064	.0044
SLvsCH*Recall size	.0083***	.0026	.0082**	.0028	.0082**	.0028	.0100*	.0044
Severity	–.001	.0012	–.0008	.0012	.0002	.0006	–.0244	.0196
Initiator (Gov. category)								
- Producer	–.0065	.0059	.0002	.0044	–.0024	.0055	–.0090	.0109
- Both	–.0154	.0369	–.0461	.0608	–.0402	.0529	–.0415	.0463
Year	–6.00E-04	4.00E-04	–.0007	.0009	–5.00E-04	1.00E-03	–.0007	.0009
Leverage	–8.90E-06	3.38E-05	1.00E-04	1.00E-04	4.38E-05	5.69E-05	.0001	.0001
R&D	–.1446	2.13E-01	.7222***	.1156	.9463***	1.89E-01	.8288***	.1472
Age	1.4E-05**	3.26E-05	.0002***	.0000	21.3E-05***	3.79E-05	.0003**	.0001
Production facilities	–.0003*	1.00E-04	–1.00E-04	1.00E-04	–.0002*	1.00E-04	–.0002*	.0001
Total assets	–1.90E-08	1.58E-08	2.01E-08	2.55E-08	2.86E-08	3.11E-08	1.92E-08	2.51E-08
Reputation	1.20E-03	2.60E-03	.0051*	2.20E-03	5.80E-03	3.00E-03	.0069**	.0025
Overall automobiles recalled	1.86E-10	6.55E-10	2.87E-10	3.07E-10	3.01E-10	3.94E-10	1.67E-10	3.88E-10
Days between recalls	–2.80E-05	2.48E-05	–2.50E-05	2.8 E-05	–3.20E-05	.000026	–.0000312	2.60E-05
GDP	.0006	.0033	.0016	.0021	.0012	.0022	.0026	.0027
Crisis	.0041	.0057	.0118	.0067	.0094	.0067	.0160	.0078
Intercept	1.2583	.7955	1.2781	1.814	.979	1.9534	1.2655	1.9068
Unobserved firm effects	Clustered st errors		Clustered st. errors		Clustered st. errors		Clustered st. errors	
Sample size	315		315		297		312	
R^2	.079		.0969		.1096		.1579	

*** p<.01, ** p<.05, * p<.1.

Appendix A. Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	MM22	1.00																	
2	SLvsCH	–.18*	1.00																
3	Recall size	–.18*	.40*	1.00															
4	Severity	–.09	.34*	.67*	1.00														
5	Initiator government	.07	–.18*	–.24*	–.14*	1.00													
6	Initiator firm	.01	.08	.11	.10	–.90*	1.00												
7	Initiator both	–.18*	.24*	.31*	.11	–.35*	–.09	1.00											
8	Year of recall	–.02	–.22*	–.10	–.08	.29*	–.28*	–.06	1.00										
9	Leverage	.02	.03	.00	.01	.06	–.06	.00	.16*	1.00									
10	R&D	.180*	.00	–.05	.02	–.03	.06	–.05	–.27*	.04	1.00								
11	Age	.03	–.07	–.02	.07	.01	–.03	.06	.31*	–.07	.06	1.00							
12	Production facilities	–.12*	–.06	.01	–.08	–.10	.11*	–.01	.16*	–.10	–.35*	–.01	1.00						
13	Total assets	–.07	.01	.05	–.01	.04	–.08	.09	.26*	.06	–.72*	–.10	.01	1.00					
14	Reputation	.03	.05	.01	.01	.10	–.13*	.04	.17*	.27*	–.26*	–.33*	–.16*	.49*	1.00				
15	Overall automobiles recalled	–.08	.24*	.39*	.24*	–.08	.01	.16*	–.11	.00	–.21*	.04	–.03	.30*	–.06	1.00			
16	Days between recalls	–.03	–.04	–.02	–.04	–.03	.02	.02	–.16*	–.11	.04	–.11	–.01	–.04	–.10	.12*	1.00		
17	GDP	.00	–.16*	–.19*	–.06	.11*	–.14*	.03	.27*	–.05	–.15*	.13*	.05	.03	.06	–.20*	–.15*	1.00	
18	CrisisGFC?	.04	.24*	.14*	.06	–.22*	.21*	.03	–.39*	–.24*	.18*	–.20*	–.04	.01	–.06	.41*	.08	–.59*	1.00
	Mean	.00	.13	.49	.00	.77	.20	.03	2011.76	–.93	.04	89.76	54.71	223014	5.77	2359325	49.42	1.82	.14
	SD	.06	.33	1.52	1.52	.42	.40	.18	3.47	18.85	.01	18.99	14.84	94699	.86	3256367	67.31	1.27	.35

* Significant at .05%

Appendix B. Examples of margin of related sliced cases

We present 4 examples where we either treated cases as sliced and merged them (examples 1 and 2), or where we faced recalls that are similar (same firm and same defective component), but we consider them as independent due to the recall summery (examples 3 and 4)

Examples of sliced recalls

Example 1: merging two related Ford cases

Recall Number	Recall Date (MM/DD/YYY)	Component	Firm	Summary
16V643000	09/06/2016	LATCHES/LOCKS/ LINKAGES:DOORS:LATCH	Ford	Ford Motor Company (Ford) is recalling certain model year 2012-2015 Ford Focus, 2013-2015 Ford Escape and Ford C-MAX, 2015 Lincoln MKC and Ford Mustang, and 2014-2016 Ford Transit Connect vehicles. A component within the door latches may break, preventing the doors from latching and/or leading the driver or a passenger to believe a door is securely closed when, in fact, it is not.
15V246000	04/24/2015	LATCHES/LOCKS/ LINKAGES:DOORS:LATCH	Ford	Ford Motor Company (Ford) notified the agency on April 23, 2015, that they are recalling certain model year 2013-2014 Ford Fusion and Lincoln MKZ vehicles manufactured July 1, 2012, to May 31, 2013, and 2012-2014 Fiesta vehicles manufactured February 1, 2012, to May 31, 2013. On April 30, 2015, Ford expanded the recall to cover an additional 119,567 vehicles, including certain model year 2011 Ford Fiestas manufactured from November 11, 2009, to May 31, 2013 and certain model year 2013 Ford Fusion and Lincoln MKZ vehicles manufactured from February 1, 2012, to June 30, 2012. A component within the door latches may break making the doors difficult to latch and/or leading the driver or a passenger to believe a door is securely closed when, in fact, it is not.

Example 2: merging two related Toyota cases

Recall Number	Recall Date (MM/DD/YYY)	Component	Firm	Summary
15V689000	10/22/2015	VISIBILITY:POWER WINDOW DEVICES AND CONTROLS	Toyota	Toyota Motor Company (Toyota) is recalling certain model year 2009-2011 Tundra, Sequoia, Corolla, Corolla Matrix and Scion xB, 2008-2011 Highlander and Highlander Hybrid, 2007 Camry and Camry Hybrid, 2009 Camry and Camry Hybrid, 2006-2011 RAV4, 2006-2010 Yaris, and 2009-2010 Scion xD and Pontiac Vibe vehicles. During the manufacturing of the Power Window Master Switch (PWMS), grease lubricant may have been inconsistently applied to the sliding electrical contacts.
12V491000	10/10/2012	VISIBILITY:POWER WINDOW DEVICES AND CONTROLS	Toyota	Toyota is recalling certain model year 2007-2009 Camry, Camry Hybrid, RAV4, Corolla, Corolla Matrix, Tundra, Sequoia, Highlander, Highlander Hybrid, Yaris, Scion xB, Scion xD and Pontiac Vibe vehicles. The power window master switch assemblies in some of these vehicles were built using a less precise process for lubricating the internal components of the switch assemblies. Irregularities in this lubrication process may cause the power window master switch assemblies to malfunction and overheat.

Examples of similar but unrelated recalls (chunked recalls)

Example 3: two recalls from the same producer (Ford) that are similar but not related

Recall Number	Recall Date (MM/DD/YYY)	Component	Firm	Summary
12V553000	11/30/2012	EXTERIOR LIGHTING:HEADLIGHTS	Ford	Ford is recalling certain model year 2013 Fusion vehicles, manufactured from February 3, 2012, through October 20, 2012, for failing to conform to the requirements of Federal Motor Vehicle Safety Standard (FMVSS) number 108, "Lamps, Reflective Devices, and Associated Equipment." The affected vehicles may not have had the low beam headlamp projector coating properly cured during its manufacturing process.
15V248000	10/10/2012	EXTERIOR LIGHTING:HEADLIGHTS	Ford	Ford Motor Company (Ford) is recalling certain model year 2015 Lincoln MKZ vehicles manufactured February 17, 2014, to March 19, 2015, and equipped with daytime running lights (DRL). In the affected vehicles, the parking lights do not reduce their light output from a DRL level when used in conjunction with the headlights. As such, the light output may exceed the the permissable amount allowed by Federal Motor Vehicle Safety Standard (FMVSS) number 108, "Lamps, Reflective Devices, and Associated Equipment."

Example 4: two recalls from same producer (GM) that are similar but not related

Recall Number	Recall Date (MM/DD/YYY)	Component	Firm	Summary
13V220000	05/24/2013	ELECTRICAL SYSTEM	GM	General Motors LLC (GM) is recalling certain model year 2013 Cadillac ATS and model year 2013 Cadillac XTS; model year 2014 Chevrolet Impala; and 2013 Chevrolet Sonic vehicles. Originally, in May 2013, GM recalled 1,627 model year 2013 Cadillac ATS and model year 2013 Cadillac XTS; and model year 2014 Chevrolet Impala vehicles. In October 2013, GM informed the agency that it was adding model year 2013 Chevrolet Sonic vehicles to this campaign , representing an additional 8,050 units. The total number of vehicles being recalled is now 9,677. On the affected vehicles, the brake lamps may intermittently flash without the brakes being applied and the cruise control may disengage. Thus, these vehicles fail to conform to the requirements of Federal Motor Vehicle Safety Standard (FMVSS) No. 108, "Lamps, reflective devices, and associated equipment."
13V173000	05/06/2013	ELECTRICAL SYSTEM	GM	General Motors (GM) is recalling certain model year 2012 and 2013 Buick LaCrosse and Regal, and model year 2013 Chevrolet Malibu Eco vehicles equipped with eAssist. These vehicles may have a condition in which the Generator Control Module (GCM) may not function properly. This could cause a gradual loss of battery charge and the illumination of the malfunction indicator light.

Conclusion

The product recall phenomenon is very large and is growing; as such, it has attracted a lot of attention from marketing scholars, leading to a substantial number of published studies in premier marketing journals. The goal of this thesis was to extend existing knowledge about the impact of product recalls on a recalling firm and its suppliers as well as about possible defense mechanisms that managers could use to protect firm' market value.

Our findings differ from the omnipresent opinion that product recalls, on average, impact firms value. Namely, our results show that, on average, product recalls do not hurt a firm's performance. Since recall events are frequent, investors expect their occurrence in the future. Thus, they adjust their beliefs of the impact of product recalls on the firm's future performance based on signals, such as the size of the recalls and managers' ability to control the crisis. Hence, affected firm's (both directly and indirectly) behavior during and prior product recalls has a strong impact on investors' expectations regarding a firm's future performance.

In essay 1, we showed that when producers announce large-scale recalls, their suppliers' market value decreases. The main reason for this newly detected phenomenon is the power that producers can wield over their suppliers to mitigate the negative effects of product recalls. Our results also showed that suppliers can protect their market value by fully disclosing the strength of the relationships with their customers. In that case, investors will be able to estimate the damaging impact on suppliers. However, if the relationship is not disclosed, investors will assume the worst-case scenario (i.e., a strong relationship between suppliers and recalling producer), which will lead to larger divestment from the impacted suppliers.

In our essay 2, results indicated that, in most cases, it is more advantageous for managers to make one large recall announcement due to the same product crisis (chunking recalls), than to make several smaller related recalls (slicing recalls). By slicing recalls, managers send a signal to investors that they are not in the control of the crisis, which will have a negative impact on investors' expectation; asking themselves "how and where will this crisis end"? Interestingly, for extremely large recalls, the slicing strategy proved less detrimental to recalling firms' market value. We argue that being "the largest" in a given period will make investors believe that the firm is dealing with a severe systematic problem that is not easily solvable.

In summary, we hope that this thesis will be insightful for both managers and scholars and that more studies regarding the possible actions that could prevent negative effects of product recalls will follow.