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Abstract

This paper studies equity market responses to major automotive recalls. Using event studies combined with volatility models and causal tests for three specific auto recalls (Ford 2005, Toyota 2010, and GM 2014), the study examines both immediate value effects and spillovers between closely related auto companies, as well as the rise in interest in these issues, proxied by Google Trends. There is no single recall pattern. Toyota suffered the largest decrease in value among the three companies studied and had the highest spillover effects, while GM had the weakest. Toyota is noted for being an outlier with an “anti-herding” characteristic. An anti-herding trait among investors might indicate that they are separated from the rest of the sector. Ford disseminates information more effectively among market participants. In contrast, information can spread more easily across volatile industries, and search interest keeps pace with fluctuations, so the attention given to the recall could potentially transmit some of the recall’s risk across industries. Interestingly, public investor attention as measured by search intensity and intensity of media discussions around a recall announcement tends to correspond to periods of heightened volatility, whilst its link to the transmission risk across related firms suggests potential benefits for some automobile firms that can swiftly respond to changes brought on by rising scrutiny following a recall. Taken together, we highlight the market and pricing-related impacts of automotive recalls, which, in addition to being actual regulatory events, should also be viewed as financial information events that result in revised investor expectations, price revaluation, and intra- and inter-industry contagion.

Keywords: Automotive Recalls, Supply Chain Contagion, Event Study, Granger Causality, Google Trends, Volatility Spillover.

1. Introduction

If auto safety problems arise, the company might say nothing, issue a mandatory recall, or act on its own to fix the problem. US authorities, such as the National Highway Traffic Safety Administration (NHTSA), can order a recall when a defect poses a safety issue that increases the risk of crashes or injuries, or when a car does not comply with federal safety laws. Some defects could lead to a recall. Some examples include mechanical failures of car parts, electrical system components malfunctioning and overheating, car software bugs, parts supplied by another firm being faulty, or safety rules and standards being violated.

A recall rarely remains isolated to a single vehicle model. Cars contain thousands of parts and are composed of multiple tightly linked mechanical, electronic, and software components. Consequently, a defect may originate from a shared supplier and affect several automakers that use the same component, or it may stem from a design, manufacturing, or software issue specific to a single automaker and spread across many of that firm’s vehicle models (Huang and Radighieri 2022). Both situations are common in the automotive industry. Because supply chains and production ecosystems are highly interconnected, recalls

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can disrupt production, sales, and investor perceptions beyond the initially affected vehicles (Astvansh and Eshghi 2023). Mukherjee et al. (2021) called this phenomenon “hiding in the herd,” describing a situation in which investors may struggle to identify a safer alternative because defects can affect multiple manufacturers simultaneously. As a result, investors may perceive a recall not merely as an individual firm’s misfortune but as an industry-wide concern.

Just-in-time production is prevalent in the automotive industry. Because of this efficient system, minor part issues quickly escalate into larger problems. Initially, an engineering issue can escalate into a larger problem with significant financial and reputational consequences, as Ford and GM have shown recently.

Costs of recalls rarely extend beyond the issuing company. In an integrated industry where interdependence is common, investors will assess and discount firms’ stock prices if they assume the fault will also affect competitors and suppliers because of shared risk (Pupovac et al. 2026). Conversely, companies can also benefit when their competitors are unable to sell cars due to a major fault (Zhou et al. 2019). What drives these reactions, increased or decreased firm valuation, are empirical questions that this study seeks to answer.

The market reaction to an automotive recall may depend not only on the size of the recall but also on the circumstances surrounding the event. A recall case in point is that manufacturers’ voluntary recalls can enhance perceptions by demonstrating management leadership and responsibility to customers (Liu et al. 2017; Eilert et al. 2017). Another scenario is that a recall has already been disclosed, investigated, or is related to prior recalls; therefore, an announcement of another recall will be less salient to investors, as it provides little new information. Besides, the defect’s severity can impose different effects.

More severe defects, including those related to fatalities or injuries, as well as legal and political risks, could have stronger negative effects (Bernon et al. 2018). In short, investors’ and consumers’ responses differ from one recall event to another, depending on management’s response, the information provided, and the severity of the concern.

Next, this study discusses whether firm profitability affects the stock market reaction to automotive recalls. High profitability may be double-edged: on the one hand, recalls dealing a loss on high-profit corporations show investors recall events could ruin a firm’s high earnings trend, reputation, and product quality in the future; on the other hand, it is good to recall if well-financed firms can handle and pay all possible costs. Hence, it is ambiguous; return on assets (ROA) will resolve such questions about the profit trend. This study measures profit trend only through ROA (Govindaraj et al. 2004). ROA tells us a lot about the return on equity (ROE) trend; in other words, if the asset earns high returns, it makes shareholders happy. ROA and shareholders’ equity will not be directly proportional, though the returns on assets, equity, and debt determine ROA. This advantage will ensure accurate results in cross-country analysis by avoiding differences in comparisons between countries with different financing systems.

Furthermore, beyond the basic study of abnormal return estimates, this paper asks additional questions focusing on valuation and contagion, information demand and information spillovers, recall fatigue, and supplier-driven sources of recalls. More specifically: Can major recalls affect a fixed depression in their shareholders’ value? Are competitors negatively affected through contagion or boosted by substituting recalls? Can information search demand account for market volatility and returns? Can movements in the stock of the recalling company be used to give a prediction of broad movements in share trends within the sector? Does the market fade over time in its reaction to the same magnitude as originally to similar news announcements caused by events like these? Once recall fatigue has set in, does the market become more sensitive to the announcements, or does it gradually ignore them? Are shared supplier defects viewed differently from defects produced by a single manufacturer? Finally, do firms with stronger quality and reliability reputations experience stronger negative stock-market reactions because recalls represent a larger violation of consumer and investor expectations and reduce the value of accumulated reputational capital?

Two specific contributions are being made. First, we integrate Google Trends data as a real-time measure of both information demand and investors’ awareness, thereby making them central to the abnormal-return modeling. Second, our methodological combination of standard event study methods with novel quasi-experimental and predictive design components allows us to disentangle causality and predictable outcomes from mere correlation. Since the dataset spans 10 years, the findings will also offer insight into how recall information affects market perception and response over time.

2. Literature Review

This section reviews how recall research has evolved over the last couple of decades beyond cost estimation and examines whether recalls trigger investor responses beyond immediate stock losses.

2.1 Recalls and Market Reactions

Although the costs of a product recall can be severe, recall research now extends far beyond the balance sheet. Instead, much research on this phenomenon now centers on the effects on shareholder beliefs, cross-firm spillover, and supply-chain relationships.

Using recall announcements, Jarrell and Peltzman (1985) investigated their impact on shareholder wealth in the drug and automotive industries. They find that the cumulative abnormal returns (CARs) at announcement dates are statistically significant and negative. They also find that the losses of market value are often many times higher than the actual recall costs of \$77 million.

Even within the automotive sector, Rupp (2004) reported that the penalty for the stock price was harsher when the recalls were caused by safety concerns, when the number of vehicles affected was large, or when the recall was the first or second safety concern to affect the same car model. This pattern suggests that stock market investors view product recalls as an indicator of broader quality problems rather than just individual product failures.

Automobile recalls also spill over into other markets and other companies. Research finds that when a manufacturer recalls automobiles due to defects, its non-recalled competitors suffer negative stock price reactions, as consumers view the companies in the industry similarly in terms of quality, regulation, and industry-wide quality concerns. Liu and Varki (2021) demonstrated that recall by trusted firms tends to decrease their less-trusted competitors' market value rather than increasing their own value through sales substitution. Jovanovic (2021) found nationwide spillovers of -0.15% in abnormal stock returns immediately following auto recall announcements, along with evidence that retailers shift their vehicle purchases away from the recalled automaker and toward nonrecalled brands, especially if those brands are in the same country.

While not all recalls reach a wide audience immediately, once news of a recall spreads to major newspapers and online sources, and then to social media sites, the number of people talking about the event can explode. The increased attention these factors attract can lead consumers to view the product recall more severely and amplify investor reactions.

The downstream suppliers also suffer negative abnormal returns due to their exposure to potential customer recalls, as a defective product from one firm can prompt numerous companies to take drastic action to protect consumer safety. Pupovac et al. (2026) reported that supplier stock prices suffer when news of their original equipment manufacturer (OEM) customers' recall announcements appear. Eilert et al. (2017) found that stock prices punish companies when recall announcements lag the actual recall of defective products, and found that such delays result in companies being penalized more than they would have been had they been upfront.

2.2 Spillover and Contagion in the Supply Chain

Product recalls are often studied in isolation, as if they were distinct events of the individual firm, with the recall of a product resulting in repair, litigation, and bad reputation only for the manufacturer that issues the recall. However, recalls sometimes extend beyond the recalling firm, with indirect spillover effects on related entities. Product-recall announcements serve, at least in certain cases, as information events that reveal a shared weakness within a product category or a supply chain, potentially prompting stakeholders to re-evaluate non-recalled brands. Product-Harm-Crisis literature supports the systemic view and shows that product recalls damage competing products by decreasing their brand equity, as consumers hold the recalling firm liable. Drawing on the perspective of product-harm crises literature, recalls could damage competitor brand equity because consumers hold competitor brands "guilty by association" (Cleeren et al. 2017). Hence, recalls were not simply considered as a firm-specific occurrence. One form of spillover was horizontal, impacting competing firms.

Spillover effects persist throughout much of the current literature. Liu and Varki (2021) found that when recalls occur on high-reliability brands, there are negative spillovers because market observers view the recalled firm as a symbol of industry-wide concerns rather than as a single firm responsible for the mistake. On the other hand, recalls may also provide a distinct competitive advantage for other retailers. Zhou et al. (2019) documented a contrary outcome during the crisis, in which many auto companies (e.g., Ford, Hyundai, Chevrolet) experienced problems with their braking systems and airbags. Premium manufacturers (e. g., Audi) increased sales through advertising campaigns that exploited consumers' newfound distrust of less reliable brands, such as those involved in recalls. Steven et al. (2014) linked recalled quality with offshore suppliers and contract manufacturers. This highlights the industry-wide implications of sourcing products globally. Ni et al. (2014) found that recalls could destroy the financial value of retailers who carry the product, especially in cases of hazardous defects or when the recalling brand also carries the retailer's own brand goods.

Pupovac et al. (2026) extended the discussion to the vertical supply chain. They presented evidence of product-recall contagion, in which suppliers of companies involved in a recall experience a stock price decline when news of their OEMs' recall announcements surfaces. Their results identify a contagion effect, intensified when the OEM accounts for more than 21% of the supplier's revenues and weakened by the supplier's voluntarily disclosed information about their customer relations, potentially reducing information asymmetries. Vertical spillover, according to Li et al. (2026), is the financial losses incurred by supplier firms in the automobile sector (characterized by a high dependence placed by vehicle manufacturers on shared components) from their buyers' recalls of products because they find out that the investors will begin to value the integrity of the network of the buyer. The contagion of automotive recalls is two-way, involving both horizontal and vertical spillovers (firms supplying components). This kind of contagion between firms has important implications, including competitive issues, as rival companies can step in to fill the void. All this goes towards strengthening the case for highlighting in greater detail whether the actual recall event (or series of events) is firm-specific, multi-firm-induced, or indeed driven by suppliers recalling the product. Taking the above into consideration helps provide a much better understanding of the magnitude of the adverse effects of automotive recalls, which reverberate across the stock markets of affected players.

2.3 The Role of Media and Attention

Since media coverage and public attention matter, in a traditional finance view, the reaction to a recall is further determined by media coverage and investor sentiment. Then simple disclosure recalls are news on the internet (social media or Google) that updates investor expectations about future sales, lawsuits, brand, and reputation. In traditional finance, media coverage could tell us how quickly news is incorporated into prices. Tetlock (2007) showed that negative press written in pessimistic language tends to result in a price decrease and higher abnormal trading volume on the current day (Tetlock et al. 2008). Meanwhile, negative words in firm-specific stories are associated with lower future earnings and stock returns. Peress (2014) further indicates that media coverage helps spread information. When there is a strike in the newspaper industry, there will be less volume and return dispersion in the security. Henceforth, traditional media coverage further amplifies market reaction to the recall announcement.

The rise of the digital age accelerated the further diffusion of information. Tirunillai and Tellis (2012) found that user-generated content is associated with stock market performance, with abnormal returns and volumes affected by volatility. When it comes to recalls, the source of this social media activity may matter. Lee et al. (2015) indicated, based on a literature review of communications during recall crises, that. In contrast, firm-generated communication can lessen negative price reactions; user-generated content (e.g., from forums) can magnify them. Extending this, Hsu and Lawrence (2016) found that social media activity during recall crises affects shareholder value, with brand equity moderating the relationship. This could be important to major automaker brands, whose pre-existing strength in brand reputation and public discussion online can heavily determine the extent to which stock prices react.

The spread of news in the digital age has undoubtedly accelerated recalls across different social media sites. Using Granger causality, Xu et al. (2024) inferred that an increase in Twitter sentiment about Tesla's product recalls leads to an indirect spillover effect on Chinese EV manufacturers such as NIO and BYD.

Borrowed from Borah and Tellis (2016) is the notion of a “perverse halo effect,” in which, in certain high-technology markets, consumers doubt entire product categories if a leading brand fails to live up to expectations. Da et al. (2011) pointed towards a direct measure in the use of the Google Search Volume Index as a proxy for the level of timely investor attention.

In the Automotive Industry, where human safety is one of the most important and brand trust is another, all of these channels are important. Recall that those exposed to more news headlines/posts and negative sentiment, or to greater search activity, may exhibit larger negative excess returns when facing recalls.

2.4 Reputation and Industry Leader

Reputation and leadership in the automotive industry shape investors' market reaction to recalls. The recalls themselves comprise not only technical revelations but also bad news regarding quality, reliability, and management. It may be especially true for firms that have established themselves in this regard, as recalls are seen as a violation of stakeholders' expectations. For example, Rhee and Haunschild (2006) described reputation as sometimes being a 'liability' in the U.S. automobile industry, because reputed companies cause product defects and face more severe market reactions, as the unexpectedness to the public of such news is far stronger. It is modeled by Jovanovic (2021), demonstrating that recall signals low product quality or effort, leading the company to lose valuable reputational capital and, in turn, firm value. The recalls would thus reduce investors' expectations of a car manufacturer's sales, pricing, and profitability.

There is a theoretically ambiguous effect identified in the literature (Hsu and Lawrence 2016) about the effect of having or lacking a good brand/corporate reputation: does having a good name stand a firm in good stead, or does it increase its market penalty by having let consumers down? Hsu and Lawrence (2016) highlighted strong brand equity as a valuable asset when recalls occur (especially in the age of social media), as it can mitigate serious damage. While a positive corporate reputation may be a liability for a firm after a recall, product-level reputation may cushion its impact (Majid and Rhee 2018). Hence, reputation can either increase backlash from angry investors who have been led astray by their company's failure or serve as an advantage for firms by fostering loyalty and product goodwill.

The dynamic is especially relevant to the automobile industry, where customers rely on brand trust (Liu and Varki 2021). Recalls by firms with relatively high product reliability generate strong spillover effects (negative) to competing firms on their market value, according to our dataset. That is, if a trusted automobile recall occurs, it indicates more about the information content, and therefore, investors adjust their expectations for the whole industry (Liu and Varki 2021). In addition, firms with leadership will attract more public attention to their automobile recalls. For instance, after Toyota's recall disaster, the company's public estimation plummeted, while the media framing and crisis response played a critical role in the public trust and reputational loss (Da et al. 2011; Fan et al. 2013; Bowen and Zheng 2015; Fang et al. 2024).

Also, recall timings and management interact with reputation aspects. Stock markets penalize recall delays with severity and timing affecting each other, depending on factors such as brand reliability and reputation (Eilert et al. 2017). The greater reputational costs seem to affect leaders and firms more, leading to delayed responses. It remains an empirical question what the role of reputation is; automakers are at least partially shielded by the brand equity they possess. When recalls involve large players at the top of brand reputation, they can incur larger negative abnormal returns, to the extent that quality perceptions associated with large reputable brands are shattered.

2.5 Information Dissemination and Recall Fatigue

The information environment in which recalls occur can affect how investors and consumers respond. Voluntary product recalls show that managers are proactive and responsible, whereas under governmental pressure or mandatory recalls may signal either unwillingness to recall without external pressure or a delay in recalling. However, evidence for their truth is mixed. Rupp and Taylor (2002) found that, in the case of car recalls, the decision to initiate a recall accounts for a substantial part of the actual recall process. Shareholders do not punish government-instigated recalls more severely than voluntary recalls because, according to (Rupp 2001, 2004), shareholders consider the severity of the defects, the size of the recall,

and press coverage, among other factors. While proactive recalls may save value, they may also signal a severe defect (Chen et al. 2009). In the long term, proactive crisis management can mitigate the lasting negative impact of recall volume on automotive firms (Liu et al. 2017).

The timing of the recall, the communication channel, and stakeholders' reactions are other factors that influence it. Quick action immediately after the company discovers the alleged defect will signal that it acts with transparency (Eilert et al., 2017). The time difference in announcing a company's recall relative to other announcements results in stock market penalties. This suggests that investors place particular value on the timing and speed of firm responses. Communication beyond investor relations is needed to restore consumer demand (Reilly and Hoffer 1983). Given consumers' low recall compliance rate, regulators and firms faced considerable challenges in completing corrective actions (Pagiavlas et al. 2022). Consumers' willingness to participate in actual corrective action response on variables such as remedy type, corporate reputation, and the likelihood of the incident (Raithel et al. 2024).

High recall rates can lead to a phenomenon known as "recall fatigue". Seeing constant recall notifications, consumers may become inattentive and repair less, increasing safety and regulatory risks down the line. However, the recall environment across the industry is also a factor of interest to investors. Javadinia et al. (2024) noticed that car manufacturers experience milder declines in stock prices when they announce a recall during periods of high recall intensity. This links to "Recall Clustering": when firms start recalls after their peers, "hiding in the herd," their negligence will be diffused across other announcements, and attention towards the issue will be diluted, as the problem might seem to be across industries instead of firm-specific (Mukherjee et al. 2021).

The decision to initiate recalls, as well as their timing and intensity, may influence market reactions. Firms that voluntarily recall may face milder punishment when the recall is timely. Firms immersed in an intense recall environment may dampen negative returns. This study would view voluntary recall initiation and recall environment intensity as potential moderators of stock market responses to auto recall announcements.

2.6 Knowledge Gap

There remain unanswered questions. While much prior research considers CAR estimates, other research focuses exclusively on regression evidence. Furthermore, little empirical work has taken the next step by examining the effects of both returns and volatilities in a combined design, employing causal tools simultaneously. Lastly, whether constant recall exposure has caused any decline in market sensitivity over time is not known, nor is it known whether supplier-wide defects are treated differently from manufacturer-only defects. Furthermore, little has been done to relate the intensity of Google Trends searches to the causal spillover effects of both legacy automakers and manufacturers in modern, tech-centric sectors. Studies have confirmed the increased prevalence of recalls across society (see Appendix Figure B2), but little has been done to determine whether markets have become more complacent about recalls. Recall fatigue is an explicit theory put to the test through comparison of how the market reacted to the recall events of 2010 in Toyota compared to the minor stock market dip during the recall events of 2014 involving General Motors, when, although the severity of recall events was similarly large, investors reacted much differently between the two cases.

2.7 Hypotheses

Based on the literature, we propose:

- H1. Large-scale recalls result in negative CAR for the recall firm.
- H2. Recall events trigger negative returns in a matched control group of industry peers.
- H3. Higher Google Trends search intensity is associated with increased conditional volatility in the stock of the recalling firm.
- H4. Returns of the recalling firm Granger-cause returns of the peer group in the short run, indicating a lead-lag information transmission.

- H5. The magnitude of negative CAR associated with product recalls diminishes over time as the market becomes desensitized to such events, particularly for firms with a history of recalls.
- H6. Firms with stronger quality and reliability reputations experience stronger negative stock-market reactions following recall announcements because recalls represent a larger violation of consumer and investor expectations and reduce the value of accumulated reputational capital.

2.8 Research Methods

2.8.1 Event-study methodology and abnormal returns

Event studies remain the most common method for measuring the market response to news. The basic idea of an event study is first to estimate a normal market return based on the security's historical performance, then calculate the difference between the actual stock return and the normal return, and finally interpret the average of these differences to assess abnormal stock performance. These papers show that the method works well even in simple applications. MacKinlay (1997) reviews these contributions and summarizes the method. In addition, subsequent studies have investigated areas where the method has practical weaknesses. Papers consider event-induced variance, cross-sectional correlation, clustering, and the non-normal distribution of stock returns. The article by Kothari and Warner (2007) can help readers understand when the method is most effective and when caution is warranted. We still consider it a reasonable way to start when the goal of the analysis is to examine how a stock is valued after a piece of news or other information arrives.

2.8.2 Cross-sectional herding and investor behavior

In economics, herding refers to the situation in which investors buy or sell more than fundamentals alone would imply. There are a variety of reasons: information cascades (Banerjee 1992), reputation (Bikhchandani et al. 2018), and limited rationality. The evidence is stronger for the two former conditions, as he finds that herds strengthen under increasing uncertainty and in the presence of greater prominence of public information. Christie and Huang (1995) propose an interesting test of this idea by examining whether dispersion narrows during extreme moves. Chang et al. (2000) enhanced this by considering cross-sectional absolute dispersion (CSAD), which can account for the variation in dispersion with market returns (i.e., nonlinearity). Subsequently, many such tests are developed for various markets and situations. More recently, evidence suggests that herd behavior may be intensified by ambiguous negative news and uncertainty about firm value (Daniel et al. 1998; Barberis et al. 1998). Product recall provides a situation conducive to such behavior because they typically involve a synchronized reaction that could spill over to affect the entire market. That literature motivates the present use of CSAD tests surrounding recall windows. This paper examines whether CSAD falls over the course of a recall event, implying increased herding activity.

2.8.3 Volatility modeling and asymmetric market responses

Financial returns display volatility that fluctuates over time and tends to come in bursts, justifying the use of conditional heteroskedasticity models in empirical financial research. Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) model, which allows the variance at a particular point in time to be a function of prior shocks, whereas Bollerslev (1986) enhanced the model to introduce the generalized autoregressive conditional heteroskedasticity (GARCH) model, which allows for persistent volatility.

Recalls fit this pattern because they raised questions about potential liabilities, future damage to brand name and public reputation, and future regulatory controls. Hence, we will estimate standard GARCH and asymmetric GJR-GARCH specifications, with the latter allowing negative recall news to affect volatility more than positive news.

We, therefore, estimate results from both standard GARCH models, which allow the conditional variance to vary symmetrically, and asymmetric GJR-GARCH models, which permit negative recall-related shocks to have a different impact on volatility than positive ones.

2.8.4 Causal inference in panel settings and active spillovers

Difference-in-differences, as explained in standard references such as Imbens and Wooldridge (2009), exploits variation in treatment over time to compare a treated group with a control group while accounting for general shocks and time-invariant differences. Research by Goodman-Bacon (2021) and de Chaisemartin et al. (2024) showed that these estimators fail when treatment timing is not simultaneous or when treatment effects are nonconstant across units. Thus, researchers often include additional diagnostics, such as comparing different cohorts, conducting event studies, and using placebo tests.

The selection problem is more complex. Firms are not assigned randomly to the recall pool; they enter the group depending on when the product's safety flaw is discovered, when the firm decides to report it, or when regulators act. Treated firms may be different from untreated firms before the event. A good comparison group should resemble treated firms with respect to observed characteristics that existed before the recall announcement.

Propensity-score matching is designed to address that issue. The method estimates the likelihood that a given firm is treated and pairs each treated firm with a control firm whose estimated probability of being treated is close to that of the treated firm. The probability of being treated is estimated via logistic regression, incorporating firm-level variables from before the event: recent stock returns, volatility, and other related features. Using a single probability score is more convenient than making many exact matches across many variables at once.

$$p(X_i) \equiv P(D_i = 1|X_i) \quad (1)$$

Here, T_i is the treatment indicator (whether firm i belongs to the group subjected to a recall), while X_i represents a set of observable pre-treatment characteristics for the firm i . This equation is estimated using logit or probit regression models. The model's scores can then be used to approximate the outcome for a treated firm if it has not been recalled.

$$\widehat{ATT} = \frac{1}{N_T} \sum_{i \in \{D=1\}} (Y_i - \hat{E}[Y_j(0)|i \text{ is matched to } j]) \quad (2)$$

In Equation (2), ATT is estimated by comparing the treated firm i to the matched control firm. To ensure that treated firms are only paired with controls that are similar in their predicted treatment likelihoods, we use nearest-neighbor matching within a caliper. This caliper restricts how different the logit-transformed propensity scores of a treated firm and its match can be. Matching is done without replacement.

Estimates of a direct treatment effect may not tell the full story, as news of the recall might affect firms connected to the recalling firm, such as those in its supply chain or customer base. To analyze this information transmission, we turn to Granger-causality tests. Granger causality tests whether past values of one series can help forecast another (Granger 1969). Granger causality is not a test of structural causality but still serves to measure the extent of predictability in cross-sectional market behavior. Researchers often use Granger tests to examine volatility transmissions and the dissemination of news (Diebold and Yilmaz 2009). In a product recall, a ticker-level analysis allows us to examine price-movement contagion from a recalled firm's stock prices to other firms' prices over short horizons. For example, stock price declines at a recalled manufacturer might spread to stock prices of suppliers, customers, or even competitors in related product categories. We use difference in differences (DiD) design and Granger tests together to distinguish two questions that past research has sometimes confused. The first is what the recall did to treated firms compared to the counterfactual scenario they faced without a recall. At the same time, the question is whether the event and subsequent market response can serve as a trigger for more general information transmission.

3. Data

We use the daily returns of the firms being recalled, namely Ford and General Motors, along with their industry peer Toyota and a set of industry controls, plus SPY as our market-return proxy. We use the adjusted closing prices and the trading volume to calculate daily simple returns and align the trading days. To measure public attention for each event, we use Google Trends search volume. ROA of Ford, General Motors, and Toyota is extracted from the SEC for the companies.

In our analysis, we consider three large automobile recalls, each involving a different automaker; two of the recalls (Ford and GM) appear to cross different firms and suppliers. Among 81 manufacturers recorded by the NHTSA (ref) between January 1966 and May 2026, General Motors had the highest total (1,715), followed by Ford (1,709) and Toyota (338). For details on other manufacturers, see Tables B1 and B2 in the Appendix.

The January 2005 Ford recall concerned a faulty cruise control deactivation switch installed in millions of Ford and Lincoln models from the 1990s and early 2000s. Because the switch was always powered on, the brake master cylinder was at risk of overheating, potentially leading to an engine fire. Later, the 2010 Toyota recall raised concerns about unintended acceleration in millions of vehicles worldwide due to a specific physical defect: a poorly secured floor mat that trapped a faulty accelerator pedal, causing the car to surge forward. Combined with the reported deaths of drivers, coupled with the widespread media attention, the crisis led to severe stock price depreciation and brand damage for Toyota. Finally, in February 2014, General Motors announced its recall of millions of small cars, including Chevrolet Cobalt and Saturn Ions, because of faulty ignition switches that tended to slip out of position while in motion while disabling the engine, power steering, power brakes, airbags, and internal electronic systems unexpectedly and potentially lethally.

To specify the event date for each recall, we use the day that Google Trends shows the greatest peak in search volume for that recall episode. As an increasing number of researchers use search volume to capture investor attention (Ayala et al. 2024; Chen and Lo 2019; Aouadi et al. 2013; Chen 2017), our work extends this line of research. Google Trends data have been shown to capture effective information demand, especially because public awareness may arise at times different from official disclosures by regulatory agencies or manufacturers. Furthermore, the intensity of search activity is useful in the auto industry because it may distinguish the technical discovery of a fault (the origin of the recall) from the widespread recognition of the associated safety issue; these are often two different dates. Google searches are, therefore, likely to contain rich views on recall events, early information diffusion, the stickiness of attention to recall events, variations in investors' attention across different stock markets, and perceptions of retail investors.

4. Methodology

Figure 1 illustrates the pipeline overview (data preparation → parallel analyses → robustness).

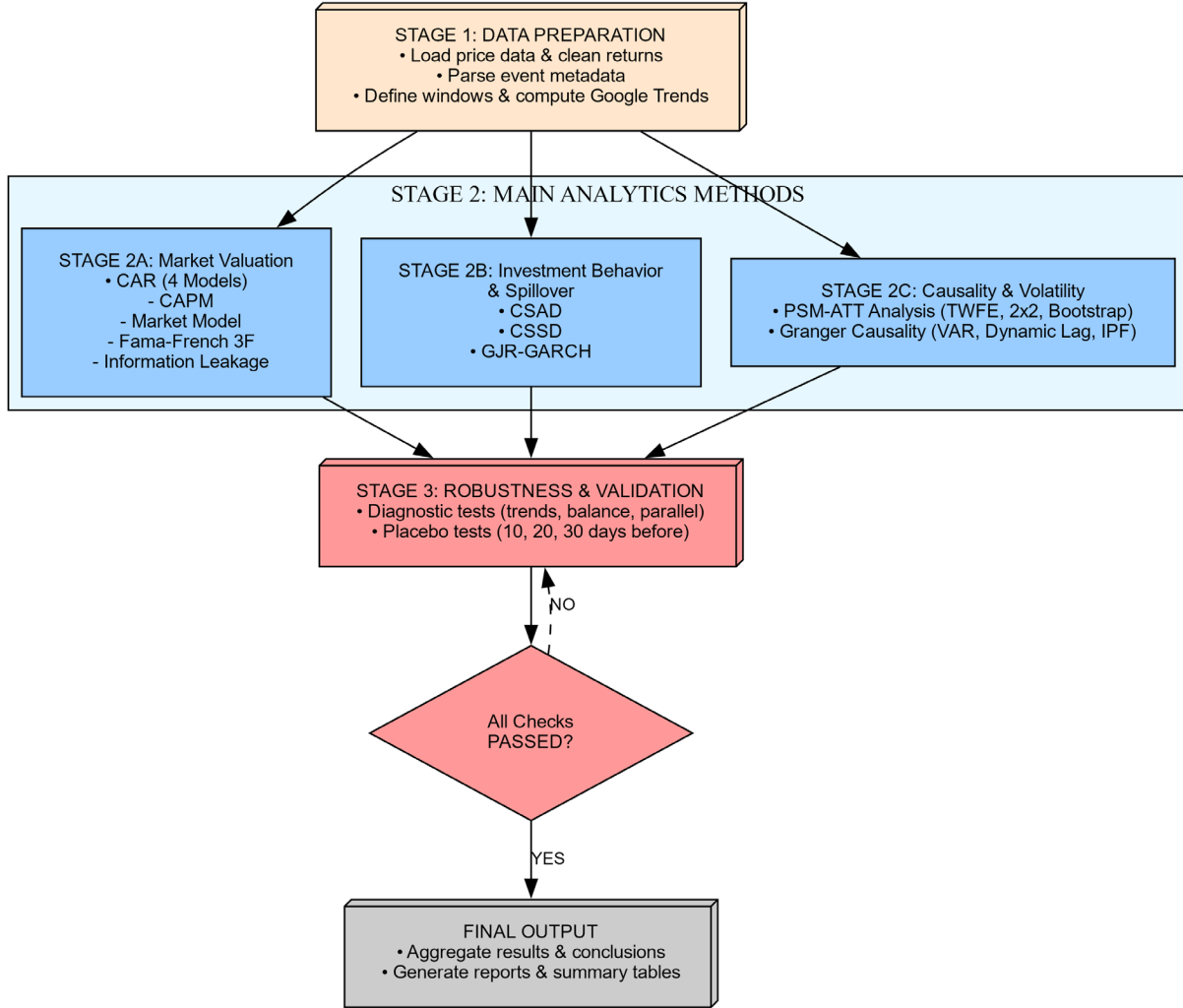


Figure 1: Pipeline flowchart.

4.1 CAR Models for Event-study

We test four event-study return models to isolate the effect of recall events on stock returns. We include the capital asset pricing model (CAPM), the market model (MM), and the Fama-French three-factor model (FFTF) in periods when factor data are available, and we augment the latter with Google Trends search intensity. Each model assumes the same event window definition but employs a distinct approach to estimating the asset's expected return over that window.

Here, abnormal return (AR) is the gap between the realized return and the model-based expected return on a given day. CAR then sums those daily gaps across the event window so the total effect can be read as a single figure.

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \quad (3)$$

In the baseline event-study setup, the expected return is derived from a market regression estimated over the estimation window. CAR is then formed by summing the daily abnormal returns over the event window $[T1, T2]$.

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{i,t} \quad (4)$$

Statistical significance is assessed with t-statistics based on residual variation in the estimation period. Using multiple return models reduces the likelihood that a single benchmark alone drives the result.

In the market model, a stock's return is split into a market-related component and a firm-specific residual. That residual is where recall news or other company-level information is most likely to appear.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \quad (5)$$

In the market-model specification, the expected return is expressed as a constant plus the market component. The constant α_i captures the asset's average return that is not explained by market movement, the slope coefficient β_i measures sensitivity to market returns, and the error term $\varepsilon_{i,t}$ absorbs the idiosyncratic return in period t .

CAPM provides a narrower benchmark for expected return. In that setting, an asset is expected to earn the risk-free rate plus compensation for systematic risk, and the event-study version is written in excess returns.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \quad (6)$$

In Equation (6), the excess-return relation is written in standard CAPM form. The market risk premium ($R_{m,t} - R_{f,t}$) measures exposure to the broad market, and the error term $\varepsilon_{i,t}$ captures the return component not explained by that exposure. For a correctly priced asset, the average abnormal component should be close to zero.

The Fama-French three-factor model extends CAPM by adding size and value effects. Because it absorbs more common variation, it provides a stricter benchmark for judging whether recall-period returns are unusual.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \varepsilon_{i,t} \quad (7)$$

In Equation (7), the excess return can be explained by market fluctuations ($R_{m,t} - R_{f,t}$), the size premium SMB_t , and the value premium HML_t . The loadings indicate whether firms respond to fluctuations in the market and other premiums. The three-factor structure shows the rest.

There may be some unusual search activity, not accounted for in normal risk factors through any unusual search activity proxy, shown as search intensity ($Trend_t$), from Google Trends, which explains this return.

$$R_{i,t} = \alpha + \beta R_{m,t} + \gamma Trend_t + \varepsilon_t \quad (8)$$

Equation (8) shows how Google search trends could modify the actual return equation if they attract sufficient investor attention. The Google Trends model (Equation 8) incorporates a direct investor attention measure into the expected-return equation. This allows us to determine whether unusual search activity, proxied by search intensity ($Trend_t$), explains part of the abnormal price response not captured by standard market risk factors.

The coefficient $\hat{\beta}$ measures exposure to market-wide movements but is also sensitive to investors' attention. Once these influences have been removed, there remains a component of the return that accounts for the abnormal part.

$$E[R_{i,t}] = \hat{\alpha} + \hat{\beta}R_{m,t} + \hat{\gamma}Trend_t \quad (9)$$

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \quad (10)$$

To construct an attention measurement, keyword searches from the period are collected; each search is scaled to a new value ranging from 0 to 100 following Google's style, and these are added together to form an attention measurement. When Google Trends appears to have a strong relationship with search demand and stock returns, as evidenced by a positive coefficient, for every change in Google Trends demand, abnormal search volume and, in turn, return volatility can be observed. This shows the media's attention and the extent to which other investors will overreact similarly.

4.2 CSAD and CSSD Cross-sectional Analysis

To study investor behavior, we compute both the cross-sectional standard deviation (CSSD) and the cross-sectional absolute dispersion (CSAD) for the industry. The question of whether returns exhibit an exceptional coincidence is examined when recalls occur.

Christie and Huang (1995) proposed CSSD, which sums the distance of each return from the mean across each cross-section. The equation for this calculation is:

$$CSSD_t^2 = \frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N-1} \quad (11)$$

Logically, the disparity should widen if market conditions change because firms may differ in their betas. If investors move together closely, such dispersion can decline or be tighter around the benchmark. Indicators are developed for scenarios of extreme markets that Christie and Huang try to address.

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \quad (12)$$

If a negative coefficient were statistically significant in Equation (12), it would indicate that investors are strongly aligned in their investment views based on the market signals they receive. Therefore, lower CSSDs indicate less dispersion in stock returns and higher correlation or covariance among them, given similar investor reactions.

CSAD (Chang, Cheng, and Khorana, 2000) serves similar functions, less in terms of restricted type, only at the extreme levels of dispersion in returns, but more in general application, which enables it to track average deviation in market prices from 0 (or no change in prices over time). When returns of shares move with much tighter correlation between similar shares of recalling or linked firms than their dispersion (or deviation) with the prices of respective stocks, it could imply that the relations that exist between the dispersion of returns on either market movement or the price movement of respective stocks that follow it might be flattened:

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 R_{m,t}^2 \quad (13)$$

With closer investor action, volatility will decrease when returns are correlated. Conversely, greater volatility means more diverse asset returns.

As behavior could move contrarily for the market up or down, we also consider the effects caused by market direction.

$$CSAD_t^U = \alpha + \gamma_1^U |R_{m,t}^U| + \gamma_2^U (R_{m,t}^U)^2 + \varepsilon_t \quad (14)$$

$$CSAD_t^D = \alpha + \gamma_1^D |R_{m,t}^D| + \gamma_2^D (R_{m,t}^D)^2 + \varepsilon_t \quad (15)$$

We then add an interaction term to test differences across market states directly.

$$CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 \quad (16)$$

As an extension of this specification, negative and statistically significant parameters imply strong herding.

4.3 GARCH/GJR-GARCH for Volatility Modeling

GARCH(1,1) and GJR-GARCH models are used to estimate volatility. We seek to answer whether the GARCH and GJR-GARCH models predict similar responses to abnormal shocks and if there is a difference regardless of whether normal or GJR-GARCH is used, thereby determining what exactly drives investor behavior while comparing each model's predictions of the different reactions.

A standard GARCH model treats positive and negative shocks symmetrically. In contrast, a GJR-GARCH model does not, as positive and negative shocks have asymmetric effects on volatility under its restriction that adds indicators for bad news.

$$\sigma_t^2 = \omega + \alpha_1 * \varepsilon_{t-1}^2 + \dots + \alpha_p * \varepsilon_{t-p}^2 + \gamma_1 * I_{t-1} * \varepsilon_{t-1}^2 + \dots + \gamma_o * I_{t-o} * \varepsilon_{t-o}^2 + \beta_1 * \sigma_{t-1}^2 + \dots + \beta_q * \sigma_{t-q}^2 \quad (17)$$

The equation describes conditional variance as a function of a constant, lagged squared residuals ε_t^2 , lagged variance σ_t^2 , and the asymmetric shock term $\gamma_j I_{t-j} \varepsilon_{t-j}^2$. In Equation (17), negative news causes larger volatility reactions. The conditional variance is a function of the variables above and is significant, explaining the relationship between negative shocks via an asymmetrical coefficient γ_j .

Equation (18) states that the conventional $p = 1$, $o = 1$, and $q = 1$ in their numerical model's implementation phase: in other words, which of the volatility models from the other market will predict stock price movements better for the two models, each of which will have one or more variables and more than one variable related:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^o \gamma_j I_{t-j} \varepsilon_{t-j}^2 + \sum_{k=1}^q \beta_k \sigma_{t-k}^2 \quad (18)$$

with parameters using $p=1$, $o=1$, and $q=1$.

GARCH estimates are obtained by comparing and changing according to probability errors over models that assume 4 methods (normal and the students, including the asymmetrical students, as well as generalized normal ones and log-likelihood values, which vary according to which model among them fits better while providing a detailed analysis), since any of the 4 methods from two estimations may change (both GARCH and GJR-GARCH models), it can affect GARCH and, thus, affect the outcome that GARCH was based upon. GJR-GARCH is, therefore, the more stable of the two.

4.4 DiD-TWFE and PSM-ATT for Causal Inference

For the causal inference method with a comparison group, two models will be used: two-way fixed effects (TWFE) and propensity score matching- average treatment effect on the treated (PSM-ATT). However, its interpretation would depend on some of the TWFE assumptions: TWFE absorbs differences from unit-specific factors and changes from common factor effects over time, such as general trends. These results will not hold, though: they are sensitive and might require event study plots, covariate balance analysis, or placebo exercises, which means DiD would also require robustness checks, such as testing for parallelism in the trend assumption for its validity.

$$y_{it} = \alpha_i + \lambda_t + \sum_{k=-K}^L \tau_k \cdot \mathbb{1}(t - t_i^* = k) + \epsilon_{it} \quad (19)$$

where y_{it} refers to the outcome variable for the unit i at time t ; α_i is the unit-specific fixed effects, which captures time-invariant heterogeneity: a recall has an impact that spans across the time period for each of the units, so the effect of the recall is absorbed. λ_t are the time-specific fixed effects and capture common time shocks, meaning there will be similar movement together, and thus absorb the effect attributable to shifts in the overall macroeconomic outlook. τ is the coefficient that we want for the average treatment. ϵ_{it} is the error or some form of volatility.

If the treatment given appears correct for placebo periods when a recall occurs on each period, along with each, such errors can also be seen arising after placebo periods show up too; hence, this implies that if there is a placebo test, in addition to this analysis or event-study plot, an attempt is made to establish if all conditions given above have symmetry to provide some evidence.

$$SMD_j = \frac{\bar{x}_{1,0}^{(j)} - \bar{x}_{0,0}^{(j)}}{\sqrt{(s_{1,0}^{2(j)} + s_{0,0}^{2(j)})/2}} \quad (20)$$

Where: $\bar{x}_{g,0}^{(j)}$ is the mean of the covariate j for group g in the pre-period; $s_{g,0}^{2(j)}$ is the variance of the covariate j for the group g in the pre-period.

Standard asymptotic inference has a disadvantage in a few clusters because of its limitations. When such cases occur, to improve reliability, it is imperative to use techniques such as the wild cluster bootstrap alongside the regression model. Hence, the uncertainty is smaller when it is estimated. Such a model must contain a balanced group. First, for the logistic assignment recall, the treatment and the nearest untreated firm for each treated firm are paired as nearest neighbors using the caliper rule. Based on the calibrated score, firms that are far from the propensity score cutoff would be excluded to ensure only close pairs remain.

$$P(D_i = 1 | X_i) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_k X_{ik})}} \quad (21)$$

The score in question is produced from the standardization of the pre-recall variables, which are the lagged returns $R_{i,t-1}$ and $R_{i,t-2}$ (1-day and 2-day lags), a short rolling mean $MA_{i,t,3}$, and a short rolling standard deviation $\sigma_{i,t,5}$ (5-day rolling standard deviation of returns). Standardization ensures equal impact of the variables within the match.

The accepted control is the one with the smallest admissible distance in the score space, and matching is done without replacement so that the same control firm is not reused.

ATT is then estimated by comparing post-event outcomes for treated firms with those of their matched controls. In this application, it represents the average return effect for firms that actually experienced recalls.

$$\widehat{ATT} = \frac{1}{N_m} \sum_{i \in \text{Matched Treatment}} Y_{i,\text{post}} - \frac{1}{N_m} \sum_{j \in \text{Matched Control}} Y_{j,\text{post}} \quad (22)$$

We evaluate that estimate with both a standard two-sample t-test and a bootstrap based on 1,000 resamples. The bootstrap produces an empirical distribution for ATT, from which the standard error and confidence interval are obtained.

4.5 The Ticker-by-Ticker Granger Causality Analysis

To study predictive transmission under H4, we estimate bivariate vector autoregression (VAR) systems linking the treatment portfolio to the control portfolio and then run ticker-level Granger-causality tests over lags 1-6.

The VAR sample combines 60 trading days before the event with 60 days after it. Because the Takata event involves several manufacturers, we report both ticker-specific evidence and an aggregated summary. For GM, lag selection is based on the most informative p-value among the candidate lags.

To test for information spillovers between the treatment and control portfolios, a bivariate VAR model of order is estimated:

$$\begin{aligned} R_t^{\text{treat}} &= \alpha_1 + \sum_{i=1}^p \beta_{1,i} R_{t-i}^{\text{treat}} + \sum_{i=1}^p \gamma_{1,i} R_{t-i}^{\text{control}} + \epsilon_{1,t}, \\ R_t^{\text{control}} &= \alpha_2 + \sum_{i=1}^p \beta_{2,i} R_{t-i}^{\text{treat}} + \sum_{i=1}^p \gamma_{2,i} R_{t-i}^{\text{control}} + \epsilon_{2,t} \end{aligned} \quad (23)$$

The Granger test asks whether lagged values of one return series improve forecasts of the other. We complement those tests with impulse-response functions, allowing the time profile of a shock to be traced directly. The model order is chosen using standard information criteria.

4.6 Rolling Correlation Analysis: Trading Volume vs. Google Trends

To determine whether transaction volume shows trends similar to those in Google Trends, we measure both. We use a 20-day window because it makes analysis easier without forcing correlations across the entire sample period, which would make the results variable.

$$r_k = \frac{\sum_{t=k}^{k+w-1} (V_t - \bar{V}_k)(I_t - \bar{I}_k)}{\sqrt{\sum_{t=k}^{k+w-1} (V_t - \bar{V}_k)^2 \sum_{t=k}^{k+w-1} (I_t - \bar{I}_k)^2}} \quad (24)$$

where $\bar{V}_k$ and $\bar{I}_k$ are the mean in their respective intervals of time.

After estimating a local correlation for each window, we can determine the proportion of windows with significant correlations before checking whether the local estimate is indeed not zero. This greater proportion implies there were more significant linkages to attention during rolling periods.

4.7 Market Reaction, Profitability, and Reputation

We can formulate, from the data, two types of models to investigate how firm profitability (H6) and its reputation affect the market's reaction to recall (H7). ROA is the ratio used to measure profitability; $ROATrend_i$ represents the trend in the firm's ROA, which is the difference between the current and previous ROA. Since this will be used for only three recalling firms in the current study (Ford, Toyota, and GM), the models illustrate events based on case scenarios to show how they are affected or how the firms can be managed. The value should be close to 0 to justify the absence of a difference between the treatment and control groups. The dependent variable, $ReactionMagnitude_i$, is defined as the negative event-day CAR. The primary OLS formulation is:

$$ReactionMagnitude_i = \beta_0 + \beta_1 ROATrend_i + \epsilon_i$$

To test whether firms with stronger quality and reliability reputations experience steeper valuation drops (H7), we proxy accumulated reputational capital using historical recall intensity. We track the total long-run recall burden ($TotalRecalls_i$) from 1966 to 2026. A firm with fewer historical recalls is considered to have stronger reputational capital. We model the CAR as a function of total recalls:

$$CAR_i = \alpha + \beta \times TotalRecalls_i + \epsilon_i$$

A positive β implies that firms with higher accumulated recalls experience *less* negative stock reactions, consistent with the hypothesis that a strong reputation is violated more sharply by bad news. As a secondary check, we isolate immediate recall intensity using the recall count during the event year ($EventYearRecalls_i$):

$$CAR_i = \gamma + \delta \times EventYearRecalls_i + u_i$$

5. Results

We organize our empirical findings into four main groups: valuation, volatility and attention, spillovers, and cross-sectional behavior. In particular, it is striking that events in the initial recall period elicited much stronger reactions than those in the 2014 events, when the market reaction was either weak or system-wide.

5.1 Valuation Effects

To address these hypotheses, we compare the abnormal announcement-date returns across the same four asset-pricing models used in H1 and H2. Using several alternative benchmarks is intended to isolate the market valuation effects of product recalls from broader market trends or changes in investor attention. As shown in Table 1, we observe distinct negative abnormal returns in the stock valuations of Ford and Toyota. The abnormal returns on the event dates are much smaller, and in some cases even positive, for GM and Takata. This difference could mean that recall risk valuations change over time and that the type of event might matter more for its valuation impact.

Table 1a: Consolidated CAR Results – Event: Ford Recall

Model	Day 0 AR	Mean AR	T-stat	p-value	Final CAR
CAPM	-0.29%	-0.40%	-2.021	0.048*	-12.38%
Market Model	-0.22%	-0.33%	-1.649	0.105	-10.10%
Fama-French 3F	-0.26%	-0.37%	-1.886	0.065	-11.55%
Google Trends	2.76%	-0.08%	-0.421	0.675	-2.47%

Table 1b: Consolidated CAR Results – Event: Toyota Recall

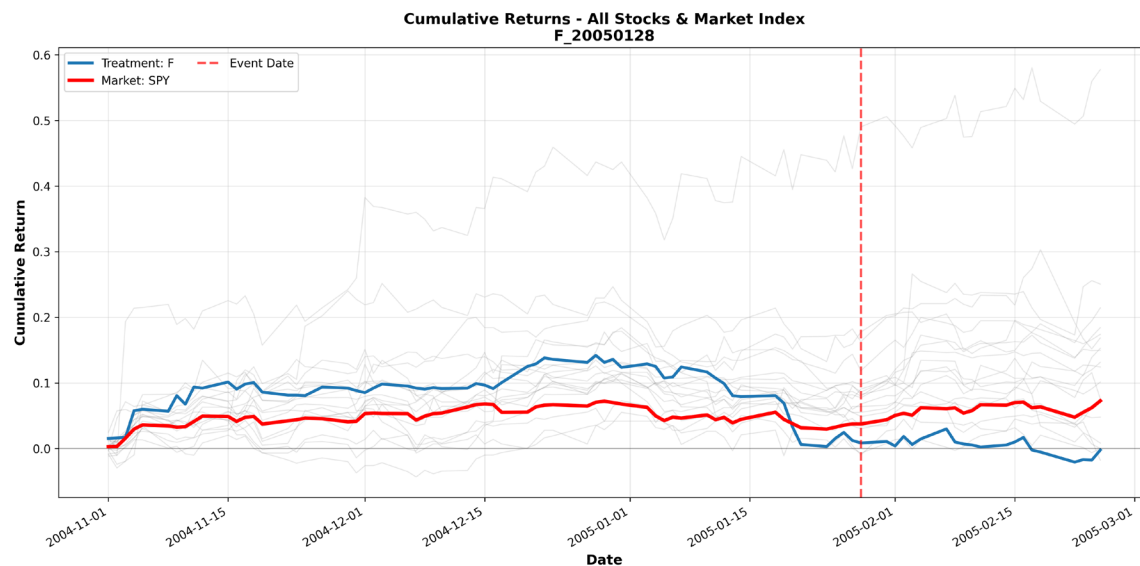
Model	Day 0 AR	Mean AR	T-stat	p-value	Final CAR
CAPM	-8.13%	-0.42%	-1.538	0.130	-12.90%
Market Model	-8.27%	-0.55%	-2.028	0.047*	-17.01%
Fama-French 3F	-8.18%	-0.46%	-1.717	0.092	-14.40%
Google Trends	-3.04%	0.14%	0.517	0.607	4.32%

Table 1c: Consolidated CAR Results – Event: GM Recall

Model	Day 0 AR	Mean AR	T-stat	p-value	Final CAR
CAPM	1.01%	-0.35%	-1.395	0.169	-10.59%
Market Model	0.98%	-0.38%	-1.498	0.140	-11.37%
Fama-French 3F	1.00%	-0.36%	-1.433	0.158	-10.87%
Google Trends	0.98%	-0.34%	-1.351	0.183	-10.25%

Notes. * Indicates significance at $p < 0.05$. Daily 0 AR represents the announcement period, when market pricing responds to the initial disclosure of news. Mean AR is the abnormal return relative to Day 0, whereas T -statistics are computed from the abnormal returns of firms in each recall group. Final CAR refers to the cumulative abnormal return 1 year after the event. The equation is detailed in Appendix C below.

Considering the CAPM as a benchmark, Ford recall shows an average abnormal return that is statistically significant, but its CAR is 12.38% on Day 4 after the recall announcement. Considering the inclusion of Google Trends, however, the trend-based abnormal returns were positive at +2.76%, and the total number of cars shrank slightly to -2.47%. Considering the combined results, the Ford share price is expected to drop in the short term. Still, given the small magnitude of the decline as reflected in Google Trends and its impact on investors' attention (as seen in the trend itself), the market is considered to have overreacted to the news of the Ford recall.

**Figure 2:** Cumulative returns around Ford recall.

In Figure 2, the blue Ford line begins to differ from the red market line immediately after the event marker and slopes downward sharply thereafter. This long-term decline signifies a true shareholder value loss where investors evaluate the long-run cost of the problem at face value. This provides evidence to support H1. The blue lines for the competitors continue to drift downward and lag the market. This pattern is evidence of contagion, in which news of Ford's recall leads market participants to believe the problem is widespread across the automotive industry, thereby supporting H2. The bottom-right panel of Figure 3 shows that the CAPM, market model, and Fama-French model specifications move in a similar manner. They begin to decline slightly before $t = -8$ and, throughout the event window, decrease further, cumulatively accounting for a shareholder loss of 10% to 12%. This pattern provides support for H1. The Google Trends model diverges from the others in this figure. Investors' attention wandered, reducing some of the measured valuation losses shown by the other measures.

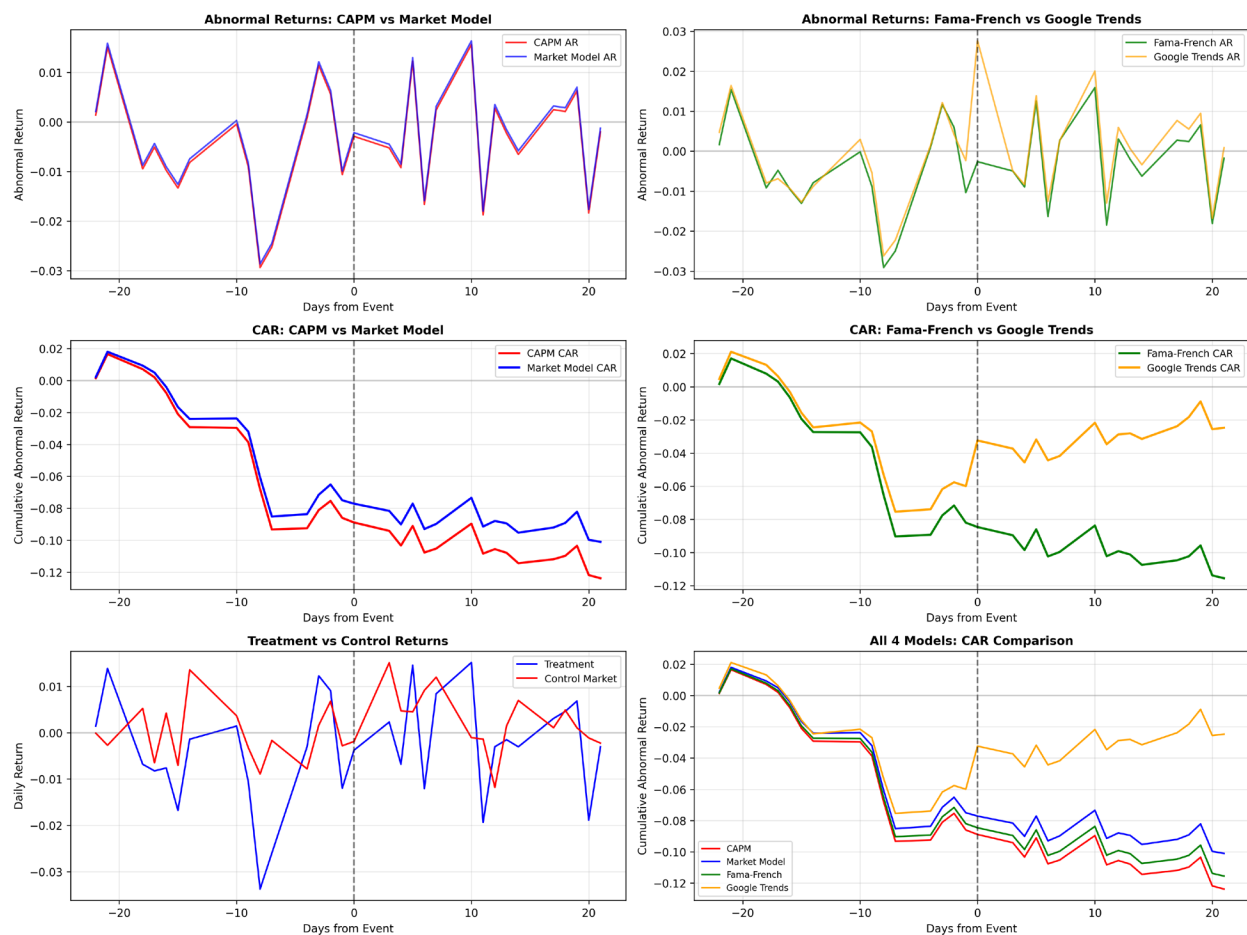


Figure 3: Multi-model CAR comparison for Ford recall. Note: Regarding media noise and Google Trends data, the divergence is clearest in the sample and would have a strong impact.

For Toyota's 2010 recall, Market Model: Day 0 = -8.27% and Final CAR = -17.01%. The Fama-French model remains negative, though it is statistically less significant. Toyota has incurred losses due to changes in risk factors, but most remain specific to Toyota. As the bottom-left and bottom-right panels indicate, the two models also diverged on Google Trends after Day 0, with a notable drop in the media noise. Toyota's treatment line declines, while the market line and competitor lines continue to rise. This divergence between the market and competitors in the bottom-right section strongly supports H1, as competitors are not falling alongside Toyota. The top-left panel of Figure 5 shows about an 8% loss for Toyota on Day 0, after their

earlier trended gains. As depicted in the top-right and bottom-left panels, the standard models suggest about -17% abnormal returns for Toyota, while the Google Trends model suggests a return to positive territory (+4.32%). This implies that attention and valuation do not move in lockstep in the wake of a scandal.

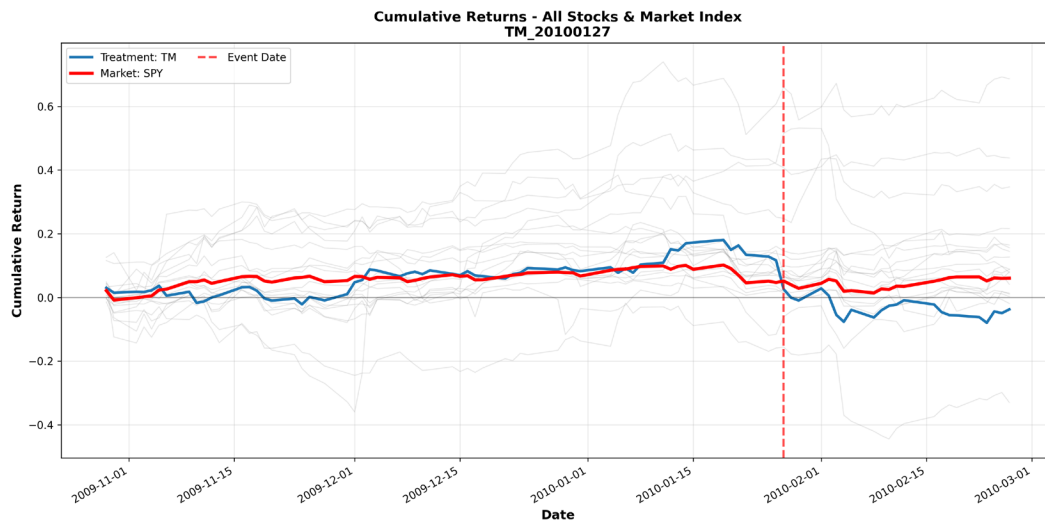


Figure 4: Cumulative returns around Toyota recall.

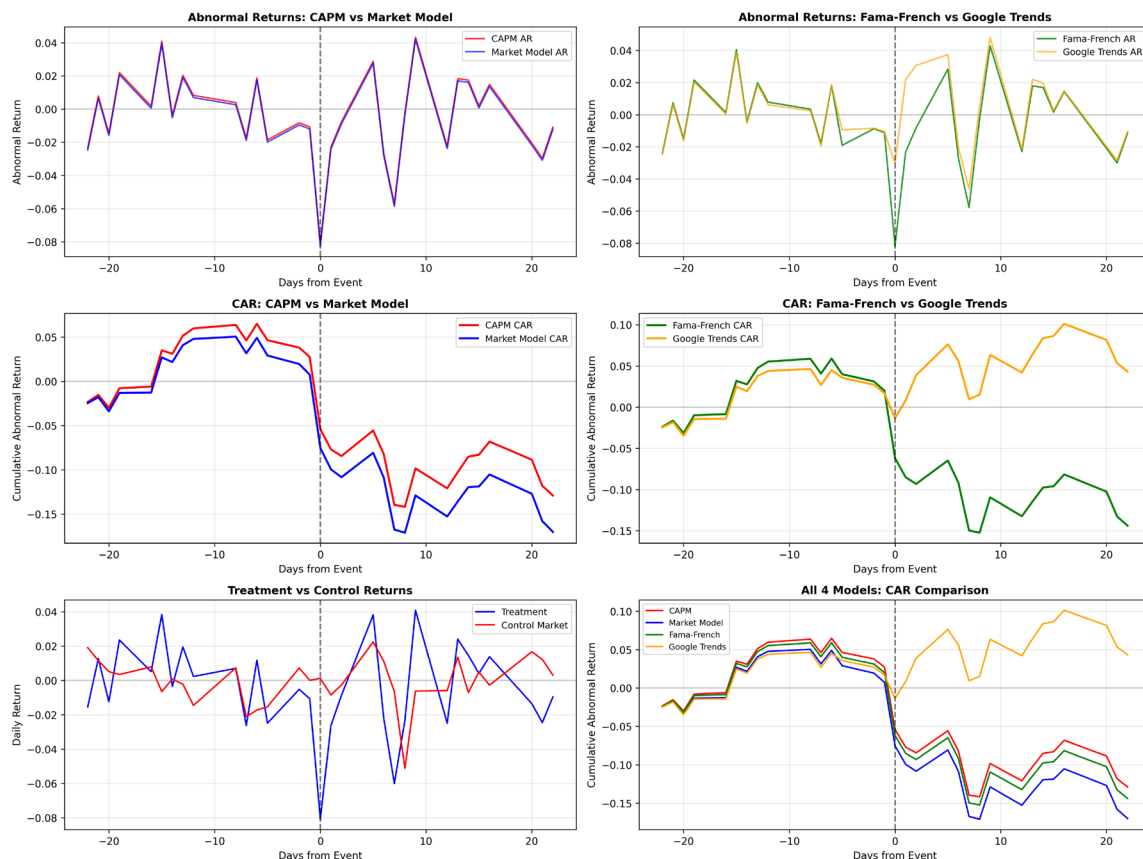


Figure 5: Multi-model CAR comparison for Toyota recall. Note: The market model shows the most pronounced negative trend, confirming the crisis's idiosyncratic severity.

The 2014 recall due to faulty ignitions had no statistically significant impact across the four GM car models affected. They stayed close to the 2014 CAR average for 2010-2014. The variance of their CAR scores is so high that the CARs remain inconclusive. Furthermore, the muted market reaction to the 2014 GM recall, compared with the earlier Ford and Toyota events, supports the presence of recall fatigue (H5), suggesting that markets may have become desensitized to major auto recalls over time.

Figure 6 shows that the GM treatment line tracks the market line through the post-event window. GM reduced uncertainty in this way or had already partially priced in most of the risk. However, the market still reacts in a way that does not support H1 or H2. In 2014, investors still seemed tolerant of GM's recalls.

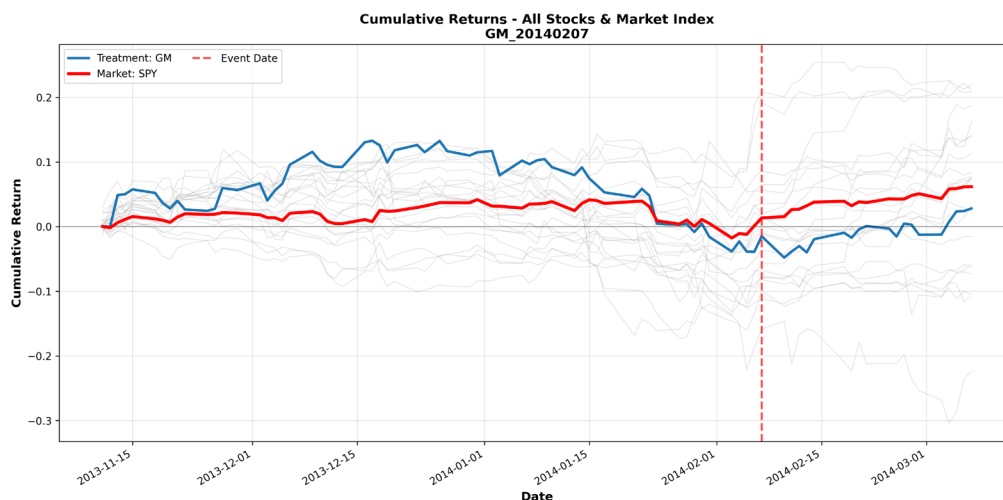


Figure 6: Cumulative returns around GM recall.

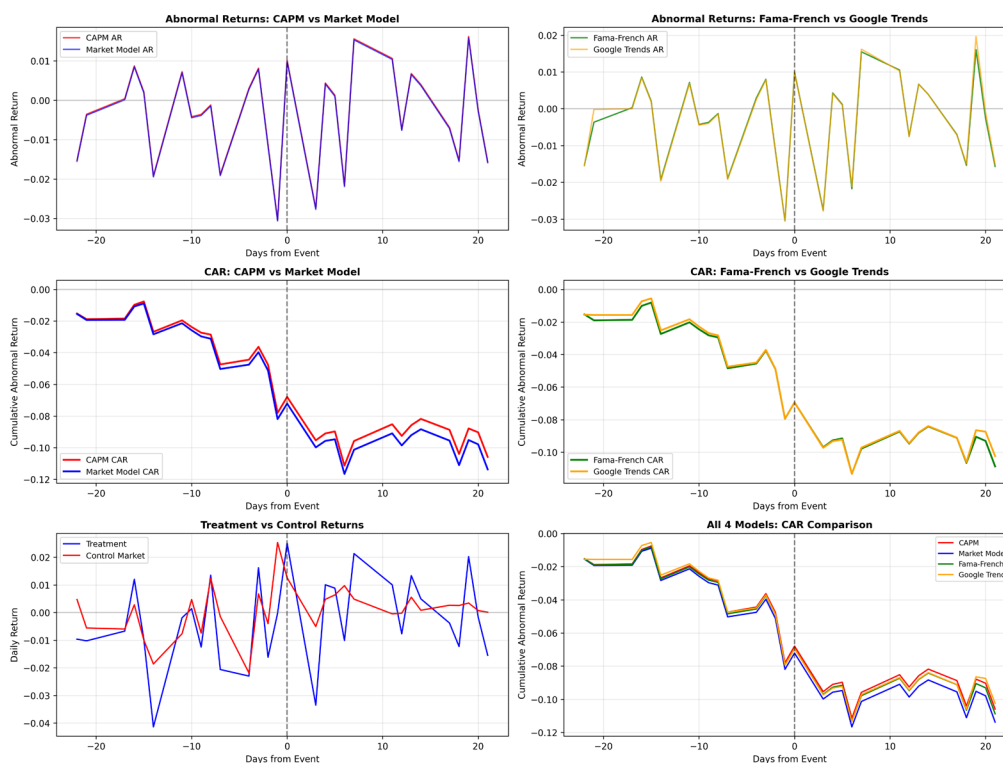


Figure 7: Multi-model CAR comparison for GM recall. Note: All four models show a consistent but statistically insignificant downward trend.

The market reacts much more severely here than earlier in the study (2010 and 2012). GM shows volatile behavior, with a big increase in CAR on Day 0, partially supported by the risk having been incorporated into prices before the recall was announced. The cumulative paths look a little different for GM cars. The CAPM prediction ends with a potential loss of about 8%, and the augmented Google Trends model ends at +1%. Because the models have not reached a negative conclusion, this pattern supports H5 a bit more than H1.

We employ two difference-in-differences methods with two-way fixed effects and propensity score matching to examine the evidence for the hypotheses.

DiD-TWFE compares the recalled firm with a broad industry control group, whereas PSM-ATT constructs a matched control group from peers with similar pre-event returns, volatility, and momentum.

Table 2: Comparative causal inference results (DiD-TWFE vs. PSM-ATT).

Event	DiD-TWFE	DiD-TWFE p-value	PSM-ATT	PSM-ATT p-value
Ford (2005)	-7.75E-04	0.806	-3.10E-03	< 0.001***
Toyota (2010)	-2.73E-03	0.591	-2.16E-03	0.0094**
GM (2014)	2.70E-04	0.946	-1.61E-03	0.0305*

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 2 reports the two sets of causal estimates side by side. The differences between them show how strongly the choice of counterfactuals can shape the inference.

This discrepancy might have resulted from global turbulence affecting the sector as a whole during the crisis. For the PSM-ATT, we find a negative, statistically significant coefficient, which appears to support H1. Furthermore, based on matched data, Toyota appears to have lost more value than the most similar non-Toyota firms in our control group. In contrast to Toyota, the DiD-TWFE value is close to zero for GM, whereas the PSM-ATT coefficient remains negative and significant. Comparing matched firms with similar returns suggests the market penalized GM as well, though apparently not as much as it did Toyota. Broad sector analyses might not capture this drop due to the sector's overall turmoil, yet matched data suggest a governance-related cost for GM.

5.2 Volatility and Public Attention

Table 3 presents the results from testing H3 and examines how volatility influences public interest, as measured by Google Trends. We used GARCH(1,1) models to recover the conditional volatility parameter, and Google Trends search volumes as a measure of investor interest, quantified as the Search Volume Index (SVI). Note that even if valuation gains are only temporary, their impacts on risk and public attention were substantial and persistent and not explained by other variables.

Table 3: Volatility and attention metrics.

Event	GARCH α (Shock)	GARCH β (Persistence)	Volatility ($\alpha + \beta$)	Peak Attention (SVI)	Attention Change (Post vs Pre)
Ford recall	0.068	0.929	0.996	59.23	19.87%
Toyota recall	0.065	0.922	0.987	50.00	73.92%
GM recall	0.038	0.721	0.758	54.67	17.72%

The GARCH model results indicate that volatility persistence is another characteristic of recall crises. Ford and Toyota show near unity in volatility persistence: when a shock is encountered, the greater risk is that it remains embedded in the share price for a long time. For investors, the risk premium is to remain at higher levels long after the shock hits the public domain. For Takata, although the shock parameter is the highest of the sample, volatility persistence is the lowest. The combination could be of a quick, systemic shock rather than a prolonged spell of instability. It quickly responds to the event and prices it without

entering a persistent volatility regime. In relation to this point, Figure 8 displays how Google Trends reflects media attention surrounding a crisis, especially volatility. We see an almost threefold increase in search intensity on the recall announcement date. The mean volume of searches then continues to rise, on average, to more than 20% above the pre-recall level.

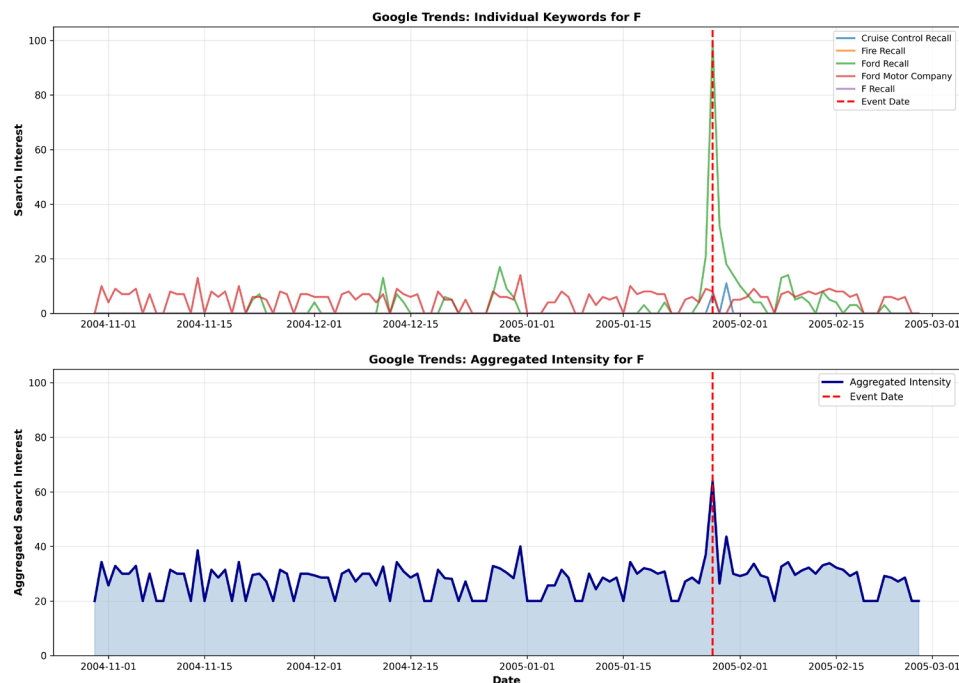


Figure 8: Google Trends intensity for Ford recall.

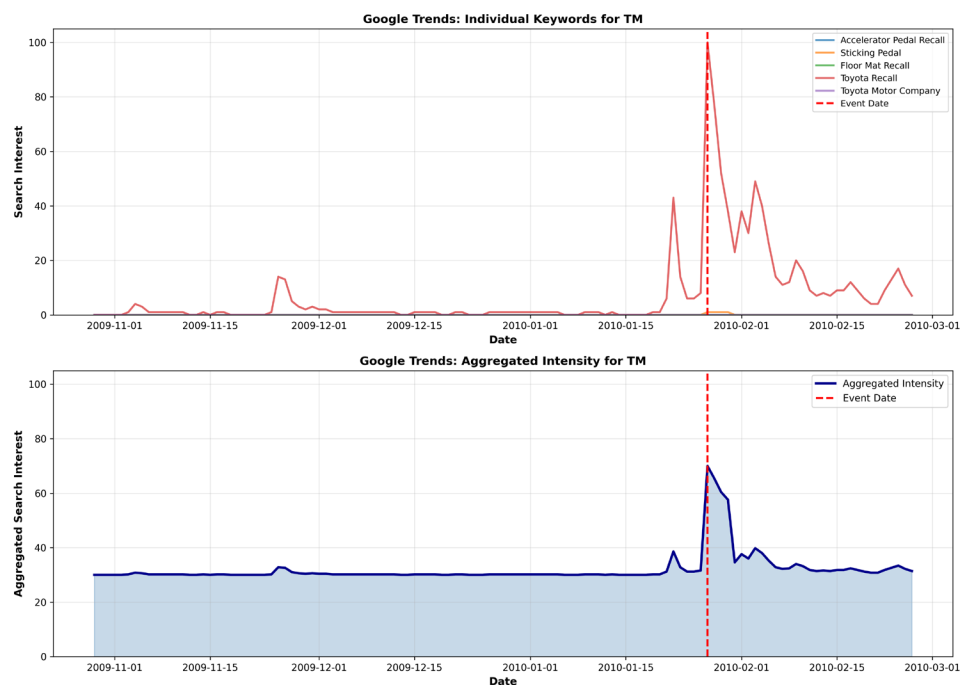


Figure 9: Google Trends intensity for Toyota recall.

A more persistent relationship between market risk and investor attention is evident in the results derived from our GARCH estimations, which support Hypothesis 3.

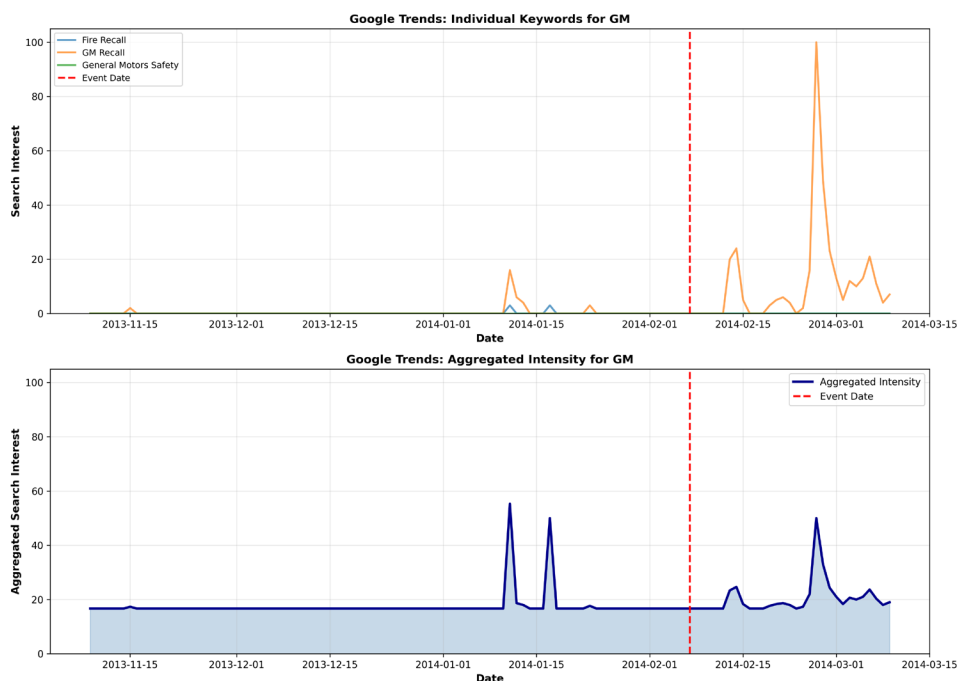


Figure 10: Google Trends intensity for GM recall.

Table 4 shows a clear behavioral difference between firm-specific crises and systemic crises.

Table 4: Rolling Correlation Analysis (Trading Volume vs. Attention)

Event	Pearson r	Spearman ρ	Rolling Sig. Windows (5%)
Ford recall	-0.097	-0.207	0.00%
Toyota recall	0.352*	0.587*	11.10%
GM recall	0.15	0.158	6.30%

Note: Significance denoted by * ($p < 0.05$).

Figure 10 shows a substantial peak in attention to the GM events, which promptly dies down afterward. The media event cycle seems much shorter and shock sensitivity much lower than in the others. The data pattern of H5 is, therefore, a plausible one for this case.

The univariate GARCH models described in Section B.4 of the Appendix can measure specific firm risk. Instead, rolling correlation provides a more direct view of contagion by examining whether trading volume tracks the intensity of Google Trends around a major event. To illustrate the pattern of spillover contagion, we consider a 120-day window around each event and calculate the proportion of 20-day rolling windows that exhibit a statistically significant correlation.

The strongest evidence we found of a correlation-driven response comes from the Toyota event in February 2010, which might be loosely called the **black swan** event. It is the only event for which the share of significant correlations exceeds 10% (11.10%). One interpretation is that people reacted by participating less because there were no clear winners or losers: in such situations, there's widespread uncertainty.

It might be that Ford in 2005 differs from the latter events as a consequence of an evolving phenomenon in which trading volume is increasingly sensitive to digital search activity over time. Ford shows no significant rolling windows. This suggests that the market pays no attention to Google searches.

One possible explanation is that, before the iPhone era, it was difficult to integrate search into market behavior. Significant correlations for Toyota, on the other hand, indicate that by 2010, searches on the Google platform had become a good indicator of market trading behavior.

5.3 Causal Spillovers

To determine whether a recalled firm leads the market or reacts to it, we examine the direction and timing of information flow. We estimate bivariate Granger-causality models and impulse-response functions within a VAR framework. The test is whether the treated firm's returns help predict the control group and whether the control group feeds back into the treated firm.

Table 5. Granger causality and spillover tests.

Event	Lag	T → C (p-val)	C → T (p-val)
Ford recall	1	0.288	0.218
Toyota recall	1	0.032*	0.272
GM recall	2	0.862	0.642

Note: Significance denoted by * ($p < 0.05$). T→C (Treatment to Control) indicates spillover from the recall firm to the industry. C→T (Control to Treatment) indicates feedback from the industry to the recall firm. p-values are for the 'ALL' combined industry group.

Toyota is the most affected by systemic shocks in the sample. Beyond the aggregate statistics, ticker-level results show meaningful causal effects on direct peers. Toyota's returns help predict price movements in Honda, Ford, and the retailer Lithia Motors. The event, therefore, does not look confined to Toyota alone.

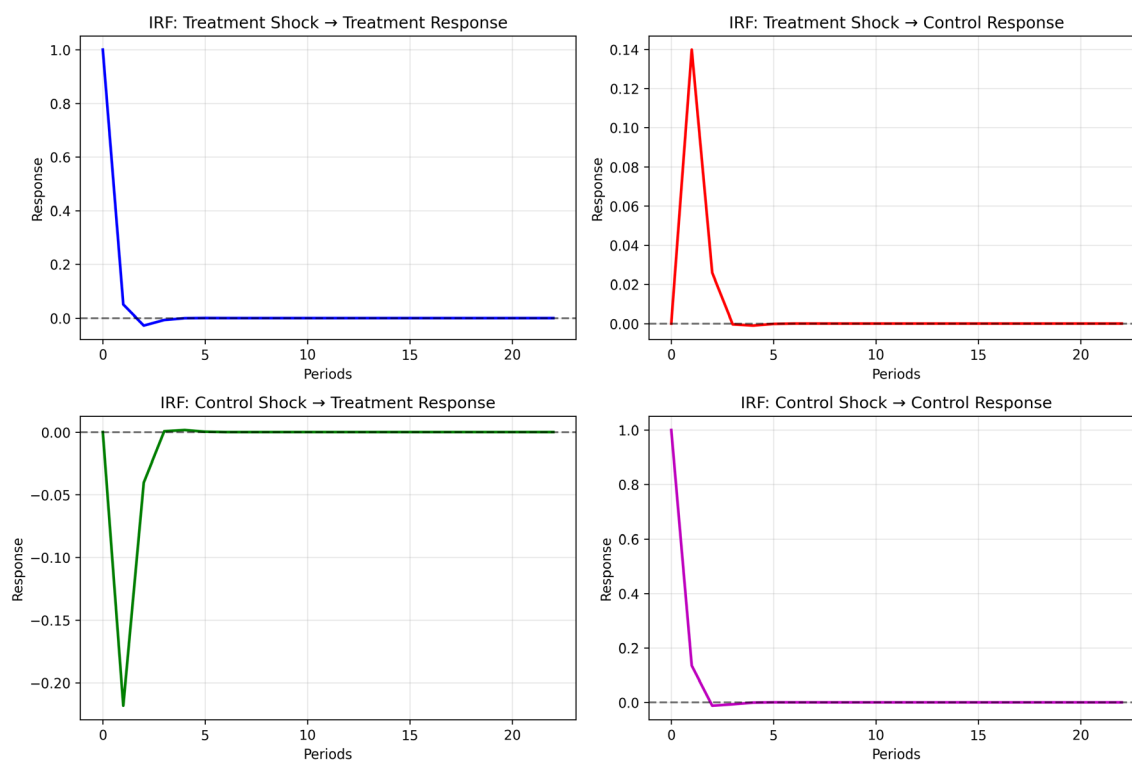


Figure 11. Impulse response function for Toyota recall.

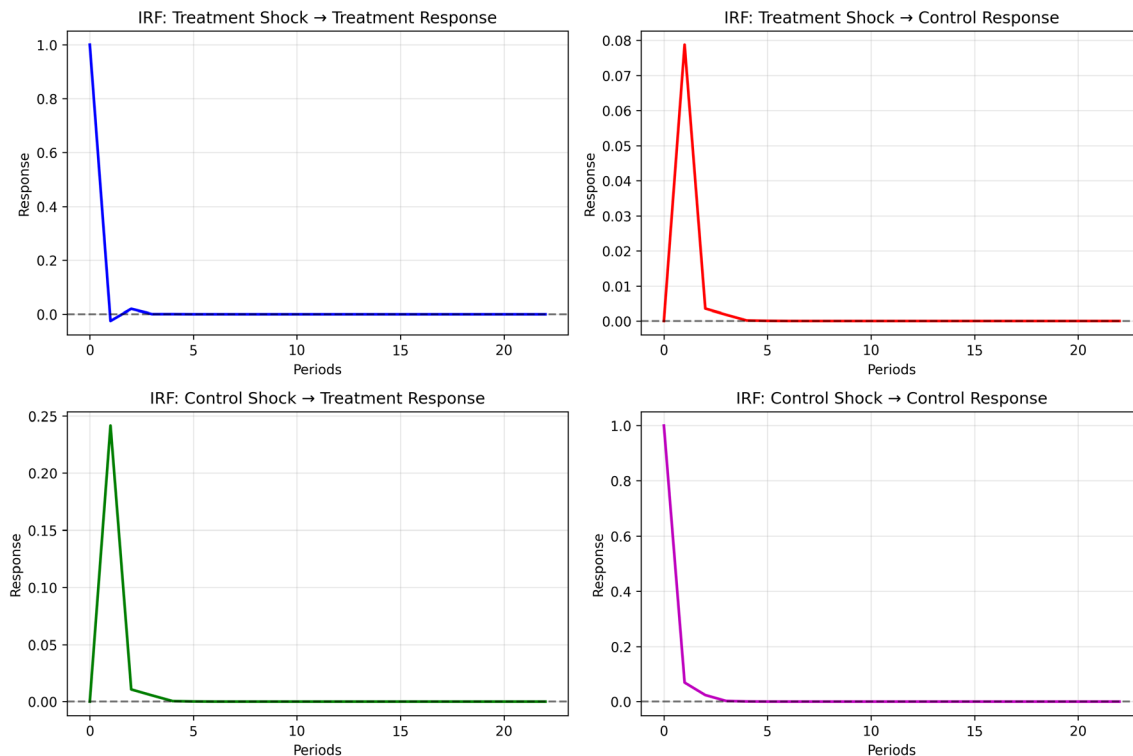


Figure 12. Impulse response function for Ford recall.

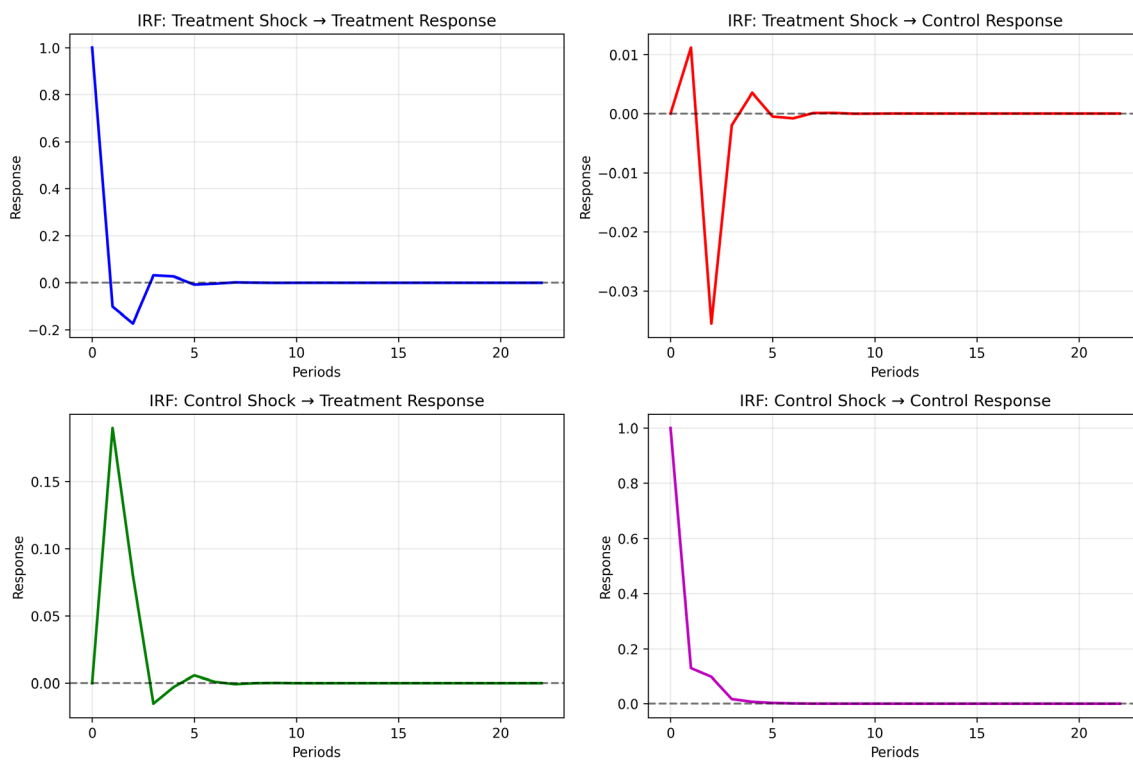


Figure 13. Impulse response function for GM recall.

We find support for this argument in our impulse-response analysis. Figure 11 summarizes how industry returns respond over time to each crisis by sector. Industry returns experienced a negative shock for 3 to 4 days before returning to the mean. Toyota's recall prompted the automotive market to re-evaluate sector-level safety risks. As with the Japanese market, we find no spillover in industry returns beyond that for Japanese companies alone. In this case, responses are sharp but short-lived, with full mean reversion within one to two trading days.

In contrast, Ford shows no significant aggregate spillover over other automakers in Figure 12; its only significant tick-level links are with specific partners, Autoliv and AutoNation. Unlike the other companies, GM has the most idiosyncratic response pattern in the sample (see Figure 13). The stock market largely distinguishes between GM's legal and managerial failures and systemic risks to the auto industry. The impulse-response for industry returns over time is minimal and not significant. The event was treated more as a GM-specific governance problem than as a manufacturing flaw shared by peers.

The impulse-response function peaks with a delay. Rather than an immediate reaction, this pattern appears to track a slower market recognition of the supplier crisis across different brands. It may suggest a distinct form of contagion moving through the supply chain with a lag.

Based on our ticker-level Granger-causality results and impulse-response functions, every recall affects the issuing firm. Only Toyota, though, seems to produce a clear sector-wide information spillover. Ford and GM affect related firms in a much narrower way. A broader market response is likely to depend on the exact type of recall and how easily investors can trace the source of the shock.

5.4 Market Behavior Analysis

Understanding investor behavior in a crisis requires more than tracking price changes alone. We, therefore, ask whether investors move together in a panic, implying herding, or move separately, implying anti-herding. CSAD provides the first cut, and CSSD then shows whether the same pattern changes between rallies and sell-offs.

Table 6: CSAD and CSSD results.

Event	CSAD γ_2 coefficient	CSAD p-value	CSSD β^{UP}	CSSD p-value	CSSD β^{DOWN}	CSSD p-value
Ford recall	45.44	0.48	1.24E-02	1.97E-44	9.50E-03	4.19E-28
Toyota recall	41.64	0.03*	2.11E-02	1.12E-62	1.65E-02	7.58E-37
GM recall	-15.17	0.61	3.70E-03	3.00E-03	1.30E-03	3.42E-01

Note. Significance denoted by * ($p < 0.05$).

Behaviorally, we find evidence of anti-herding during the Toyota recall. This suggests investors distinctly penalized the offending firm while holding or buying peer stocks, rather than engaging in a sector-wide panic. Investors seem to have treated Toyota as distinct from the rest of the market. For GM, by contrast, the estimates do not show clear evidence of either herding or anti-herding.

As volatility picks up, the discount on Toyota increases far more than predicted by typical pricing models: Investors dump Toyota while continuing to hold or buy other automakers like Honda and Ford, essentially "shorting" Toyota in an isolated manner. The findings are consistent with our Granger-causality evidence. Thus, the evidence suggests that investors "single out" Toyota for repricing rather than engage in a broad selloff across the industry sector. CSAD captures only a portion of stress, whereas the new indicator CSSD shows more clearly how dispersion behaves during market rallies and sell-offs. Looking at the statistics reported in Table 6, we observe that return dispersion around rallies and sell-offs is always symmetric, and it increases faster for upside moves than for downside moves. Once again, Toyota has the strongest estimated coefficients, suggesting to investors that this particular automaker is different even in times of market crashes.

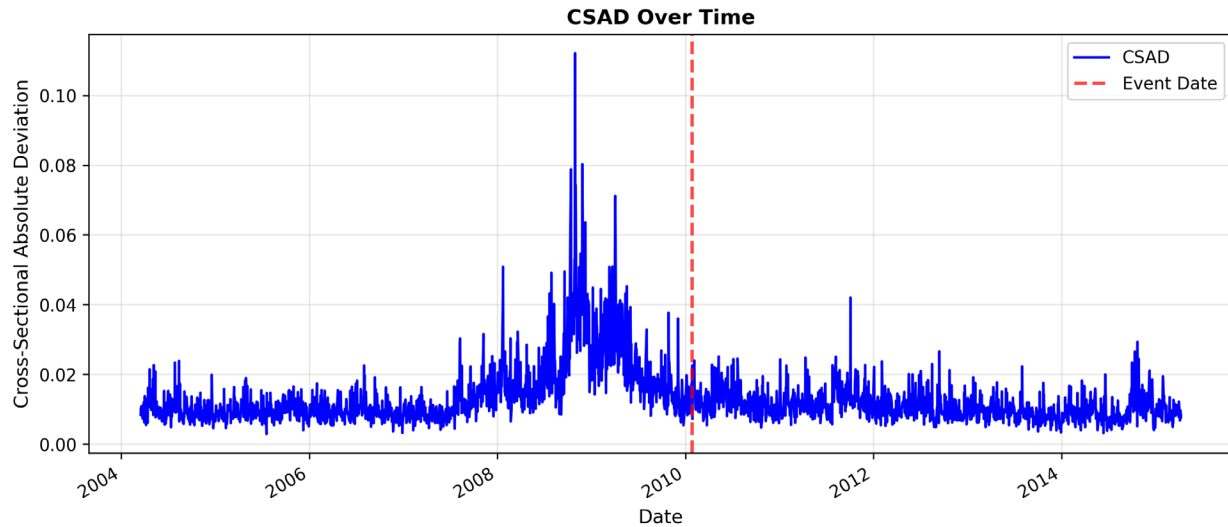


Figure 14: CSAD plot for Toyota recall. Note: The scatter plot illustrates that dispersion increases non-linearly with market returns, confirming anti-herding behavior.

As volatility increased, the gap between Toyota and other sector stocks widened far more than rational pricing rules would have predicted. The evidence also indicates that Toyota was sold off while other stocks were bought or held. This was the pattern among Honda and Ford relative to Toyota, the only distressed stock within the cluster. This particular phenomenon is consistent with Granger-causality statistics and indicates that investors differentiated Toyota stocks within the industry, not just the industry as a whole. CSSD is a measure of dispersion between 20 stocks in the sector and also reflects stress within the cluster. In particular, Table 6 reveals some asymmetries: Dispersion increases less on downturns than it does on upturns. Once again, Toyota had the highest volatility among other stocks. However, even in bear market conditions, Toyota continued to behave differently compared with the rest of the companies in the sector.

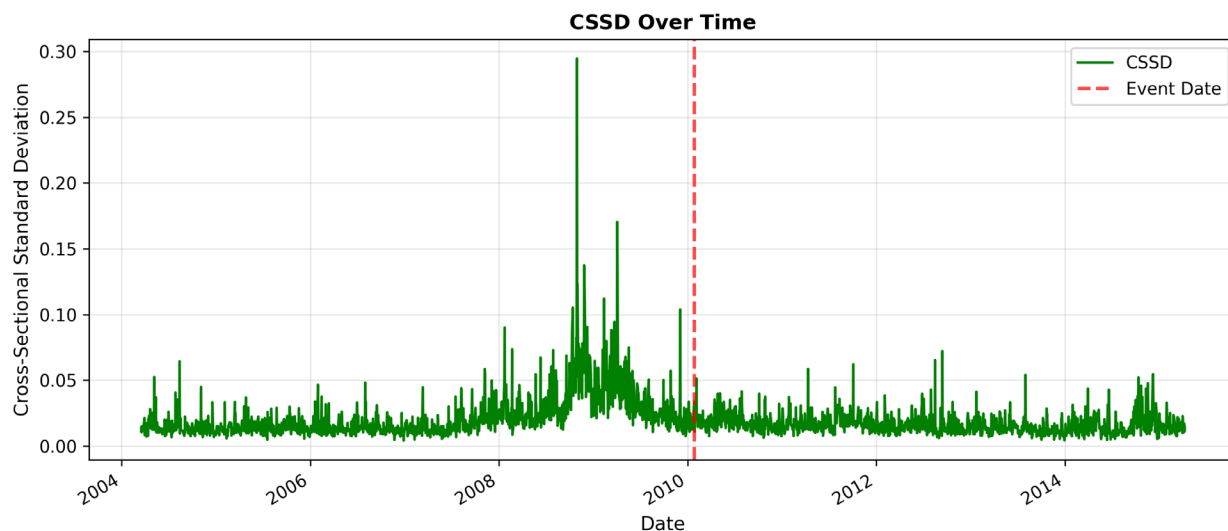


Figure 15: CSSD plot for Toyota recall. Note: The slope is steeper for positive market returns, indicating that rallies drove greater differentiation than sell-offs.

5.5 Market Reaction on Profitability and Reputation

Our analysis reveals distinct differences in the 3-day CARs across the three manufacturers: Ford (-1.80%), GM (-1.67%), and Toyota (-11.13%). The OLS estimation for the ROA trend model yields an R^2 of 0.987 and an F-statistic p-value of 0.0720. The ROA Trend coefficient (β_1) is 3.1238 ($t = 8.809$). This positive and large coefficient increase indicates that an improving profitability trend is associated with a stronger market reaction (a steeper 3-day stock decline). This finding is consistent with Hypothesis 6. Toyota dominates this cross-firm variation: it had the highest positive ROA trend (+0.0219) leading into its recall, while simultaneously suffering the largest negative 3-day CAR. In contrast, Ford and GM had negative ROA trends (-0.0056 and -0.0099, respectively) and experienced much milder market reactions.

Table 7a. OLS results of profitability and market reaction.

Sample size: 3 firms; $R^2 = 0.987$; Adj. $R^2 = 0.975$; F-statistic p-value = 0.0720.

Variable	Coef.	Std. Err.	t	P> t	95% CI
Const	0.0420	0.0051	8.308	0.0763	[-0.0222, 0.1062]
ROATrend	3.1238	0.3546	8.809	0.0720	[-1.3820, 7.6296]

Table 7b. OLS results of profitability and market reaction.

Fit Metric	Value
R-squared	0.987
Adj. R-squared	0.975
F-statistic	77.598
Prob (F-statistic)	0.0720
Observations	3

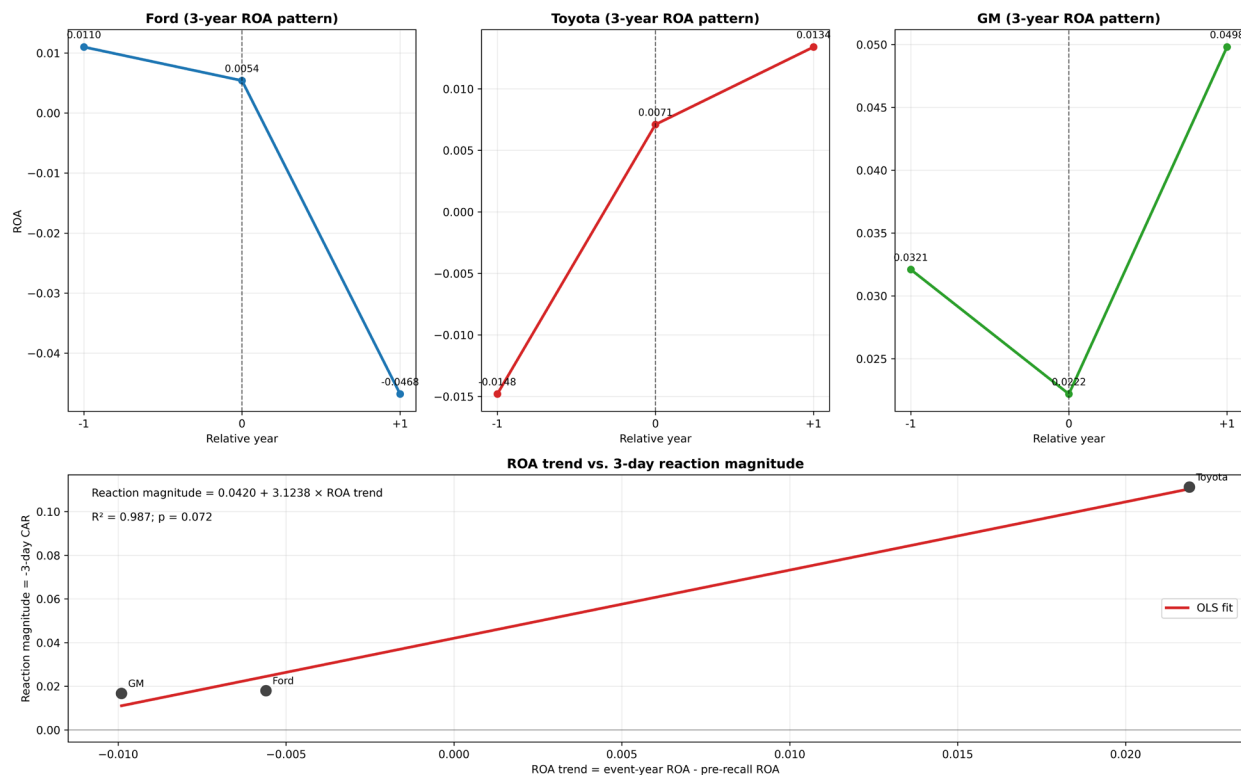


Figure 16. ROA trend and 3-day recall reaction across Ford, Toyota, and GM.

There appears to be support for Hypothesis 6, which states that the market would punish a firm if the recall were poorly managed. The total recalls have a positive correlation with a firm. Its value ($\beta=0.99$, $\sigma=0.007$) is significant, whilst in this three-firm sample, Toyota records 338 recall cases, which implies that higher ROA indicates it will recover quickly from its effects, thereby providing weak support for Hypothesis 6. Since Toyota has the smallest recall cases when it came to third-party cars (that is, with 338 total recalled cases, whereas GM has 1715, which was the most cars recalled in the three events to consider), it is expected to have less severe effects compared to GM, which has suffered due to this reason. This indicates that Toyota shareholders did not benefit from their company after cases of heavy recalls, as it had the severest 3-day CAR. Given the small number of companies, we could not provide more robust general solutions.

Table 9a: Results of reputation and market reaction.

Model	Variable	Coef.	Std. Err.	t	P> t
Total recalls	TotalRecalls_1966_2026	0.000068	0.000001	123.108	0.0052
Event-year recalls	EventYearRecalls	0.000799	0.001347	0.593	0.6591

Table 9b: Results of reputation and market reaction.

Model	R-squared	Prob (F-statistic)
Total recalls	1.000	0.0052
Event-year recalls	0.260	0.6591

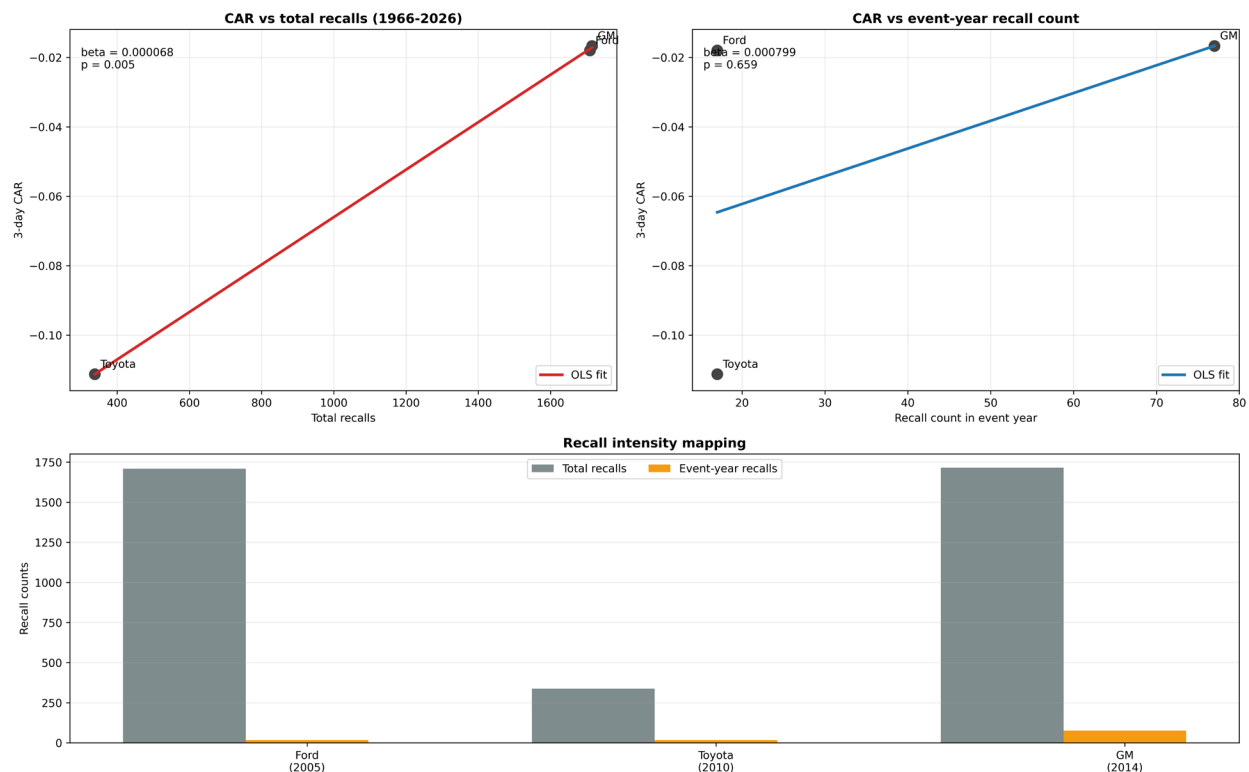


Figure 17. Recall intensity and 3-day CAR for Ford, Toyota, and GM.

Conversely, the secondary check using event-year recalls was not informative ($\delta = 0.000799$, $p = 0.6591$, $R^2 = 0.260$). However, the findings in general still held, and a comprehensive model is required for this issue, which we left for future research.

6. Discussions

6.1 Key Findings

Though large recalls do not consistently exhibit significant negative abnormal returns over a 22-day event window, the market seems capable of pricing these costs quickly or associating them with broader sectoral issues than particular businesses. Contagion, in a stock market sense, also varies, and not all affected firms receive comparable negative reactions. Market CARs are usually negative and statistically insignificant. Nevertheless, Granger causality tests show that major events can exhibit short-run predictive power, though the scope of spillovers is highly idiosyncratic. While systemic 'black swan' events like Toyota's recall exhibited informational spillover that predicted peer price movements, behavioral metrics revealed this did not trigger a blind, sector-wide panic. Instead, investors engaged in anti-herding, specifically isolating and penalizing Toyota while holding or buying peer stocks. Conversely, more common crises like those of Ford and GM primarily affected only their direct supply chain partners, without broader behavioral shifts in the market. Overall, it is apparent that recalls receive tremendous press coverage, although the mean valuation effects may be small. Yet firm-specific characteristics or even coincidences in firm names might lead to varying degrees of contagion, with some firms being much more heavily affected than others.

The severity of abnormal returns in a crisis appears to be heavily driven by expectations. The firm whose ROA experienced the strongest upward trend with the cleanest long-run record (Toyota) experienced the most drastic fall in valuation. Conversely, manufacturers with numerous historical recall burdens and downward-sloping ROE (Ford and GM) barely faced any market reaction. This supports the theory of long-run recall fatigue. Since event-year counts of recalls are not informative compared to the multi-decade historical record of recall-burdened firms, it seems clusters of news for a short period are not enough to protect a firm. They cause decades-long histories of recall-related issues, which seem to already price in risk, thereby cushioning the firm from a shock when the safety issue arises.

6.2 Implications

Regulators and firms should understand that whilst high public attention as expressed through searches can play a significant part in the level of short-term volatility and coincide with a trading boom in systematic events ('black swan' events such as the Toyota recall) cannot be counted upon universally, investors must become a diligent monitor of the exposure of the stock in question to spillover effects by keeping up to date on each firm's latest product defect scandals. The evidence gathered suggests that a direct supply chain network could be subject to spillover effects, and investors are advised to take this into account as a source of market risk. As illustrated by our case, however, reputational capital could worsen vulnerability in crisis times. In Toyota's case, an excellent record of quality combined with rising profits gave the firm a strong base from which to defend itself.

The long-run recall burden analysis further reinforces this explanation. The firms hit by the fewest price penalties were those with the highest cumulative recall totals, such as Ford and GM. Counterintuitively, the firm with the most severe negative three-day CAR (-3.5%) is Toyota, which has the fewest long-run recall burdens, as the statistics show. This could indicate that those well-known firms with a strong reputation for quality and reliability are hit harder by investors when the expectation of continuous premium performance is broken. A strong reputation for quality, coupled with strong profits, makes Toyota look as secure a business as possible. When a 'black swan' recall comes out of the blue, investors may overreact and sharply alter their expectations of the firms' future cash flows. By contrast, firms such as GM, which face high recall rates each year, would suffer a loss of CAR. However, investor reaction will likely be more rational than that towards premium-quality firms, given prior understanding that annual recalls are a fairly

common practice in the car industry. When a 'black swan' recall shatters that assumption, investors may violently revise their expectations of future cash flows. While further large-sample research is needed to generalize this effect, firms with high reputational capital should be aware that their past good standing may not buffer them against stock-market losses; instead, it may set the stage for a steeper market correction.

Our final sample is limited to U.S.-traded stocks, but future work should explore whether the same phenomenon occurs globally across markets with varying regulatory frameworks. More advanced analysis of the news could improve the accuracy of our Google Trends proxy by focusing solely on relevant news, even using sentiment analysis of news reports. Additionally, as done by Pupovac et al. (2026), it would be valuable to use the difference-in-differences setup directly on supplier data rather than firm data to map upstream effects.

7. Conclusion

The analysis combines valuation effects, causal evidence, and behavioral research on how investors perceive and process bad news associated with automotive recalls. It finds that automotive stock market reactions to recall vary over the course of a 21-year study period. The study singles out Ford as having experienced the largest and most consistent decline in relative stock market valuation in the matched analysis. It also highlights Toyota as a key case in which investors differentiate and assign liability as if the defect were a 'black swan' event. Before the crisis, Toyota's high reputation for quality may have led to elevated investor expectations, which, when the recall failed to meet them, could have resulted in greater damage than expected. Reputational capital indeed acts as a dual-edged sword. At the same time, it can provide a safeguard during normal operations; in times of significant failure, it amplifies the market's repercussions when the company's image deviates.

The findings also suggest that managers can monitor their key clients' stock market performance early to discern sector-wide turmoil. They are likely to value the market's recognition of the source and scope of the defect more than the problem's severity. For this reason, firms should treat recall incidents not only as operational or regulatory events but also as financial news, which can modify investors' beliefs, affect the company's market value, and, in some situations, create a flow-on effect for related firms and suppliers' market share.

Recalls announce the revelation of risk about the firm in particular, and the exposition of supply chains and investor beliefs in response. The limitations of the sample and the presence of only one subject in our report make generalizability weak; however, it presents some evidence that may extend to broader issues of recalls, reputational capital, and market reaction. With expanding resources, including more samples and details on the supplier and the news, this could lead to further study into whether recalls will be limited to the firm that caused them or trigger a broader market reaction.

Declarations

The Appendix for this working paper is available from the authors upon request.

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