How Do Brands Change Their Advertising Spending in Response to A Rival Brand's Product Recall?

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Abstract

A brand manager can interpret a rival's product recall as an opportunity to preempt sales and/or signal superior quality by raising their brand's ad spending. Conversely, they may interpret the recall as a threat that may harm the substitute brand's image and/or lead buyers to draw unfavorable comparisons between the substitute brand and the recalling brand. Such interpretation nudges the manager to suppress their brand's ad spending. The authors test the interpretations empirically in the context of 62 substitute car models' responses to a model's recall. They assess the response over 31 weeks and 308 geographical regions, leading to 591,976 model-week-region observations. Regression discontinuity in time (RDiT) analysis reports that, on average, a substitute brand responds by lowering its ad spending by 50%, suggesting that threat interpretation dominates opportunity interpretation. A decomposition of spending by type suggests that substitute brands increase their spending on price advertising by 25%, decrease spending on quality advertising by 71%, while making no adjustment to brand advertising. This nuanced analysis suggests that substitutes attempt sales preemption, avoid quality signaling, and are not worried about brand spillover. Supplementary, a follow-up analysis reports that this advertising strategy strengthens the positive spillover effect of a brand's recall on its substitute brands' sales volume. The key findings hold for another major automobile recall event in the same market. The findings contribute to the literature on the management of quality perception while informing substitute brands' managers on their response to a brand's quality failure and whether the response helps or hurts the substitutes' sales. Further, the findings build an empirical foundation for future analytic investigation on strategic interactions among brands when a quality defect occurs.

Keywords: product recall, spillover, quality management, contagion, competition, advertising, sales

1 Introduction

"At the end of the day, *safe and high-quality transportation* is a reasonable request from a customer. We want to be able to provide *peace of mind* to customers and all of our vehicles are safe" – General Motors' (GM's) marketing chief Susan Docherty when asked why GM is offering incentives to Toyota owners for switching to a GM car in response to Toyota's recall (italics added for emphasis).[1]

Brands in a product category sell products that substitute for one another. These brands aim to elicit consumers' favorable evaluations, relative to other brands in the same category, thus boosting their sales volume. Typically, brands achieve this aim by advertising aggressively (Cleeren et al., 2013; Giannetti & Srinivasan, 2021; Liu et al., 2014). A brand's advertising spending (hereafter, ad spending) can lead consumers to perceive the quality of the brand's products more favorably, resulting in positive purchase decisions (Kirmani & Wright, 1989). Further, a brand's adjustments in its ad spending could influence consumers' perceptions of the product, potentially affecting their purchase decisions (Lodish et al., 1995). For example, frequent increases in ad spending can increase product demand (Nijs et al., 2001). While increasing advertising to boost sales is a beneficial strategy in regular times (Joshi & Hanssens, 2010), do substitute brands follow the same strategy after a brand in their product category issues a product recall for its defective products?[2]

For example, after faulty batteries in Galaxy Note 7 led Samsung to recall the smartphone in 2016, other phone makers started advertising fiercely to seize Samsung's loss of sales (Auchard & Ten Wolde, 2017). In another example, Toyota Corporation recalled in 2010 its cars that had a sticky accelerator pedal and halted sales of 10 affected car models. In an explicit response to Toyota's recall, General Motors (GM) offered a multitude of incentives to Toyota owners who switched to a GM car (Hardigree, 2010). As the opening quote suggests, GM's chief marketing officer positioned these incentives as GM's way to meet car buyers' needs for high-quality transportation and peace of mind (Hardigree, 2010). Ironically, some of GM's brands that were heavily advertised in the wake of Toyota's recall used the same accelerator pedal that Toyota used. While experts opined that GM's strategy would not lift GM's sales, buyer opinions were mixed (Lancaster, 2010).

When a brand recalls its defective products, a substitute brand's manager (in the same product category) may wonder whether prospective buyers will perceive the substitute brand to have superior quality or inferior quality, relative to the recalling brand (Borah & Tellis, 2016; Jacobs & Singhal, 2020). That is, the recall triggers *perception spillover* (Shi et al., 2022) in the substitute brand's manager (see Figure 1). If the manager believes that the recall may cause the buyers to view their brand favorably

[1] https://jalopnik.com/gm-offers-incentives-to-toyota-buyers-looking-to-avoid-5458379

[2] Consistent with spillover literature (e.g., Borah and Tellis, 2016), we take the perspective of the brand that experiences the spillover and may decide whether/how to respond to the spillover. We thus use the term "substitute" for the brand whose spillover (in perception and behavior) we study.

relative to the recalling brand, they interpret the recall as an opportunity. In contrast, the threat interpretation prevails if the manager believes the recall may evoke buyers' unfavorable comparisons.[3]

This perception spillover may translate into a strategic response (or behavioral spillover). That is, whether a substitute brand's manager interprets the recall as an opportunity, or a threat determines how they respond to a brand's recall. Because a recall relates to product safety and quality, and likely makes the prospective buyers re-evaluate the recalling brand and its substitutes, adjusting the substitute brand's ad spending is a fitting response strategy. We propose three adjustments a substitute brand's manager may make to their brand's advertising spending.

First, if the substitute brand's manager believes that the recall presents them an opportunity to preempt the recalling brand's loss of sales, they adopt a *sales-preemption strategy*, which is observed in an increase in the substitute brand's ad spending (Roehm & Tybout, 2006; Zhou et al., 2019). Second, the manager may fear that buyers may draw unfavorable comparisons between the recalling brand and the substitute, damaging buyers' perceptions of the substitute brand (Borah & Tellis, 2016; Jacobs & Singhal, 2020).[4] Such threat interpretation may cause the managers to pursue a *harm-avoidance strategy*, which shows up in a decrease in their brand's ad spending. Third, interspersed between these two clear-cut strategies triggered by perceptions of opportunity and threat, respectively, is another that we label a *quality-signaling strategy* (Raghubir & Corfman, 1999; Zhou et al., 2019).[5] This strategy relates to how much the substitute emphasizes in its ads the quality of its products. If the manager believes the substitute brand is dissimilar enough to the recalling brand, they may signal superior quality and thus evoke buyers' favorable comparisons. Such signaling manifests in increased ad spending (especially, advertising the product's quality). However, if the substitute is similar to the recalling brand, the manager may worry about buyers' unfavorable comparisons, and thus suppress signaling their brand's quality—that is, lower their brand's ad spending (Raghubir & Corfman, 1999; Zhou et al., 2019). In summary, how the substitute brand's manager adjusts their brand's ad spending—on average—is a priori unclear, which motivates us to ask: *In response to a brand's product recall, does a brand of substitute products in the same product category increase its ad spending (i.e., opportunity interpretation dominates threat interpretation), decrease it (i.e., threat dominates opportunity), or leave it unchanged (i.e., opportunity and threat interpretations cancel out each other)?*

While it is valuable to know which interpretation (i.e., opportunity or threat)—if either—dominates a substitute brand's response to recall, this knowledge doesn't directly divulge the substitute's strategy. We reason that a substitute's strategy can be discerned through the *type* of its advertising

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[3] An opportunity (a threat) refers to an event that brand managers perceive will boost (impede) the brand's performance (Connelly and Shi, 2022).
[4] Unfavorable (favorable) comparisons mean that the substitute/advertised brand has a lower or the same level of quality (higher level of quality) than the recalling brand.
[5] We thank a reviewer for coining the terms of sales-preemption strategy, quality-signaling strategy, and harm-avoidance strategy.

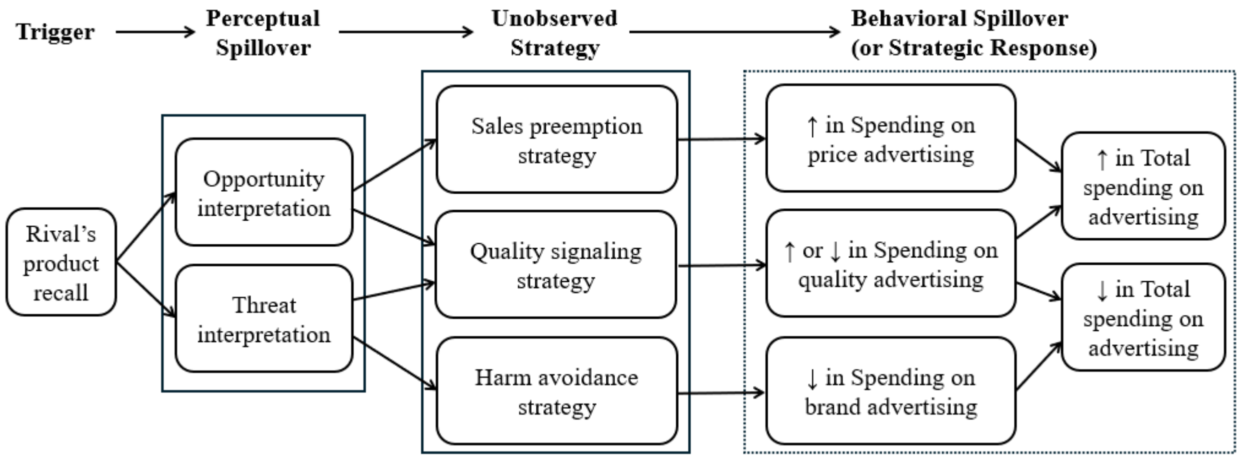
creatives (Dowling, 1986). Therefore, our primary focus and the core contribution of our research lies in assessing the manufacturer's adjustment to its advertising type.

In line with our three proposed strategies, we consider three foci of advertising type (Anderson & Renault, 2006; Lee et al., 2018) (Figure A1 in the e-companion provides one example of an advertisement of each focus). First, if a substitute wants to preempt the recalling brand's loss in sales, it will increase its spending on advertising *that emphasizes the substitute's competitive prices or discounts* (hereafter, price advertising) (Jedidi et al., 1999). Second, the substitute's harm-avoidance strategy should manifest in a dip in its spending on advertising *that emphasizes its brand* (i.e., brand advertising) (Parment, 2014; Roehm & Tybout, 2006). Third, if the substitute brand's manager chooses to signal the superior quality of their brand, they will raise the brand's spending on advertising *that stresses the quality of its products* (i.e., quality advertising) (Du et al., 2015).[6] However, if the manager fears that emphasizing quality may draw buyers' unfavorable comparisons between the recalling brand and the substitute, they may lower their brand's spending on quality advertising.[7] Importantly, the manager may adjust the three types of ad spending simultaneously. For instance, the manager might increase price advertising while decreasing quality advertising and brand advertising. Together, these decisions create a portfolio of the substitute's advertising strategies in response to a recall. The theoretical rationale for the coexistence of these three foci—consistent with the three response strategies we proposed—motivates a second-order question: *In response to a brand's product recall, does a brand of substitute products in the same product category increase, decrease, or leave unchanged their spendings on price advertising, quality advertising, and brand advertising?*

[6] We acknowledge that an ad can mention all three (and perhaps, more) of a product. We address this concern in two ways. First, ads of car models (e.g., 2023 Toyota Corolla) usually *focus* on only one characteristic, thus alleviating the concern. Second, empirically, we measure the ad's focus and thus classify an ad's content into one of the three foci.

[7] These three foci are consistent with marketing literature that has established that product ads emphasize the product's price (Jedidi et al., 1999), quality (Du et al., 2015), or brand (Parment, 2014). Further, product recall literature has considered the recalled product's price, quality, and brand as three relevant marketing variables, meaning that considering all three is relevant to the phenomenon (e.g., Chang & Wildt, 1994; Hoch & Ha, 1986; Roehm & Tybout, 2006). Last, we talked with representatives from Kantar Media, and they confirmed that for car brands, the ads emphasize one of these three characteristics.

Figure 1: Conceptual Framework



We answer the two questions empirically, using the Volkswagen Group's recall of its cars marketed under the New Sagitar model in China. Volkswagen announced the recall on October 17, 2014. Therefore, we consider the 16-week period from June 30, 2014, to October 19, 2014, as the prerecall period. Our postrecall period includes 15 weeks, beginning from October 20, 2025, to February 1, 2015. Following the method used by extant research on car recalls (Borah & Tellis, 2016; Rubel et al., 2011), we identify 62 car models (which we consider as *brands*)—owned by 33 manufacturers—that are substitutes of New Sagitar. Next, we monitor these 62 car models' weekly ad spending in 308 prefecture-level divisions,[8] leading to 591,976 substitute model-week-prefecture observations. We use the regression-discontinuity-in-time (RDiT) method (Ozturk et al., 2019) to measure the impact of Sagitar's recall on substitute models' ad spending.

Our RDiT analysis reveals three key findings. (1) On average, substitutes respond by *lowering* their total spending on advertising by 50%, suggesting that substitute brands interpret a recall more as a threat than an opportunity. (2) We classify each ad creative by each model on whether it emphasizes price, quality, or brand. Subsequently, we decompose total ad spending by type: "spendings" on price advertising, quality advertising, and brand advertising. Empirical tests suggest that substitute brands follow a nuanced strategy. They boost their spending on price advertising by 25%. This finding is consistent with the sales-preemption strategy. Next, substitutes curb their spending on quality advertising by 71%, indicating that they fear it will draw buyers' unfavorable comparisons between Sagitar and the substitute brand. The adjustment to brand ad spending is insignificant, indicating the absence of a harm-avoidance strategy. (3) A supplementary analysis reveals that substitutes' response strategy of

[8] Chinese prefecture-level division (hereafter, prefecture, for brevity) is an administrative division of the People's Republic of China, covering 299 cities (municipalities with the right to govern surrounding countries), 4 prefectures (subdivisions of provincial-level divisions), 30 autonomous prefectures (residents are mainly ethnic minorities), and 3 leagues (prefectures of Inner Mongolia). Details on https://en.wikipedia.org/wiki/Prefectures_of_China.

suppressing total ad spending pays off. Specifically, Sagitar's recall *lifted* its substitutes' sales volume—on average—by 35.3%. The substitute's ad spending weakens this positive spillover such that each unit of ad spending (where a unit is equivalent to RMB 10,000) weakens the positive main effect by 23.1%. The theoretical insight is that the substitute's ad spending elicits consumers' unfavorable comparisons between the substitute brand and the recalling brand. Therefore, by lowering its total ad spending, a substitute brand prevents any unfavorable comparison and, by extension, the potential weakening of the positive spillover. Further, this weakening effect is sourced exclusively from the substitutes' adjustment in spending on quality advertising. The insight is that the substitutes' strategy of lowering spending on quality advertising strengthens the positive spillover and is thus a wise move.

We earlier reasoned that whether the manager of a substitute brand boosts or suppresses their brand's spending on quality advertising depends upon whether they interpret a recall as an opportunity or a threat. One way to empirically identify the interpretation is by separating the substitute brands in terms of whether they are similar or dissimilar to the recalling brand (Roehm & Tybout, 2006). Specifically, we explore heterogeneity in the substitutes' responses by two characteristics that proxy similarity between Sagitar and substitute car models: (1) whether the focal model is a direct (vs. indirect) substitute of Sagitar[9], and (2) whether the substitute is manufactured by the same joint venture that manufactured Sagitar. Results suggest that a direct (vs. indirect) substitute lowers spending on price advertising and spending on quality advertising while not adjusting spending on brand advertising. The insight is that relative to an indirect substitute, a direct substitute views another brand's recall more as a threat than an opportunity and thus chooses to lower its visibility on price and quality. In other words, by lowering its spending on price advertising and spending on quality advertising, the direct substitute strives to avoid being associated with the recalling brand. Next, a substitute from the same (vs. different) manufacturer *raises* its overall spending, but this raise is sourced exclusively from quality ad spending. The theoretical insight is that consumers may inevitably associate the recalling manufacturer's substitute brands with the recalling brand (i.e., "guilty by association"). Anticipating this association, substitute brands from the recalling manufacturer must fight harder to differentiate their quality and mitigate consumers' guilty-by-association interpretation.

We report five robustness tests using an alternate prerecall period, an augmented local linear strategy, an alternate estimator, a falsification test, and other advertising efforts. Last, aiming to boost the generalizability of our findings, we replicate the identified effects with another car recall event in the same market, and obtain consistent results.

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[9] We consider a substitute car model to be a direct substitute of Sagitar if buyers who eventually bought a Sagitar car searched for information for the former model. For example, if a buyer who buys Toyota Corolla searched for information about Honda Civic, we consider Honda Civic a substitute of Toyota Corolla.

Our findings contribute to the product recall literature (Table 1 positions our manuscript relative to the relevant literature). This literature has documented that a recalling manufacturer adjusts its ad spending to mitigate the adverse effects of the recall (Gao et al., 2015). While it is important to understand how a recalling manufacturer adjusts its overall ad spending in response to its own recall event, there is limited knowledge among academics and managers regarding how *brands of substitute products* adjust their ad spending, and whether these adjustments *vary by advertising type*. Consequently, our research contributes primarily by demonstrating that, in response to a brand's recall, its substitute brands undertake a nuanced strategy. Specifically, they boost spending on price advertising, curb spending on quality advertising, and maintain spending on brand advertising. These asymmetrical adjustments reveal the theoretical insight that substitutes interpret the recall as both an opportunity and a threat. This dual interpretation prompts them to seek positive spillovers while mitigating negative impacts.

Our results are consequential for managers of substitute products, substitute brands, and ad agencies. We inform them how substitutes astutely adjust their ad spending in response to a brand's recall. Further, we show that, on average, a brand's recall helps the substitute's sales, and that by diminishing their substitute brand's ad spending, managers help appropriate the positive spillover on sales.

We structure the rest of the manuscript as follows. Section 2 provides conceptual arguments from spillover theory. Section 3 describes the data and empirical method. Section 4 describes the main results, while Sections 5, 6, and 7 present heterogeneity results, robustness checks, and empirical extensions, respectively. Section 8 concludes with a discussion of the implications of our research for academics and managers, and the future attention the research merits.

Table 1: Positioning Table

Note: We include all studies that have examined the impact of a brand's product recall on the substitute firm's/brand's (1) managerial decisions or (2) sales.

Study	**Substitute firm's or brand's strategic response to a recall?**	**Variation in response variable by types?**	**Effect of a recall on the substitute firm's or brand's sales?**
This article	✓	✓	✓
Barber and Darrough (1997) *Journal of Political Economy*	×	×	×
Borah and Tellis (2016) *Journal of Marketing Research*	×	×	✓
Collins, Simon, and Tennyson (2013) *Journal of Economic Behavior & Organization*	×	×	✓

Cawley and Rizzo (2008) *Beyond Health Insurance: Public Policy to Improve Health*	×	×	✓
Crafton, Hoffer, and Reilly (1981) *Economic Inquiry*	×	×	✓
Dowdell, Govindaraj, and Jain (1992) *Journal of Financial and Quantitative Analysis*	×	×	×
Dranove and Olsen (1994) *Journal of Law and Economics*	×	×	✓
Freedman, Kearney, and Lederman (2012) *Review of Economics and Statistics*	×	×	✓
Liu and Varki (2021) *Journal of Business Research*	×	×	×
Mackalski and Belisle (2015) *Journal of Brand Management*	×	×	✓
Van Heerde, Helsen, and Dekimpe (2007) *Marketing Science*	×	×	✓

2 Theory

2.1 Spillover Effect in Product Recall

A discrete incident related to an entity may unintendedly impact the perceptions, decisions, and/or outcomes of an observer that is related to the entity (Hersel et al., 2019). The incident is called the *trigger*, and the effect on the observer is known as *spillover* (Ahluwalia et al., 2001; Shi et al., 2022). Typically, the triggered entity is a firm or a brand, and the observer is another firm or brand. Importantly, the spillover literature takes the observer's perspective.

Research has shown that a negative trigger involving a firm can impair the performance outcomes of other firms in the same industry—that is, a *negative spillover* or a *contagion* effect (Borah & Tellis, 2016; Cleeren et al., 2013; Lei et al., 2008). In contrast, other studies have documented that a firm's misfortune could boost other firms' performance—that is, a *positive spillover* or a *competitive* effect (Dowdell et al., 1992; Govindaraj et al., 2004; Reilly & Hoffer, 1983). Paying heed to the possibility of the coexistence of contagion and competition, we use the term "substitute" (rather than rivals or peers) for brands that sell products that can substitute the recalled product.

Categorization (Mervis & Rosch, 1981) and associative network theories (Collins & Loftus, 1975) posit that buyers categorize products by structuring product-related information in their memory as a network. Product information appears as nodes linked by a commonality (e.g., manufacturer name, country of origin). When buyers become aware of a product implicated by a recall, the recall activates the link between the focal brand and its substitutes, making accessible the buyers' evaluations of the latter (Borah & Tellis, 2016; Bourdeau et al., 2007; Simonin & Ruth, 1998). In addition, if the buyers perceive the recall as diagnostic of the substitutes, they may generalize the recall and believe that its root cause is endemic to the industry (Cleeren et al., 2013; Freedman et al., 2012). According to the accessibility-diagnosticity framework (Feldman & Lynch, 1988), this guilty-by-association/similarity perception could adversely influence buyer behavior toward the substitutes, resulting in a negative spillover or contagion.

Conversely, if buyers perceive the recall as nondiagnostic of the substitutes, they would view the recall as unique to the recalling brand, isolating the adverse effect and not generalizing it to the substitutes (Roehm & Tybout, 2006). Consequently, buyers may choose the substitute brands in place of the recalling brand, resulting in a positive spillover or competitive effect (Dowdell et al., 1992; Govindaraj et al., 2004; Reilly & Hoffer, 1983).

2.2. Managers' Strategic Response in Anticipation of Spillover from Recall

A brand's manager observes actions taken by other brands in the same product category. More concretely, they evaluate the action on salience, relevance, and significance (Shi et al., 2022). Next, they determine whether/how the action would impact their brand, and how they can respond to the "trigger," aiming to mitigate negative spillover and appropriate positive spillover (Zhou et al., 2019).

Following a brand's recall, the managers of substitute brands may anticipate a spillover (Shi et al., 2022). However, as the preceding subsection suggests, they are likely unsure whether the recall would evoke favorable or unfavorable comparisons between the recalling brand and its substitute brands. That is, the managers do not know whether the recall would cause a positive spillover and/or a negative spillover in terms of buyers' evaluations, which in turn would cause a lift, a dip, or no change in the substitutes' sales. Consequently, the managers may vary on whether they interpret the spillover trigger—recall, in our case—as an *opportunity*, a *threat*, or both (Guo et al., 2020; Shi et al., 2022). This interpretation determines managerial response in anticipation of the spillover. Because a recall relates to consumer safety and product quality, we view adjustment to ad spending as the quintessential response variable.

Whether the manager of a substitute brand interprets a recall as an opportunity and/or threat is unobservable. However, one can proxy the manager's interpretation by the direction of their adjustment to ad spending. Specifically, if a substitute brand's manager increases their ad spending in the wake of the recall, the increase suggests that the manager views the recall more as an opportunity than a threat. This dominance of opportunity means that the manager increases ad spending to (1) preempt the recalling brand's loss in sales and/or (2) signal the superior quality of their products (Zhou et al., 2019). Thus, the increase aims to capitalize on the positive spillover (or competition). In contrast, if the manager decreases their brand's ad spending, the decrease indicates threat interpretation dominates opportunity interpretation. As a result, the manager lowers their brand's ad spending to (1) prevent buyers from drawing unfavorable parallels between the recalling brand and the substitute brand and/or (2) avoid the potential harm to their brand owing to guilty-by-association (Connelly et al., 2020; Raghubir & Corfman, 1999). Last, we foresee that the two interpretations may cancel each other, leading to a zero net effect.

Figure 1 depicts our conceptual framework and summarizes the three strategic responses (i.e., sales preemption, quality signaling, and harm avoidance) to a recall.

2.3. A Substitute Brand's Adjustments to its Advertising Spending and Changes in Buyers' Utility

Buyers make purchasing decisions based on the net utility they perceive from a product, considering its value (determined by quality and brand) *and* its price. A substitute brand can influence buyers' utility and purchasing decisions by adjusting their "spendings" on price advertising, quality advertising, and brand advertising. More concretely, increasing spending on price advertising can enhance buyers' perception of value, preempting the substitute's opportunity to capture the recalling brand's lost sales (Fornell & Wernerfelt, 1987; He et al., 2018). Conversely, a substitute's increase in its spending on quality advertising and/or spending on brand advertising can mitigate buyers' discounting of the substitute's product quality and/or its brand, when considering the substitute's product after the recall (Ashforth & Lee 1990; Carberry & King 2012; Marcus & Goodman 1991). The increase in spending on quality advertising and spending on brand advertising can thus maintain buyers' likelihood of purchasing the substitute's products. However, the magnitude of the discount may depend on the substitute's characteristics. For example, quality advertising or brand advertising by a substitute brand that features in buyers' consideration set along with the recalling brand may elicit weaker discounting than similar advertising by a substitute brand manufactured by the recalling manufacturer.

In summary, the substitute brand can create a portfolio of spending on price advertising, quality advertising, and brand advertising to influence buyers' purchasing decisions, which will affect how these substitutes respond to the recall. Although we cannot directly observe buyers' utility function, we empirically examine whether the substitute's adjustments to its ad spending (hereafter, ad adjustments) moderate its sales in the periods following the focal recall. Such examination helps us understand whether the substitute's ad adjustments pay off.

3 Data and Method

3.1. Empirical Context

Volkswagen Group (VW) allied (1) with Shanghai Automotive Company to establish the joint venture (JV) Shanghai Volkswagen Automotive (SAIC-VW) in October 1984 and (2) with First Automobile Works (FAW-VW) Group to set up FAW-Volkswagen in 1988. These two JVs made Volkswagen Group one of the first overseas automobile makers to sell domestically manufactured cars in China.

Volkswagen introduced the model *New Sagitar* in 2011 to replace the "old" Sagitar, which Volkswagen had released in 2006. FAW-VW manufactured the New Sagitar (hereafter, Sagitar) using the fifth-generation Volkswagen Jetta platform. Volkwagen positions Sagitar as an "A-class" mainstream family car.[10] The model offers various versions to target a broader customer segment. It provides two wheelbases, three engine types, and three transmission options.[11] This model's cars are priced between RMB 131,800 (US$ 19,646) and RMB 185,800 (US$ 27,645).

On October 17, 2014, Volkswagen unexpectedly announced a recall of 563,605 Sagitar cars manufactured between May 2011 and May 2014 (YahooNews, 2014). This recall was a response to a defect in the car's rear axle arm that could cause the rear suspension to break and thus lead to fatal accidents. This recall was the largest automobile recall event in China in 2014 and included about 11.3% of all cars recalled in China in 2014.[12]

3.2. Sample

We measure the impact of Sagitar's recall on substitute models' ad spending by identifying a balanced prerecall period and a postrecall period. Specifically, our prerecall period comprises 16 weeks,[13] beginning on Monday, June 30, 2014, and ending on Sunday, October 18, 2014.[14] We consider the postrecall period as the 15 weeks beginning on Monday, October 19, 2014—i.e., the Monday following the recall—and ending on Sunday, February 1, 2015.[15]

Car buyers determine their consideration set in two steps. First, they decide the type of vehicle they want to buy; for example, a sedan, a pickup truck, or a sport-utility vehicle. That is, they decide on the *segment*. Second, they decide on a "budget" (i.e., lower price point) versus luxury (i.e., higher price point) model within the chosen segment, leading to their consideration set that focuses on a specific *car class*. For example, if one chooses to buy a budget sedan, one's consideration set will be in A class, which includes the Toyota Corolla, Honda Civic, etc. (Deloitte, 2014). This method is consistent with consumer choice or conjoint literature, which demonstrates that customers select values of attributes in sequential order (Urban et al., 1993). Indeed, extant research on product recall has adopted this consumer selection procedure to determine substitute car models of a recalling model. For example, Rubel et al. (2011) considered Jeep Cherokee and Toyota 4Runner as substitutes for the recalling Ford Explorer. Similarly, Borah and Tellis (2016) used the Nissan Pathfinder as a substitute for the Toyota 4Runner and the Toyota Camry for the Honda Accord (read Borah & Tellis' [2016] Table M1).

[10] In China, the wheelbase length is widely used as the basis for classifying passenger vehicles. Sedan models are categorized into six types based on their wheelbase (Autohome, 2005; Hao et al., 2020): (1) A00 Class (wheelbase = 2,000–2,300 mm), (2) A0 Class (wheelbase = 2,300–2,500 mm), (3) A Class (wheelbase = 2,500–2,700 mm), (4) B Class (wheelbase = 2,700–2,900 mm), (5) C Class (wheelbase = 2,800–3,000 mm), and (6) D Class (wheelbase = 3,000 mm and above).

[11] The two engine types are 1.4 TSI and 1.8 TSI, where TSI is turbocharged stratified injected. The three transmission options are (five-speed manual, six-speed Tiptronic, and seven-speed DSG, where DSG stands for direct shift gearbox.

[12] http://union.china.com.cn/car/txt/2015-01/04/content_7568166_2.htm

[13] Our week begins on a Monday and ends on the following Sunday.

[14] We follow Ozturk et al. (2019) to include the week of recall in the prerecall period. However, our results (available upon request) are robust to (1) excluding the week of recall from our sample and (2) including it in the postrecall period.

[15] Takata Corporation announced a large recall in China (and other countries) in February 2015. Therefore, our postrecall period avoids this confounding event. https://www.qiche365.org.cn/index.php/index/article/detail/id/10340.html

Following the above method, we sample *all* models that manufacture cars that are substitutes for cars sold by the recalling model Sagitar—that is, car models that are "A-class sedans" like Sagitar (Wu et al., 2019). This sampling leads us to 62 A-class models from 33 manufacturers sold in China as of 2014 (Table A1 lists the names of the 62 models). Therefore, we examine how these 62 substitute car models adjust their ad spending in response to Sagitar's recall. We measure the substitute's weekly ad spending and subsequent sales volume in each prefecture. That is, we measure ad spending at the level of model-week-prefecture and the sales volume at the level of model-month-prefecture.

We focus on *print* advertising media for two reasons. First, relative to other types of media, print media involve a short lead time of as few as two days (Totalcom, 2018). Car brands value this flexibility because it allows them to respond to a recall promptly (Dialogue, 2023). In contrast, other advertising media—such as television and outdoor—typically require scheduling at least six months in advance (Empire, 2023). Therefore, car brands consider print media more relevant than other types of media (Venkatraman et al., 2021).[16] Second, print advertising accounted for over 30% of the share of the automobile advertising market in China in 2015 (BIA, 2015). Therefore, we focus on spending on print ads and use the spending on other types of media as controls. We obtain data on ad spending across all car classes from Meihua (https://admen.meihua.info), a leading third-party advertising agency in China. More concretely, we collect data on spending in local magazines and newspapers for all 62 car models across 308 prefectures and for each of the 31 weeks between June 30, 2014, and February 1, 2015. This resulted in a dataset of 591,976 weekly print ad records for the 31-week observational period.

Notably, Meihua uses Google's Bidirectional Encoder Representations from Transformers (BERT) to categorize print ads by their type. Evidence (Amazon, 2022) suggests that BERT achieves high performance, measured by an Area under the Curve (AUC) of 0.96 and F1 score of 0.97 (Meituan, 2022). Buoyed by this evidence, Meihua applied BERT on *archived* ads to classify an ad creative by whether it focuses on price, quality, or brand. That is, an ad has only one focus. This three-category classification is consistent with academic research (Jedidi et al., 1999; Parment, 2014) and business practice (Linkedin, 2018). Specifically, price advertising emphasizes competitive pricing or discounts on the car model (Jedidi et al., 1999). Quality advertising highlights the superior quality of the model (Du et al., 2015), while brand advertising concentrates on the brand associations of the car model (Parment, 2014) (see Figure A1 in the e-companion for examples of ad creatives in our sample).

We also check the internal validity of Meihua's classifier. Specifically, following extant research (Kopalle et al., 2017; Rice & Lu, 1988), we recruited two research assistants (RAs) to independently classify the ads by the three types of focus: price, quality, and brand. Aiming to minimize bias, we randomized the presentation order of the ads to the RAs. The inter-RA reliability score is 0.89, indicating

[16] Our empirical specification controls for spendings on TV ad, Internet ad, and outdoor ad (i.e., billboards and posters).

a high level of agreement between them. Additionally, Cohen's kappa coefficient is 0.687, which is consistent or superior to those reported in prior research (Kopalle et al., 2017; Tellis & Johnson, 2007). For ads where the RAs' classification diverged, we encouraged them to resolve the divergence through discussion and reach a consensus to categorize the ads into a singular focus. Last, the correlation coefficient between our RAs' classification and Meihua's BERT classification is 0.93, validating Meihua's classification.

As a result, we obtain a balanced data set of weekly ad spending for 62 A-class sedan models across 308 prefectures from June 30, 2014, to February 1, 2015. As Table 1 reports, a model spent RMB 280 (equivalent to US$40) on advertising in each week and prefecture. This total spending decomposes into an average of RMB 30 (equivalent to US$5) on price advertising, and RMB 250 (equivalent to US$35) on quality advertising.[17]

We collect data on social media and news media coverage to control for alternative explanations of a substitute's adjustment of ad spending. These explanations include (1) news about the substitute model, (2) buyers' interest in the substitute model, (3) social media generated by the substitute model's dealers and manufacturers and followers' engagement with these media, and (4) the substitute model's ad spending on nonprint media. Next, we elaborate on each control variable.

First, we used Factiva to count the number of news articles about substitute model i in week w and prefecture p (Ahern & Sosyura, 2014; Astvansh et al., 2022). On average, a substitute model received 0.383 media reports per week, per prefecture (Table 1).

Second, we control for buyers' overall interest in the substitute model by including in our specification an index of the volume of internet searches about the model (Guo et al., 2019). Specifically, we search Baidu Trend for the name of each model i and collect the corresponding search volume data in week w and prefecture p. A higher search volume index indicates a higher buyer interest in the model. As Table 2 shows, on average, a substitute model has a weekly search index of 146.301.

Third, we control for social media activities of the focal model's dealers and manufacturers. Specifically, we collect data from official Sino Weibo accounts of dealers and manufacturers of 62 models during the observational period (Wei et al., 2021). As Table 1 reports, on average, a model's dealer has a 0.131 probability of making a weekly Weibo post, which garners an average of 0.150 likes, 1.039 comments, and 3.391 shares per week. Further, a model's manufacturer has a 0.191 likelihood of posting content on Weibo per week. This content receives an average of 1.863 likes, 0.606 comments, and 1.645 shares per week.

[17] Conditional on nonzero spendings, a model spent RMB 88,750 (equivalent to US$ 12,666) on advertising in each week-prefecture. This total spending decomposes into an average of RMB 10,560 (equivalent to US$ 1,507) on price advertising, RMB 77,760 (equivalent to US$ 11,098) on quality advertising, and RMB 430 (equivalent to US$ 61) on brand advertising.

Fourth, we include controls for the model's ad spending on the Internet and spending on television (TV), and an indicator variable of whether the model is featured in any outdoor advertising. On average, a model spent RMB 80 (equivalent to US$11) on Internet advertising and RMB 510 (equivalent to US$ 69) on TV advertising in each prefecture each week (Table 1). Additionally, an average model has a 0.147 likelihood of spending on outdoor advertising.

Table 2. Variable Definition and Summary Statistics

Note: All spending is in units of RMB 10,000.

Variable	Measure	Data Source	Mean	S.D.	Min	Max
After Sagitar Recall	= 1 for postrecall period	VW	0.484	0.500	0	1
Total Ad_{iwp}	Model *i*'s total print ad spending in week *w* and prefecture *p*	Meihua	0.028	0.751	0	165.110
Price Ad_{iwp}	Model *i*'s spending on price advertising in print media in week *w* and prefecture *p*	Meihua	0.003	0.172	0	29.700
Quality Ad_{iwp}	Model *i*'s spending on product quality advertising in print media in week *w* and prefecture *p*	Meihua	0.025	0.722	0	165.110
Brand Ad_{iwp}	Model *i*'s spending on brand advertising in print media in week *w* and prefecture *p*	Meihua	0.0001	0.038	0	20.400
$Media_{iwp}$	The number of unique news reports about the model *i* in week *w* and prefecture *p*	Factiva	0.383	1.240	0	15
Baidu $Trend_{iwp}$	Historical trends of Baidu weekly search volume for model *i* in week *w* and prefecture *p*	Baidu Trend	146.301	120.940	0	1247.619
Dealer's Weibo $Posts_{iwp}$	= 1 if any dealer created any post on Weibo for model *i* in week *w* and prefecture *m*, and 0 otherwise	Weibo	0.131	0.338	0	1
Dealer's Weibo $Likes_{iwp}$	Number of likes for Weibo content posted by all dealers for model *i* in week *w* and prefecture *p*	Weibo	0.150	3.898	0	1881
Dealer's Weibo $Comments_{iwp}$	Number of comments for Weibo content posted by all dealers for model *i* in week *w* and prefecture *p*	Weibo	1.039	66.155	0	18194
Dealer's Weibo $Shares_{iwp}$	Number of shares for Weibo content posted by all dealers for model *i* in week *w* and prefecture *p*	Weibo	3.391	266.881	0	60624
Manufacturer's Weibo $Posts_{iwp}$	= 1 if the manufacturer posts on Weibo for model *i* in week *w* and prefecture *p*, and 0 otherwise	Weibo	0.191	0.393	0	1
Manufacturer's Weibo $Likes_{iwp}$	Number of likes for Weibo posted by the manufacturer of model *i* in week *w* and prefecture *p*	Weibo	1.863	206.530	0	117868
Manufacturer's Weibo $Comments_{iwp}$	Number of comments for Weibo posted by the manufacturer of model *i* in week *w* and prefecture *p*	Weibo	0.616	23.166	0	4248

Manufacturer's Weibo $Shares_{iwp}$	Number of comments for Weibo posted by the manufacturer of model *i* in week *w* and prefecture *p*	Weibo	1.645	86.547	0	15521
Internet Ad_{iwp}	Internet ad spending for model *i* in week *w* and prefecture *p*	Meihua	0.008	0.045	0	20
TV Ad_{iwp}	TV ad spending for model *i* in week *w* and prefecture *p*	Meihua	0.051	0.175	0	60
Outdoor Ad_{iwp}	= 1 if the model *i* has outdoor advertising in week *w* and prefecture *p*, and 0 otherwise	Meihua	0.147	0.354	0	1
Direct $Substitute_i$	= 1 if the car model *i* is a direct substitute of Sagitar, and 0 otherwise	Autohome.com	0.081	0.272	0	1
Sibling $Substitute_i$	= 1 if the model *i* is owned by VW, and 0 otherwise	VW	0.097	0.296	0	1
Substitute's Sales $Volume_{imp}$	The sales volume of the car model *i* in month *m* and prefecture *p*	Chinese Vehicle Administrative Office	20.301	64.976	0	1993

3.3. Empirical Strategy

Following prior literature on the causal impact of an unexpected trigger (Ozturk et al., 2019), we use the regression-discontinuity-in-time (RDiT) method to measure the impact of Sagitar recall on its substitute models' ad (appendix B in the e-companion provides technical detail of RDiT). Sagitar's recall serves as the temporal discontinuity in treatment. Based on a narrow time window before the event, the RDiT method allows us to estimate the counterfactual—that is, a substitute's ad spending in the absence of the Sagitar recall. Stated differently, a substitute's ad spending just *before* the Sagitar recall constitutes an appropriate counterfactual comparison to the substitute's ad spending just *after* the Sagitar recall. Unlike other identification strategies, such as Difference-in-Differences, the RDiT approach does not require a control group that is empirically similar to the treatment group (Hausman & Rapson, 2018). Because all car models in the same sedan class (i.e., A-class) are exposed simultaneously to the recall event, identifying a valid control group is infeasible.

In general, the regression discontinuity design serves as a localized experiment at the cutoff point, and its generalizability beyond the bandwidth might be limited (Hausman & Rapson, 2018). However, we reason that the local nature of RDiT is not a significant concern in our empirical setting for two reasons. First, we focus on the substitutes' ad spending on print media, which involves a shorter lead time and thus increases the face validity of our estimated effect. Second, in choosing our observational period, we follow prior research that examines observers' responses to a firm's announcement of negative news. For example, in their study of observer firms' responses to a related firm's bankruptcy filing, Ozturk et al. (2019) used a 32-week period. Further, research on the effects of recalls on managers' ad spending adjustment has used a similar time frame (e.g., around one year) (Borah and Tellis, 2016). Therefore, while RDiT generally possesses a local nature, it is well-suited to our sample.[18]

The identification assumption of the RDiT method is that no unobservable factors that affect ad spending cause a discontinuous change in the temporal cutoff. In other words, RDiT assumes that the change in ad spending is caused by the recall event rather than other unobservable factors such as seasonality. Therefore, Equation (1) below controls for observables and a series of fixed effects (FEs) to account for unobservable factors:

$$Outcome_{iwp} = \beta_{10} + \beta_{11} After\ Sagitar\ Recall_w + \boldsymbol{\theta_i} + \boldsymbol{\pi_w} + \boldsymbol{\mu_p} + \boldsymbol{\beta_{12} X_{iwp}} + \varphi_{iwp} \tag{1}$$

Subscripts *i*, *w*, and *p* index the car model, the week, and the prefecture, respectively. $Outcome_{iwp}$ denotes our set of dependent variables (DVs): $Total\ Ad_{iwp}$, $Price\ Ad_{iwp}$, $Quality\ Ad_{iwp}$, and $Brand\ Ad_{iwp}$. $After\ Sagitar\ Recall_w$ is a dummy variable that equals 1 if the focal week is "after" Sagitar's recall (i.e., the weeks from October 19, 2014, to February 1, 2015), and 0 otherwise. $\boldsymbol{X_{iwp}}$ is the vector of control variables listed earlier. We include FEs at three levels: model ($\boldsymbol{\theta_i}$), week ($\boldsymbol{\pi_w}$), and prefecture ($\boldsymbol{\mu_p}$). Model-specific FEs $\boldsymbol{\theta_i}$ allow us to account for the model-specific, time-invariant unobservables (e.g., the model's manufacturer). Week-level FEs help us control for the intertemporal differences that do not vary across models. Further, we control for prefecture-specific unobservables with the vector of prefecture-level FEs $\boldsymbol{\mu_p}$. β_{11} is our coefficient of interest, which is the average effect of Sagitar's recall on its substitutes' ad spending.

[18] We thank a reviewer for asking us to justify RDiT in our setting. The request led us to choose print media (to measure ad spending) because of its short lead time.

4 Main Results

4.1. Model-Free Evidence

Figure 2. Model-Free Evidence

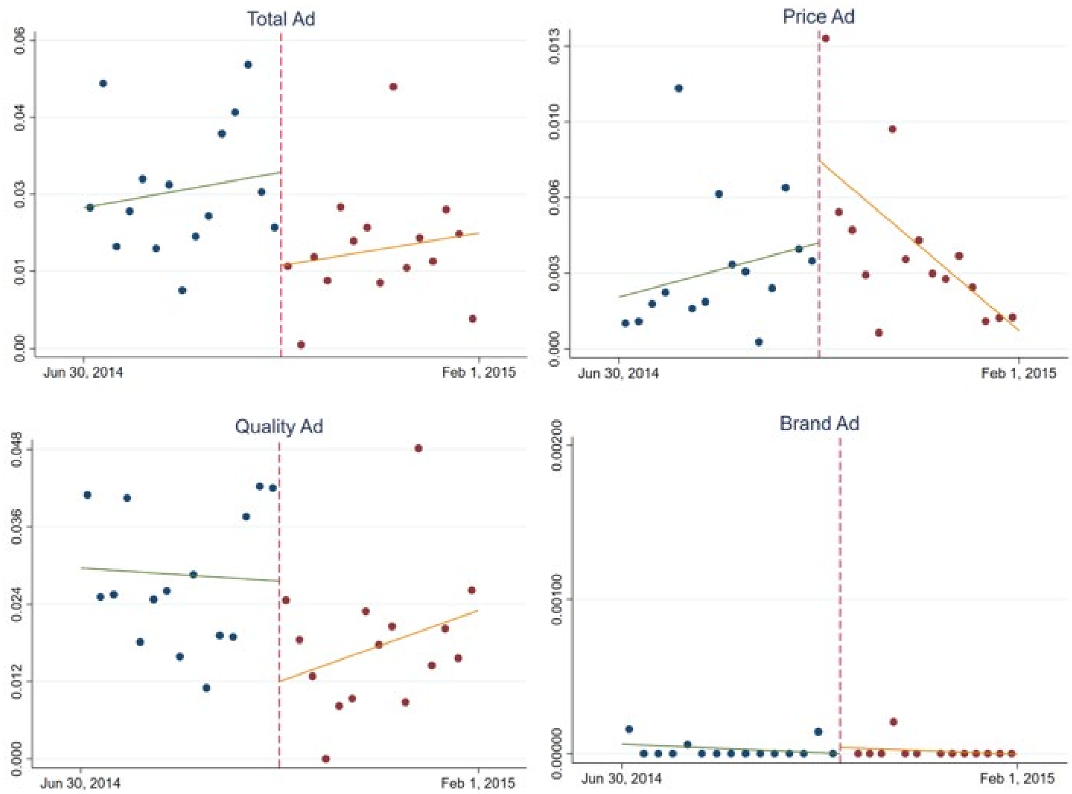

Figure 2 presents the model-free evidence of the substitute models' ad spending before and after Sagitar's recall. The X-axis covers the seven-month observational period from July 2014 to January 2015. The top left figure reveals a noticeable decrease ($p < 0.01$) in total ad spending for substitute models after the recall. A decomposition of spending by ad type indicates an increase ($p < 0.01$) in *Price Ad* following the recall, but a decrease ($p < 0.01$) in *Quality Ad*. However, we observe an insignificant change ($p > 0.1$) in *Brand Ad*. Table A2 in the e-companion provides the *t*-statistic for the model-free evidence. Next, we present the estimates from the RDiT analysis.

4.2. How Do Substitutes Adjust Their Ad Spending?

Table 3 summarizes our identified effects. The negative and statistically significant coefficient ($\beta = -0.014$, $p < 0.05$) in Column I suggests that substitute car models responded to Sagitar's recall by *lowering* their total spending on advertising. Specifically, in each week and each prefecture following the recall, Sagitar's substitutes spent on advertising—on average—0.014 × 10,000 = RMB 140 (or US$ 19) *less* than what they spent in a prerecall week-prefecture, on average. This number amounts to a 50% drop in spending (140 ÷ 280).

Next, we decompose the substitutes' ad spending by whether the advertisement focuses on price, quality, or brand. The results in Columns II and III of Table 3 show that in response to Sagitar's recall, the substitutes *raised* their week-prefecture-level spending on price advertising (β = 0.007, p < 0.01) by RMB 70 (or US$ 10), which is equivalent to a 25% raise (70 ÷ 280), but *lowered* their week-prefecture-level spending on quality advertising by RMB 200 (β = −0.020, p < 0.01), which equals a drop of 71% (200 ÷ 280). Column IV of Table 3 shows that Sagitar's recall did not impact substitutes' spending on brand advertising (β = −0.000, p > 0.1).[19]

One may be concerned that our control variables (e.g., Internet Ad) are endogenous. We address this concern with the following three steps. First, we estimate a regression that excludes the TV, Internet, and social media variables. The estimates (Table C1) are consistent with our main analyses (Table 3). Second, prior literature (e.g., Cinelli et al., 2022) has suggested that it is common for control variables to also function as dependent variables. The effects can be biased if these additional variables "produce an unintended discrepancy between the regression coefficient and the effect that the coefficient is intended to represent" (Cinelli et al. 2022, p.1). However, the inclusion of additional variables (e.g., Internet and social media ad spending) produces estimates that are lower than or equal to the estimates produced after their inclusion (compare Table C1 with Table 3). The insight is that including the controls leads to conservative estimates. Third, following prior literature (Anderson & Hsiao, 1981; Blundell & Bond, 2000, Todd & Wolpin, 2003), we used these controls' one-period lagged values as instruments. The estimates (Table C2) were consistent results, further reducing the endogenous concern. Appendix C in the e-companion provides the details.

Table 3. The Impact of Sagitar's Recall on Substitute Models' Ad Spending

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
	I	II	III	IV
After Sagitar Recall	-0.014**	0.007***	-0.020***	-0.000
	(0.007)	(0.002)	(0.007)	(0.000)
Media	-0.005***	-0.0002	-0.005***	-0.000
	(0.001)	(0.0004)	(0.001)	(0.000)
Baidu Trend	0.236***	0.024	0.211***	0.001
	(0.048)	(0.013)	(0.047)	(0.001)
Dealers' Weibo Posts	-0.003	-0.005***	0.003	-5.82e-07
	(0.005)	(0.001)	(0.005)	(0.0001)
Dealers' Weibo Likes	-0.795**	-0.395***	-0.399	-0.001
	(0.369)	(0.098)	(0.357)	(0.006)
Dealers' Weibo Comments	0.040	-0.003	0.043	-6.38e-06
	(0.051)	(0.014)	(0.049)	(0.001)
Dealers' Weibo Shares	-0.005	0.002	-0.007	2.23e-06
	(0.009)	(0.002)	(0.009)	(0.000)
Manufacturer's Weibo Posts	-0.008**	-0.002*	-0.006*	0.0001
	(0.003)	(0.001)	(0.003)	(0.0001)

[19] We acknowledge the concern that the three foci of ad type may correlate with one another. Therefore, we estimated a seemingly unrelated regression (SUR) and find that the results hold. A table of the SUR estimates is available from the first author.

Manufacturer's Weibo Likes	0.002 (0.005)	0.0004 (0.001)	0.002 (0.005)	-1.06e-06 (0.000)
Manufacturer's Weibo Comments	-0.471*** (0.086)	-0.065*** (0.023)	-0.406*** (0.083)	0.0001 (0.001)
Manufacturer's Weibo Shares	0.049*** (0.016)	0.008* (0.004)	0.041*** (0.015)	-0.000 (0.000)
Internet Ad	1.442*** (0.066)	0.342*** (0.017)	1.101*** (0.064)	0.000 (0.000)
TV Ad	0.017* (0.009)	-0.005** (0.002)	0.022** (0.008)	-0.000 (0.000)
Outdoor Ad	0.008* (0.004)	-0.008*** (0.001)	0.016*** (0.004)	0.0001 (0.0001)
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R^2	0.041	0.017	0.036	0.002
F-statistic	17.810	15.310	13.290	0.730

Note. **p* < 0.1, ***p* < 0.05, ****p* < 0.01. Robust standard errors are reported in parentheses.

4.3. Does the Substitute's Response Strategy Payoff?

Next, we explore the effectiveness of the substitutes' response strategy (see Figure A2 in the e-companion for the model-free evidence). We estimate the model in two steps. First, because we observe the sales volume on a monthly basis, we regress $Substitute's\ Sales\ Volume_{imp}$—the substitute car model *i*'s sales volume in month *m* and prefecture *p*—on *After Sagitar Recall*, thus measuring the average effect of Sagitar's recall on substitutes' monthly sales volume (Equation 2 below).

$$\begin{aligned} &Substitute's\ Sales\ Volume_{imp} \\ &\quad = \beta_{20} + \beta_{21}\ After\ Sagitar\ Recall_m + \boldsymbol{\theta_i} + \boldsymbol{\pi_m} \\ &\quad + \boldsymbol{\mu_p} + \boldsymbol{\beta_{22} X_{imp}} + \varphi_{imp} \end{aligned} \tag{2}$$

Second, we explore how ad spending moderates the relation between *After Sagitar Recall* and the *Substitute's Sales Volume*. Because the substitute's ad spending is likely endogenous to its sales volume, we estimate a two-stage least squares (2SLS) regression to correct for the endogeneity of ad spending (Goldfarb et al., 2022). The instrumental variable (IV) must meet the relevance criterion and exclusion restriction (Barron et al., 2021; Bavafa et al., 2018). That is, the instrument should correlate with a car model's ad spending but should not directly influence its sales volume. Therefore, following previous research (Shapiro, 2018), we use the *Number of New Ad Firms* established per capita in prefecture *p* and month *m* to instrument a car model's ad spending in prefecture *p* and month *m*. New ad firms refer to new firms that classified their business in the "advertising agency business" category in their registration form (https://www.gov.cn/bumenfuwu/2017-07/07/content_5208703.htm) filed with the government. We count the number of such firms in month *m* with a registration address in prefecture *p*. Extant research suggests (Acs et al., 2013; Feldman, 1999; Harhoff, 1999) that newly established ad firms impact activities in the local advertising market for two reasons. First, an increase in the number of local advertising firms lowers the advertisers' cost of access to local advertising resources such as ad outlets (e.g., various magazines and newspapers) and media (e.g., in-print poster, magazine, and newspaper) (Chandra & Weinberg, 2018; Tai 1997). Moreover, the establishment of new firms intensifies competition among the incumbents. As a result, advertising agencies provide superior value to their clients (i.e., automobile manufacturers in our context) (Hitt et al., 1998; Horsky, 2006). Second, the proliferation of local ad firms enhances the public's perception of advertisements, amplifying a firm's inclination to invest in advertising expenditures within the local market (Arora & Forman, 2007; Gurun & Butler, 2012). This, in turn, implies that the number of newly established ad firms is positively related to the focal brand's local ad spending. Because print media is the primary avenue of advertising for the automobile industry, the expansion of local ad firms may positively affect automobile brands' ad spending in print media. Consequently, we expect a positive association between the *Number of New Ad Firms* and the *Ad Spending* variable. Further, we see no reason for a direct relation between the establishment of ad firms and a car model's sales volume. Automobile sales volume is more likely to be related to the economic condition (Kenworthy & Laube, 1999), while the establishment of new advertising firms predominantly relies on the cultural significance of the city rather than being directly linked to the local economic situation (Faulconbridge et al., 2010). Academics have concluded that the cultural importance of the city is marked by religious and artistic centers and activities, which are distinct from economic centers and functions (Grodach & Loukaitou-Sideris, 2007). Indeed, economy and culture are often regarded as two separate and incompatible aspects of social life (Throsby, 2001). Therefore, research has suggested that the establishment of ad firms is distributed across both large and small cities (Yin & Derudder, 2021), indicating that our instrumental variable meets the exclusion restriction criterion.

Empirically, we provide evidence showing that our instrument is not directly related to the number of all new firms, a proxy for local economic conditions (Gartner, 1985), which could affect local car sales (Pauwels et al., 2004). Specifically, we collected data from https://www.itjuzi.com, which provides comprehensive information (e.g., name, timestamp, location, industry, owner, and funding details) of registration of new firms. Leveraging this data source, we generate $Number\ of\ New\ Ad\ Firms_{mp}$ to measure the number of new ad firms *per capita* in prefecture *p* has newly established advertising firms in month *m.* We further generate $All\ New\ Firms_{mp}$ to measure the number of newly established firms—regardless of whether they register themselves with the government in the ad agency business category or any other—in month *t* and prefecture *m*. Table D1 reports the relation between the two variables. The insignificant effect suggests that our IV variable likely meets the exclusion restriction (Liu et al., 2017; Narang & Shankar, 2019).

This 2SLS method consists of a two-stage estimation (Goldfarb et al., 2022). In the first stage, we regress the endogenous variable (i.e., ad spending) on the IV and control variables, as specified in Equation (3):

$$\begin{aligned} Ad\ Spending_{imp} &= \beta_{30} + \beta_{31}\ Number\ of\ New\ Ad\ Firms_{mp} + \boldsymbol{\theta_i} + \boldsymbol{\pi_m} \\ &+ \boldsymbol{\mu_p} + \boldsymbol{\beta_{33}X_{imp}} + \varphi_{imp} \end{aligned} \tag{3}$$

$Number\ of\ New\ Ad\ Firms$ is the number of new ad firms per capita in prefecture *p* and month *m.*

Table D2 reports the estimates from the first stage of the 2SLS regression. As expected, the *Number of New Ad Firms* is positively associated with the focal model's *Ad Spending* variables.

We interact the fitted value of *Ad Spending* with the *After Sagitar Recall* indicator to test whether a substitute's ad spending moderates the effect of the recall on the substitute's sales (Equation 4) (Rajan & Zingales, 1998).

$$\begin{aligned} Substitute's\ Sales\ Volume_{imp} &= \beta_{40} + \beta_{41}\ After\ Sagitar\ Recall_m \times \widehat{Ad\ Spending\ variable}_{imp} \\ &+ \beta_{42}\ After\ Sagitar\ Recall_m + \beta_{43}\ \widehat{Ad\ Spending\ variable}_{imp} + \boldsymbol{\theta_i} \\ &+ \boldsymbol{\pi_m} + \boldsymbol{\mu_p} + \boldsymbol{\beta_{44}X_{imp}} + \varphi_{imp} \end{aligned} \tag{4}$$

$\widehat{Ad\ Spending\ variable}_{imp}$ denotes the fitted values obtained from Equation (3).

Table 4 reports the results. First, Column I reports that Sagitar's recall *increased* a substitute's sales volume ($\beta = 7.176$, $p < 0.01$), suggesting a competition (or positive spillover) effect. Specifically, Sagitar's recall raised the substitute's sales by an average of 7.176, equivalent to 35.3% (7.176 ÷ the mean value of 20.301). Interestingly, the competition effect is the opposite of Freedman et al. (2012) and Mackalski and Belisle (2015) findings of a contagion effect, albeit in the case of three toy recalls, and Land O'Lakes butter recall in the United States, respectively. These differences might be driven by the heterogeneity in (1) the users of cars, toys, and butter, and (2) the harm that defective products in these categories can cause to their users. For example, children are the predominant users of toys, and a defective toy poses a severe risk to this vulnerable user segment. In the case of butter, buyers can use margarine as a substitute product. Therefore, a recall by one toy or butter brand can hurt the sales of all brands in the category. However, if a buyer wants to buy a car of a brand and becomes aware of a recall by that brand, the buyer may likely choose a substitute brand rather than delay the purchase for several weeks (Chen et al., 2009). We next move to the moderation effects.

Column II reports that an increase in the substitute's total spending on advertising *weakens* the positive spillover effect ($\beta = -4.685$, $p < 0.01$). On average, a one-unit (in RMB 10,000) increase in ad spending reduces sales volume by 23.1% (4.685 ÷ 20.301). These results are consistent with the intuition that a substitute's advertising could evoke buyers' unfavorable comparisons between the recalled Sagitar model and the advertised substitute. Such unfavorable comparisons boost contagion. The insight for managers of substitute products is that they can harness the positive spillover from the recall, by lowering the visibility of their substitute products. Our earlier result (Table 3) suggests that managers are indeed making the right decision.

We next decompose the substitute model's total spending by type (i.e., price, quality, and brand) and re-estimate Equations (3) and (4). Columns III to V in Table 4 suggest that the weakening moderation effect is caused by the substitute's spending on quality advertising and not by its spending on price advertising or on brand advertising. This finding corroborates the theoretical insight we drew from Column II. That is, on average, a recall benefits its substitutes. However, the higher the substitute's spending on quality advertising, the weaker this positive spillover because quality advertising reminds customers of comparisons between the recalled product and the advertised substitute.

Table 4. The Impact of Sagitar's Recall on its Substitute Models' Sales (Column I) and the Moderating Effect of Substitutes' Ad Spending (Columns II-V)

DV =	Substitute's Sales Volume				
	(I)	(II)	(III)	(IV)	(V)
After Sagitar Recall × $\widehat{\text{Total Ad}}$		-4.685*** (0.417)			
$\widehat{\text{Total Ad}}$		6.280*** (1.140)			
After Sagitar Recall × $\widehat{\text{Price Ad}}$			-10.165 (7.598)		
$\widehat{\text{Price Ad}}$			10.405 (11.525)		
After Sagitar Recall × $\widehat{\text{Quality Ad}}$				-6.116*** (0.435)	
$\widehat{\text{Quality Ad}}$				4.076*** (1.253)	
After Sagitar Recall × $\widehat{\text{Brand Ad}}$					1983.529 (1349.812)
$\widehat{\text{Brand Ad}}$					-1079.556 (1441.527)
After Sagitar Recall	7.176*** (0.216)	7.492*** (0.217)	0.823*** (0.193)	6.915*** (0.226)	1.297*** (0.179)
Controls	Y	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y	Y
Month-FEs	Y	Y	Y	Y	Y
Models	62	62	62	62	62
Prefectures	308	308	308	308	308
Months	7	7	7	7	7
Observations	133,672	133,672	133,672	133,672	133,672
R^2	0.125	0.114	0.098	0.126	0.007
F-stat (weak IV test)		211.220	126.160	260.440	102.750

Note. *$^{*}p$ < 0.1, $^{**}p$ < 0.05, $^{***}p$ < 0.01. Robust standard errors are reported in parentheses.

5 Heterogeneity in Ad Adjustment

Thus far, our analysis has revealed that, *on average*, a substitute brand responds to a brand's recall by reducing its total ad spending. This reduction is the net of a simultaneous increase in price ad spending and a decrease in quality ad spending. Next, we explore the heterogeneity in the average adjustment in ad spending.

Buyers may compare the recalling brand and a substitute brand based on (1) whether the substitute is a "direct substitute" of the recalling brand (i.e., the recalling brand *and* the substitute brand feature in buyers' consideration set) and (2) whether the substitute is a "sibling substitute" (i.e., the two brands are owned by the same manufacturer). Next, we explore whether substitute brands' ad adjustments vary by these two characteristics.

5.1. Heterogeneity by Direct (vs. Indirect) Substitute

We investigate how direct substitution influences the adjustment in ad spending (Roehm and Tybout, 2006). Specifically, we collected additional data from the largest Chinese online automobile platform, Autohome.com (akin to Edmunds.com in the United States), to identify car models visitors browse after viewing the Sagitar model. The platform provided an overview of the foremost *five frequently viewed models*, which are recognized as direct substitutes to the Sagitar. Specifically, we identify the following five (of the 62 car models) as *direct* substitutes for Sagitar: (1) Audi A3, (2) Changan Eado, (3) Honda Civic, (4) Nissan Bluebird Sylphy, and (5) Toyota Corolla (Table A1 highlights these five names in the light gray color). By extension, the remaining 57 car models are indirect substitutes. Because these five models exist in buyers' consideration set along with Volkswagen Sagitar, they likely evoke the same brand associations in buyers as the Sagitar brand.

We generate a dummy variable $Direct\ Substitute_i$ to measure whether the car model *i* is a direct substitute of Sagitar. We test the moderating effect of direct substitutes as specified in Equation (5):

$$\begin{aligned} Outcome_{iwp} = {} & \beta_{50} + \beta_{51}\ After\ Sagitar\ Recall_w \\ & + \beta_{52}\ After\ Sagitar\ Recall_w \times Direct\ Substitute_i + \boldsymbol{\theta_i} + \boldsymbol{\pi_w} \\ & + \boldsymbol{\mu_p} + \boldsymbol{\beta_{53} X_{iwp}} + \varphi_{iwp} \end{aligned} \tag{5}$$

$Direct\ Substitute_i$ represents whether the model *i* is a direct substitute of Sagitar and β_{52} quantifies whether/how Sagitar's direct substitutes adjust their ad spending (in the aftermath of Sagitar recall) differently than Sagitar's indirect substitutes.

Table 5 reports the estimates. The effect of *After Sagitar Recall* × *Direct Substitute* on total spending is negative ($\beta = -0.060$, $p < 0.01$), demonstrating that Sagitar recall had an amplified negative effect on direct (versus indirect) substitutes' ad spending. Further, the amplified effects manifest in price ad spending ($\beta = -0.013$, $p < 0.01$) and quality ad spending ($\beta = -0.047$, $p < 0.01$).

Table 5. Heterogeneity by Direct (vs. Indirect) Substitute

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
	I	II	III	IV
After Sagitar Recall × Direct Substitute	-0.060***	-0.013***	-0.047***	-0.000
	(0.006)	(0.002)	(0.006)	(0.000)
After Sagitar Recall	-0.010	0.008***	-0.017***	-0.000
	(0.007)	(0.002)	(0.007)	(0.000)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R^2	0.038	0.012	0.034	0.002
F-statistic	17.810	15.310	13.290	0.730

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

5.2. Heterogeneity by Sibling (vs. Nonsibling) Substitute

Next, we test whether substitutes' adjustment to ad spending varies by whether the substitute model is owned by the Volkswagen Group (VW). Of the 62 car models, the following six car models are owned by VW: (1) Bora, (2) Golf, (3) Lamando, (4) Lavida, (5) Rapid, and (6) Santana (Table A1 highlights these names in the dark gray color). Importantly, Autohome.com lists none of these six models in buyers' direct consideration when choosing the Volkswagen Sagitar. That is, the set of six models and the set of five direct substitutes are mutually exclusive. We call these six brand-related models "sibling substitutes." Therefore, we generate a new variable $Sibling\ Substitute_i$ to indicate whether model i is owned by VW. We use $Sibling\ Substitute_i$ in Equation (5) to measure the moderating effect of ownership. Table 6 reports the estimates. The interaction effect—that is, the effect of *After Sagitar Recall* × *Sibling Substitute*—on total ad spending is positive ($\beta = 0.073$, $p < 0.01$). Interestingly, almost all of this effect is sourced from substitutes' spending on quality advertising ($\beta = 0.073$, $p < 0.01$).

That is, in response to Sagitar's recall, sibling substitutes raise their ad spending, and this raise is driven exclusively by spending on quality advertising. This result is the opposite of what our intuition suggests. We conjecture that because sibling substitutes and Sagitar share manufacturing processes, buyers will likely infer that siblings have the same manufacturing defects as Sagitar. That is, buyers are likely to evaluate siblings unfavorably. Anticipating this obvious unfavorable comparison, managers of sibling substitutes must defend themselves by increasing their spending on advertising the quality of their models and thus mitigating buyers' comparisons with Sagitar. The evidence thus supports the quality-signaling strategy, while supporting neither the sales-preemption strategy nor the harm-avoidance strategy.

Table 6. Heterogeneity by Sibling (vs. Nonsibling) Substitute

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall × Sibling Substitute	0.073***	-0.000	0.073***	0.0001
	(0.006)	(0.002)	(0.006)	(0.000)
After Sagitar Recall	-0.021***	0.007***	-0.028***	-0.000
	(0.007)	(0.002)	(0.007)	(0.000)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R^2	0.039	0.017	0.035	0.002
F-statistic	21.080	14.960	16.930	0.730

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

6 Robustness Checks

6.1. Robustness to Alternative Prerecall Period

One may reason that our identified effects are sensitive to the selected observational window of June 30, 2014, to February 1, 2015 (Ozturk et al., 2019). We alleviate this concern by reducing the pretreatment period from 16 weeks to 11 weeks, effectively condensing it by one month. As a result, the commencement date has been adjusted from Monday, June 30, 2014 to Monday, August 4, 2014. We replicate the main analysis with this reduced observational period. Table 7 shows that our identified effects are robust to this alternate window.

Table 7. The Impact of Sagitar's Recall on Substitute Models' Ad Spending: Robustness to Alternative Prerecall Period

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.019***	0.006***	-0.025***	1.41e-06
	(0.007)	(0.002)	(0.007)	(0.000)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	26	26	26	26
Observations	496,496	496,496	496,496	496,496
R^2	0.057	0.013	0.050	0.002
F-statistic	14.270	16.630	10.530	0.750

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

6.2. Robustness to the Augmented Local Linear Strategy

Including controls with a short observational period could lead to spurious correlations—that is, the plausibility that the identified effects were produced by chance or unobserved confounds—contaminating the causal interpretation. For instance, if the treatment coincidentally commences on a Monday, distinguishing the "Monday effect" from the intended treatment effect becomes less straightforward. We address this challenge by adopting an augmented local linear strategy (Hausman & Rapson, 2018; Ozturk et al., 2019). Using a relatively long period helps account for potential noise within the data structure, thus stripping out the effects of control variables more effectively (Hausman & Rapson, 2018). For instance, we could strip out potential biases from seasonality that may affect the identification of the true effect. Specifically, we follow a two-step procedure (Hausman & Rapson, 2018). First, we save the residuals from the estimation of the coefficients of control variables using the same period as that in our main analysis. Second, we estimate a local linear specification using only the residuals within a one-month narrower window around the treatment (i.e., Monday, August 4, 2014, to Sunday, February 1, 2015). Table 8 reports the estimates. These results further indicate that substitutes decreased ad spending following the Sagitar recall. Thus, these findings corroborate our results reported in Table 2.[20]

Table 8. The Impact of Sagitar's Recall on Substitute Models' Ad Spending: Robustness to the Augmented Local Linear Strategy

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.002***	0.002***	-0.001***	0.000***
	(0.000)	(9.68e-06)	(0.000)	(4.62e-07)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	26	26	26	26
Observations	496,496	496,496	496,496	496,496
R^2	0.829	0.935	0.996	0.500
F-statistic	2.38e+07	7.19e+06	1.03e+09	775,777

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

6.3. Robustness to Negative Binominal Estimator

We use a negative binomial estimator to mitigate the concern that our identified effects are biased by the specific functional form. The results in Table 9 are qualitatively consistent with our main results (Table 3), demonstrating that our identified effects are robust to an alternate estimator.

[20] The error term for brand ad exhibits a small variance, leading to a small but significant beta with the large sample size (Fern & Monroe, 1996). "Effects are trivially small but nevertheless significant because of large sample sizes" (Fritz et al. 2012, p. 2).

Table 9. The Impact of Sagitar's Recall on Substitute Models' Ad Spending: Robustness to Negative Binomial Estimator

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.195**	0.301*	-0.391***	-6.657
	(0.077)	(0.160)	(0.089)	(5.448)
Controls	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
Log-likelihood	-14,650	-3866	-11763	-51

Note. **p* < 0.1, ***p* < 0.05, ****p* < 0.01. Robust standard errors are reported in parentheses.

6.4. Falsification Test

Following Ozturk et al. (2019), we conduct a falsification test to mitigate the concern that unobservables bias our results. Specifically, we conduct a falsification test to forward the true recall event (i.e., October 17, 2014) by one month and assign a fake treatment as of September 17, 2014. The result in Table 10 suggests that the fake recall event does not impact substitutes' ad spending, thereby alleviating the concern that unobservables bias our results.

Table 10. Falsification Test

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.002	-0.001	-0.001	-0.000
	(0.007)	(0.002)	(0.007)	(0.000)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R^2	0.061	0.022	0.049	0.002
F-statistic	12.720	18.470	9.500	0.650

Note. **p* < 0.1, ***p* < 0.05, ****p* < 0.01. Robust standard errors are reported in parentheses.

6.5. Replication with Internet Ad Spending and Social Media Efforts

Our main analysis focused on advertising in print media. Next, we replicate the main analyses using spending on Internet advertising and social media efforts, which are also flexible to manufacturers' ad adjustment. We reproduce Equation (1) using these two advertising variables and achieve consistent findings (Table 11). Meihua (i.e., the provider of our ad spending data) does not provide disaggregated data for a car model's spending by ad type (i.e., quality, price, and brand) for Internet, TV, and outdoor media types. Therefore, we could not include variables that report disaggregated spending by ad type for these three types of media.

Table 11. The Impact of Sagitar's Recall on Substitute Models' Spending on Internet Advertising and the Number of Weibo Posts

DV =	Internet Ad Spending	Manufacturer's Weibo Posts
After Sagitar Recall	-0.001***	-0.107***
	(0.000)	(0.002)
Model Fixed Effects	Y	Y
Prefecture-Fixed Effects	Y	Y
Week-Fixed Effects	Y	Y
Model	62	62
Prefectures	308	308
Weeks	31	31
Observations	591,976	591,976
R-Squared	0.003	0.024

***Note.* *p < 0.1, **p < 0.05, ***p < 0.01.** Robust standard errors are reported in parentheses.

7 Empirical Extension: Generalization to Another Recall Event

We next test the generalizability of our findings beyond the Sagitar recall. Specifically, we collect an additional data set on a large sport utility vehicle (SUV) recall initiated by Cadillac in China during the year 2014. Cadillac Motor Car is a division of General Motors, which positions Cadillac as a luxury vehicle brand in global markets. As one of the key markets, China contributed to 73,000 vehicle sales for Cadillac, with over a 45% growth rate.[21]

At Auto Shanghai 2009, Cadillac introduced the redesigned SRX as a medium-size luxury SUV model. The model offers two types of engines (3.0 L and 3.6 L), with an all-wheel-drive system and six-speed Tiptronic transmission. The wheelbase is 2,807 mm, and the length of the vehicle is 4,851 mm. The price of the model is between RMB 429,800 and RMB 629,800.[22] In 2013, SRX sold 26,897 vehicles in China at a 24% annual growth.

On September 26, 2014, Cadillac suffered a large recall in China, affecting 107,016 SRX vehicles manufactured from 2009 to 2014.[23] This recall was triggered by a faulty rear suspension component (loose toe adjusters) that posed a safety risk. Following prior research (Borah & Tellis, 2016), we consider SUV models sold in China as of 2014 as SRX's substitutes. We collected data on 30 SUVs that accounted for more than 95% of SUV sales in 2014 (Table A3 lists names of substitute models).

Because Cadillac initiated the recall on September 26, 2014, we consider the 19 weeks from Monday, May 19, 2014, to Sunday, September 28, 2014, as the prerecall period. The postrecall period

[21] https://media.cadillac.com/media/us/en/cadillac/news.detail.html/content/Pages/news/us/en/2015/Jan/0105-cadillac-sales.html
[22] https://www.gmchina.com/media/cn/en/gm/home.detail.html/content/Pages/news/cn/en/2009/090420_New_Cadillac.html
[23] https://driving.ca/cadillac/srx/auto-news/news/gm-recalls-cadillacs-in-china-over-faulty-suspension-omponent

comprises 18 weeks, and includes the weeks from Monday, September 29, 2014, to Sunday, February 1, 2015. Using this newly created balanced sample, we estimate Equation (1). Table 12 presents the results, similar to those reported in Table 3. The consistent results suggest that the observed relations between a recall and its substitutes' ad spending are likely limited to neither the Sagitar recall nor the category of sedan cars. Instead, these effects may be generalized to other recalls and car categories.

Table 12. The Impact of SRX's Recall on Substitute Models' Ad Spending

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After SRX Recall	-0.016*	0.006***	-0.023***	0.001
	(0.009)	(0.002)	(0.009)	(0.003)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	30	30	30	30
Prefectures	308	308	308	308
Weeks	37	37	37	37
Observations	341,880	341,880	341,880	341,880
R^2	0.034	0.032	0.029	0.003
F-statistic	15.880	10.620	15.820	1.950

Note. **p* < 0.1, ***p* < 0.05, ****p* < 0.01. Robust standard errors are reported in parentheses.

8 Discussion

Following a brand's product recall, how do brands of substitute products respond? Our research answers this question, using substitutes' adjustment to ad spending as the response variable. The question is theoretically interesting because substitutes may interpret the recall as an opportunity to steal sales from the recalling brand or to assert the superior quality of their products. Interestingly, substitutes may view the recall as a threat to their own sales, driven by buyers' concerns about the quality of their products. Which interpretation—opportunity or threat—prevails can be determined by whether substitutes increase or decrease their ad spending. If substitutes spend more on advertising after the recall, we conclude that the opportunity interpretation dominates the threat view. However, if substitutes lower their ad spending after the recall, the reverse domination manifests.

Our empirical results reveal that—on average—substitutes decreased their ad spending by 50% in the weeks following Sagitar's recall. The theoretical insight is that substitutes—on average—interpreted Sagitar's recall as a threat rather than an opportunity. Thus, they attempted to lower their visibility so that they suppressed buyers' unfavorable comparisons between Sagitar and the substitutes and thus mitigated the drop in their sales volume.

A substitute's advertising is not a monolith. Specifically, advertisements can focus on price, quality, or brand. The focus determines the substitute's response strategy that underlies the change in ad spending. Therefore, we next classify each ad by whether it focuses on price, quality, or brand, thus decomposing the total ad spending into spending on price advertising, quality advertising, and brand advertising. Empirical tests reveal asymmetrical effects. First, after Sagitar's recall, substitutes raised their spending on price advertising by 25%, suggesting that substitutes interpret the recall as an opportunity to preempt Sagitar's lost sales, and they thus emphasize their competitive prices in their ads. Second, substitutes lowered their spending on quality advertising by 71%, indicating that substitutes are wary of evoking buyers' unfavorable comparisons between Sagitar and substitutes. Consequently, substitutes play down the emphasis on quality. Lastly, substitutes did not adjust their spending on brand advertising, indicating that managers of substitute brands are not concerned about negative spillover on brand image.

Substitutes' response to the recall is a performance-enhancing strategy. Specifically, we report that Sagitar's recall boosted substitutes' sales volume—on average—by 35.3%. Further, each unit (i.e., RMB 10,000) increase in ad spending weakens the positive spillover effect by 23.1%. Thus, by decreasing their total ad spending, managers of substitute products are preventing any potential weakening of the positive spillover effect.

Lastly, in further support of our theory, we explore heterogeneity in the substitutes' response by two points of similarity between the recalling brand (i.e., car model) and a substitute brand. We find that relative to an indirect substitute of the recalling brand, a direct substitute lowers its spendings on price advertising and quality advertising, whereas relative to a nonsibling substitute, a sibling substitute increases its spending on quality advertising. In what follows, we discuss the implications of our findings for theory and practice.

8.1. Implications for Theory

Operations management academics have researched how one firm's negative events or risks impact its related firms' (specifically, suppliers' and organizational customers') outcomes (e.g., Agca et al., 2021; Houston et al., 2016; Jacobs & Singhal, 2020; Wang et al., 2020). We add to this evidence by documenting not only the related firms' outcome (specifically, sales volume) but also their strategic response to a substitute's product quality failure. This addition thus contributes to the broader literature at the OM-marketing-strategy interface.

In addition, extant research has considered events that can yield unambiguously positive outcomes or unambiguously negative outcomes for the observers (e.g., Jacobs & Singhal, 2020; Van Everdingen et al., 2009). A brand's *recall* presents a theoretically interesting OM phenomenon because it can help the substitutes' outcomes but potentially also hurt these outcomes (Astvansh et al., 2024). Therefore, substitutes can interpret a recall as an opportunity, a threat, or both. The interpretation, in turn, determines their behaviors, which shapes their outcomes. In documenting that managers of substitute products, on average, decrease their ad spending, we make the theoretical contribution that these managers interpret the recall more as a threat than an opportunity (Connelly & Shi, 2022). Alternatively stated, managers foresee contagion as more likely than competition—that is, managers of substitute products are (on average) risk-averse. Taken together, we theorize these managers' interpretations and perceptions, and measure the impact of a recall on the observer managers' decisions and the observer brand's outcomes—thus presenting a more holistic picture of what transpires when a brand issues a recall.

However, our primary contribution manifests when we decompose substitutes' spending by three types. We find that managers adopt a nuanced strategy of preempting sales (by increasing their spending on price advertising) and avoiding quality signaling (by decreasing their spending on quality advertising). This nuanced finding is novel to the literature on managerial response to a brand's negative events. This nuanced strategy pays off because it helps managers maximize the positive spillover effect of the recall on the sales volume of their substitute products.

Our exploration of heterogeneity in substitutes' responses by similarity between the recalling brand and the substitute brands offers useful theoretical insights. Specifically, we report that direct (vs. indirect) substitute brands are more likely to interpret the recall as a threat than an opportunity. This interpretation manifests in "more similar" brands lowering their spendings on price and quality relative to the "less similar" substitutes. However, brands from the same recalling manufacturer (as opposed to those from non-recalling manufacturers) may lead to obvious consumer unfavorable comparisons. In this scenario, even though a threat interpretation still dominates over an opportunity interpretation, it is reflected in these sibling brands' increase in their quality ad spending.

8.2. Implications for Practice

Our findings offer two insights to managers of substitute brands. First, we report that a brand's recall increases its substitute's sales volume (specifically, an effect of 35.3% in our empirical study; read Table 3), supporting a positive spillover (or competition) effect. However, this effect weakens as the substitute boosts its ad spending. More precisely, each unit increase in advertising—equivalent to RMB 10,000—weakens the positive main effect by 23.1%. The finding of this weakening moderation effect validates managers' strategy of suppressing their substitute brands' ad spending in the wake of a product recall. Upon decomposing ad spending into its three constituents, we find that the weakening effect comes from the substitute's spending on quality advertising and not from spendings on price advertising or brand advertising. These nuanced findings inform managers that they can maximize their appropriation of the positive spillover by merely lowering their spending on quality advertising.

We return to the opening quote in the Introduction of the manuscript. Our finding suggests that by increasing its ad spending, GM weakened the positive spillover effect Toyota's recall had on GM's sales. Thus, our research supports the expert opinion and some users' comments that GM's strategy could backfire (Lancaster, 2010). To the extent that findings from the automobile industry could apply to the smartphone category, we believe that phonemakers' aggressive advertising in the wake of Samsung's recall of Galaxy Note 7 could have also backfired.

8.3. Future Research

Future research can extend our findings in three ways. First, empiricists may test the predictions using a broader and more representative sample of recalls. Relatedly, future tests of our model could use recalls in other product categories, such as consumer goods, pharmaceutical drugs, and medical devices. We limit our examination to car brands in China. Unsurprisingly, advertising academics have documented that advertising in Asia does not necessarily generalize to other markets (e.g., Tai, 2008). For example, substitute brands in North America could respond differently to a recall. Future research may consider exploring other markets. Second, we focus on manufacturers of substitute products of the recalled product. However, one could foresee that the recalling manufacturer's business customers, suppliers, and partners could also respond. Future research could not only empirically examine whether/how these parties respond, but also analytically model these responses and the resulting adjustments in their spending. Third, we focus on the substitute brands' response via their adjustments to ad spending, but these manufacturers may adopt alternate ways of response, such as tailoring their communications to investors and consumers, increasing the representation of operations executives in their top management team, seeking quality certifications, and extending additional warranty and trade credit to signal superior quality. These responses exist at the OM's interface with marketing, management, accounting, and finance. Future research could examine such alternate responses.

References

Acs, Z. J., Audretsch, D. B., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics*, *41*, 757-774.

Ahern, K. R., & Sosyura, D. (2014). Who writes the news? Corporate press releases during merger negotiations. *The Journal of Finance*, *69*(1), 241-291.

Ahluwalia, R., Unnava, H. R., & Burnkrant, R. E. (2001). The moderating role of commitment on the spillover effect of marketing communications. *Journal of Marketing Research*, *38*(4), 458-470.

Amazon. (2022). Simplifying BERT-based models to increase efficiency, capacity. *Amazon*. https://www.amazon.science/blog/simplifying-bert-based-models-to-increase-efficiency-capacity

Anderson, S. P., & Renault, R. (2006). Advertising content. *American Economic Review*, *96*(1), 93-113.

Astvansh, V., Wang, Y. Y., & Shi, W. (2022). The effects of the news media on a firm's voluntary product recalls. *Production and Operations Management*, *31*(11), 4223-4244.

Auchard, E., & Ten Wolde, H. (2017). Phonemakers pile in to exploit Samsung weakness. *Reuters*. https://www.reuters.com/article/telecoms-mobileworld-huawei-idINKBN1650HZ

Barber, B. M., & Darrough, M. N. (1996). Product reliability and firm value: The experience of American and Japanese automakers, 1973-1992. *Journal of Political Economy*, *104*(5), 1084-1099.

Barron, K., Kung, E., & Proserpio, D. (2021). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science*, *40*(1), 23-47.

Bavafa, H., Hitt, L. M., & Terwiesch, C. (2018). The impact of e-visits on visit frequencies and patient health: Evidence from primary care. *Management Science*, *64*(12), 5461-5480.

BIA. (2015). Automotive Businesses to Spend $15.1 Billion on Local Advertising in 2015. *BIA*. http://www.biakelsey.com/automotive-businesses-to-spend-15-1-billion-on-local-advertising-in-2015/

Borah, A., & Tellis, G. J. (2016). Halo (spillover) effects in social media: do product recalls of one brand hurt or help rival brands? *Journal of Marketing Research*, *53*(2), 143-160.

Bourdeau, B. L., Cronin Jr, J. J., & Voorhees, C. M. (2007). Modeling service alliances: an exploratory investigation of spillover effects in service partnerships. *Strategic Management Journal*, *28*(6), 609-622.

Cawley, J., & Rizzo, J. A. (2008). Spillover effects of prescription drug withdrawals. In *Beyond Health Insurance: Public Policy to Improve Health* (Vol. 19, pp. 119-143). Emerald Group Publishing Limited.

Chang, T.-Z., & Wildt, A. R. (1994). Price, product information, and purchase intention: An empirical study. *Journal of the Academy of Marketing Science*, *22*, 16-27.

Chen, Y., Ganesan, S., & Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *Journal of Marketing*, *73*(6), 214-226.

Cinelli, C., Forney, A., & Pearl, J. (2022). A crash course in good and bad controls. *Sociological Methods & Research*, 00491241221099552.

Cleeren, K., Van Heerde, H. J., & Dekimpe, M. G. (2013). Rising from the ashes: How brands and categories can overcome product-harm crises. *Journal of Marketing*, *77*(2), 58-77.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological review*, *82*(6), 407.

Collins, J. M., Simon, K. I., & Tennyson, S. (2013). Drug withdrawals and the utilization of therapeutic substitutes: The case of Vioxx. *Journal of Economic Behavior & Organization*, *86*, 148-168.

Connelly, B. L., Li, Q., Shi, W., & Lee, K. B. (2020). CEO dismissal: Consequences for the strategic risk taking of competitor CEOs. *Strategic Management Journal*, *41*(11), 2092-2125.

Crafton, S. M., Hoffer, G. E., & Reilly, R. J. (1981). Testing the impact of recalls on the demand for automobiles. *Economic Inquiry*, *19*(4), 694.

Deloitte. (2014). Driving through the consumer's mind Considerations for Car purchase. https://www2.deloitte.com/content/dam/Deloitte/in/Documents/manufacturing/deloitte-india-mfg-driving-through-consumers-mind-noexp.pdf

Dialogue. (2023). Driving Success: The Value of Print to the Automotive Luxury Industry. *Dialogue*. https://www.dialogue.agency/automotive_luxury_consumer_print_report

Dowdell, T. D., Govindaraj, S., & Jain, P. C. (1992). The Tylenol incident, ensuing regulation, and stock prices. *Journal of Financial and Quantitative Analysis*, *27*(2), 283-301.

Dowling, G. R. (1986). Managing your corporate images. *Industrial Marketing Management*, *15*(2), 109-115.

Dranove, D., & Olsen, C. (1994). The economic side effects of dangerous drug announcements. *The Journal of Law and Economics*, *37*(2), 323-348.

Du, R. Y., Hu, Y., & Damangir, S. (2015). Leveraging trends in online searches for product features in market response modeling. *Journal of Marketing*, *79*(1), 29-43.

Empire. (2023). Ultimate Guide to TV Advertising. *Empire*. https://theempire.com/guide-tv-advertising/

Faulconbridge, J. R., Taylor, P., Nativel, C., & Beaverstock, J. (2010). *The globalization of advertising: Agencies, Cities and Spaces of Creativity*. Routledge.

Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology*, *73*(3), 421.

Feldman, M. P. (1999). The new economics of innovation, spillovers and agglomeration: Areview of empirical studies. *Economics of Innovation and New Technology*, *8*(1-2), 5-25.

Freedman, S., Kearney, M., & Lederman, M. (2012). Product recalls, imperfect information, and spillover effects: Lessons from the consumer response to the 2007 toy recalls. *Review of Economics and Statistics*, *94*(2), 499-516.

Gao, H., Xie, J., Wang, Q., & Wilbur, K. C. (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.
Gartner, W. B. (1985). A conceptual framework for describing the phenomenon of new venture creation. *Academy of Management Review*, *10*(4), 696-706.
Giannetti, V., & Srinivasan, R. (2021). The cloud and its silver lining: negative and positive spillovers from automotive recalls. *Marketing Letters*, *32*(4), 397-409.
Goldfarb, A., Tucker, C., & Wang, Y. (2022). Conducting research in marketing with quasi-experiments. *Journal of Marketing*, *86*(3), 1-20.
Govindaraj, S., Jaggi, B., & Lin, B. (2004). Market overreaction to product recall revisited—The case of Firestone tires and the Ford Explorer. *Review of Quantitative Finance and Accounting*, *23*, 31-54.
Grodach, C., & Loukaitou-Sideris, A. (2007). Cultural development strategies and urban revitalization: A survey of US cities. *International Journal of Cultural Policy*, *13*(4), 349-370.
Guo, W., Sengul, M., & Yu, T. (2020). Rivals' negative earnings surprises, language signals, and firms' competitive actions. *Academy of Management Journal*, *63*(3), 637-659.
Guo, Y., Li, X., & Zeng, X. (2019). Platform Competition in the Sharing Economy: Understanding How Ride-Hailing Services Influence New Car Purchases. *Journal of Management Information Systems*, *36*(4), 1043-1070.
Hardigree, M. (2010). GM Offers Incentives To Toyota Buyers Looking To Avoid A Fiery Death. *Jalopnik*. https://jalopnik.com/gm-offers-incentives-to-toyota-buyers-looking-to-avoid-5458379
Harhoff, D. (1999). Firm formation and regional spillovers-evidence from Germany. *Economics of Innovation and New Technology*, *8*(1-2), 27-55.
Hausman, C., & Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. *Annual Review of Resource Economics*, *10*, 533-552.
Hersel, M. C., Helmuth, C. A., Zorn, M. L., Shropshire, C., & Ridge, J. W. (2019). The corrective actions organizations pursue following misconduct: A review and research agenda. *Academy of Management Annals*, *13*(2), 547-585.
Hoch, S. J., & Ha, Y.-W. (1986). Consumer learning: Advertising and the ambiguity of product experience. *Journal of Consumer Research*, *13*(2), 221-233.
Jacobs, B. W., & Singhal, V. R. (2020). Shareholder value effects of the Volkswagen emissions scandal on the automotive ecosystem. *Production and Operations Management*, *29*(10), 2230-2251.
Jedidi, K., Mela, C. F., & Gupta, S. (1999). Managing advertising and promotion for long-run profitability. *Marketing Science*, *18*(1), 1-22.
Joshi, A., & Hanssens, D. M. (2010). The direct and indirect effects of advertising spending on firm value. *Journal of Marketing*, *74*(1), 20-33.
Kenworthy, J. R., & Laube, F. B. (1999). Patterns of automobile dependence in cities: an international overview of key physical and economic dimensions with some implications for urban policy. *Transportation Research Part A: Policy and Practice*, *33*(7-8), 691-723.
Kirmani, A., & Wright, P. (1989). Money talks: Perceived advertising expense and expected product quality. *Journal of Consumer Research*, *16*(3), 344-353.
Kopalle, P. K., Fisher, R. J., Sud, B. L., & Antia, K. D. (2017). The effects of advertised quality emphasis and objective quality on sales. *Journal of Marketing*, *81*(2), 114-126.
Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from Facebook. *Management Science*, *64*(11), 5105-5131.
Lei, J., Dawar, N., & Lemmink, J. (2008). Negative spillover in brand portfolios: Exploring the antecedents of asymmetric effects. *Journal of Marketing*, *72*(3), 111-123.
Linkedin. (2018). Creative And Clever Advertisement Increase Your Sell. *Linkedin*. https://www.linkedin.com/pulse/creative-clever-advertisement-increase-your-sell-genius-janu?trk=public_profile_article_view
Liu, B., Cai, G., & Tsay, A. A. (2014). Advertising in asymmetric competing supply chains. *Production and Operations Management*, *23*(11), 1845-1858.

Liu, D., Lo, K., Song, W., & Xie, C. (2017). Spatial patterns of car sales and their socio-economic attributes in China. *Chinese Geographical Science*, *27*, 684-696.
Liu, D., & Varki, S. (2021). The spillover effect of product recalls on competitors' market value: The role of corporate product reliability. *Journal of Business Research*, *137*, 452-463.
Lodish, L. M., Abraham, M. M., Livelsberger, J., Lubetkin, B., Richardson, B., & Stevens, M. E. (1995). A summary of fifty-five in-market experimental estimates of the long-term effect of TV advertising. *Marketing Science*, *14*(3_supplement), G133-G140.
Mackalski, R., & Belisle, J.-F. (2015). Measuring the short-term spillover impact of a product recall on a brand ecosystem. *Journal of Brand Management*, *22*, 323-339.
Meituan. (2022). Exploration and practice of public comment search relevance technology. *Meituan*. https://segmentfault.com/a/1190000042081898/en
Mervis, C. B., & Rosch, E. (1981). Categorization of natural objects. *Annual Review of Psychology*, *32*(1), 89-115.
Narang, U., & Shankar, V. (2019). Mobile app introduction and online and offline purchases and product returns. *Marketing Science*, *38*(5), 756-772.
Nijs, V. R., Dekimpe, M. G., Steenkamps, J.-B. E., & Hanssens, D. M. (2001). The category-demand effects of price promotions. *Marketing Science*, *20*(1), 1-22.
Ozturk, O. C., Chintagunta, P. K., & Venkataraman, S. (2019). Consumer response to Chapter 11 bankruptcy: Negative demand spillover to competitors. *Marketing Science*, *38*(2), 296-316.
Parment, A. (2014). *Auto Brand: Building Successful Car Brands for the Future*. Kogan Page Publishers.
Pauwels, K., Silva-Risso, J., Srinivasan, S., & Hanssens, D. M. (2004). New products, sales promotions, and firm value: The case of the automobile industry. *Journal of Marketing*, *68*(4), 142-156.
Raghubir, P., & Corfman, K. (1999). When do price promotions affect pretrial brand evaluations? *Journal of Marketing Research*, *36*(2), 211-222.
Rajan, R., & Zingales, L. (1998). Financial development and growth. *American Economic Review*, *88*(3), 559-586.
Reilly, R. J., & Hoffer, G. E. (1983). Will retarding the information flow on automobile recalls affect consumer demand? *Economic Inquiry*, *21*(3), 444-447.
Rice, M. D., & Lu, Z. (1988). A content analysis of Chinese magazine advertisements. *Journal of Advertising*, *17*(4), 43-48.
Roehm, M. L., & Tybout, A. M. (2006). When will a brand scandal spill over, and how should competitors respond? *Journal of Marketing Research*, *43*(3), 366-373.
Rubel, O., Naik, P. A., & Srinivasan, S. (2011). Optimal advertising when envisioning a product-harm crisis. *Marketing Science*, *30*(6), 1048-1065.
Shapiro, B. T. (2018). Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of Political Economy*, *126*(1), 381-437.
Shi, W., Wajda, D., & Aguilera, R. V. (2022). Interorganizational spillover: A review and a proposal for future research. *Journal of Management*, *48*(1), 185-210.
Simonin, B. L., & Ruth, J. A. (1998). Is a company known by the company it keeps? Assessing the spillover effects of brand alliances on consumer brand attitudes. *Journal of Marketing Research*, *35*(1), 30-42.
Tellis, G. J., & Johnson, J. (2007). The value of quality. *Marketing Science*, *26*(6), 758-773.
Throsby, C. D. (2001). *Economics and culture*. Cambridge university press.
Totalcom. (2018). Why Ad Agencies Sometimes Take So Long. *Totalcom*. https://www.totalcommarketing.com/post/why-ad-agencies-sometimes-take-so-long
Urban, G. L., Hulland, J. S., & Weinberg, B. D. (1993). Premarket forecasting for new consumer durable goods: Modeling categorization, elimination, and consideration phenomena. *Journal of Marketing*, *57*(2), 47-63.
Van Heerde, H., Helsen, K., & Dekimpe, M. G. (2007). The impact of a product-harm crisis on marketing effectiveness. *Marketing Science*, *26*(2), 230-245.

Venkatraman, V., Dimoka, A., Vo, K., & Pavlou, P. A. (2021). Relative effectiveness of print and digital advertising: a memory perspective. *Journal of Marketing Research*, *58*(5), 827-844.

Wei, Z., Xiao, M., & Rong, R. (2021). Network size and content generation on social media platforms. *Production and Operations Management*, *30*(5), 1406-1426.

Wu, F., Sun, Q., Grewal, R., & Li, S. (2019). Brand name types and consumer demand: Evidence from China's automobile market. *Journal of Marketing Research*, *56*(1), 158-175.

YahooNews. (2014). VW to recall more than a million cars in China, US. *YahooNews*. https://sg.news.yahoo.com/volkswagen-recall-more-500-000-cars-china-131405570--finance.html

Yin, M., & Derudder, B. (2021). Geographies of cultural industries across the global urban system. *Geography Compass*, *15*(6), e12564.

Zhou, C., Sridhar, S., Becerril-Arreola, R., Cui, T. H., & Dong, Y. (2019). Promotions as competitive reactions to recalls and their consequences. *Journal of the Academy of Marketing Science*, *47*(4), 702-722.

How Do Brands Change Their Advertising Spending in Response to A Rival Brand's Product Recall?

E-Companion

Appendix A: Data and Sample

Figure A1. Ad Examples from Our Sample

Chevrolet's Ad Emphasizing its *Cruze* Model's Price Following Volkswagen's Sagitar Recall[24]


众筹"购车礼金业内首创金融方案购车最低 2.99 万元首付
雪佛兰全新一代科鲁兹发起 争先·登科购车召集令"

一个好汉三个帮最高众筹 4000 元购车礼金

8 万元定额贷最低首付仅需 2.99 万元

1.4T 全系车型入围节能惠民名单最高可享万元礼遇

凝聚科技智慧享受丰富驾控乐趣

Promotions for Chevrolet's Cruze

Nissan's Ad Emphasizing its *Tiida* Model's Quality Following Volkswagen's Sagitar Recall[25]

[24] http://app.why.com.cn/epaper/qnb/html/2014-11/06/content_229293.htm?div=0
[25] http://app.why.com.cn/epaper/qnb/html/2014-02/27/content_192137.htm?div=0

Driving enjoyment: introducing Tiida's features with high quality.

Convenient driving for cornering

Continuously Variable Transmission (CVT)

Honda's Ad Emphasizing its Brand Following Volkswagen's Sagitar Recall[26]

FUNTEC HYBRID艺术展开幕

青年报 车键

本报讯 日前，Honda中国携手中外艺术家在上海艺术社区M50创意园正式拉开了FUNTEC HYBRID艺术展的序幕。本次艺术展以"混合"为主题，旨在通过向公众展示活跃在国际舞台的新锐艺术家及创意团队——六岛Island6、刘真辰、UCOTA, ISHI 2BIT &NISHMOTO MOMOKO的艺术创作，对"混合"这一理念进行艺术化的诠释，让公众更容易了解到FUNTEC HYBRID技术所能带来的新价值。本次艺术展将持续展出到1月4日。

Honda希望借助FUNTEC HYBRID"混合"艺术展的平台，通过国内外艺术家的鼎力巨献，将"混合"这一理念，分享给大众，让中国的消费者提早感受到FUNTEC HYBRID的魅力，并期待由此带来的生活节奏的改变！除搭载全球最高效率双电机混合动力系统i-MMD的雅阁混合动力车型外，本次艺术展还展出了多件艺术品，其中既有通过与磁铁的"混合"形成的会"跳舞"的千纸鹤，又有能通过不断变化眼睛造型从而改变人的面貌的趣味装置，还有将听觉与视觉进行的出其不意的"混合"呈现。

Honda supports the art exhibition

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[26] http://app.why.com.cn/epaper/qnb/html/2014-12/11/content_235206.htm?div=-1

Figure A2. Model-Free Evidence for A Substitute's Sales Volume

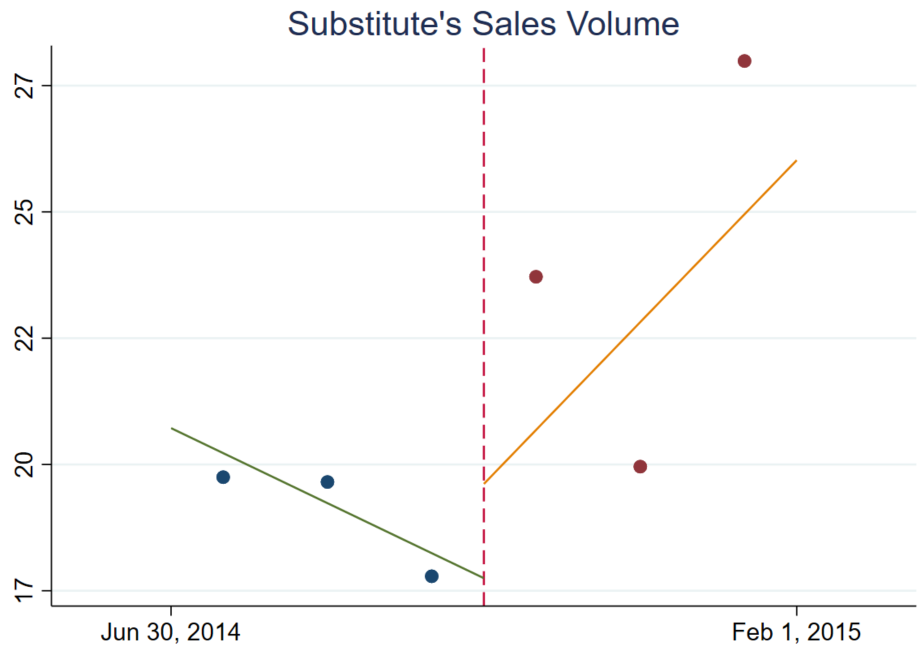

Table A1. Names of 62 Substitutes of Volkswagen Sagitar

Note: We shade in a lighter gray the names of the five *direct substitutes* and in a darker gray the names of the six *sibling substitutes*.

Manufacturer	Model	Manufacturer	Model
Acura	ILX	Hyundai	Elantra
Aeolus	S30		Avante
Audi	A3		Celesta
Baojun	630	Jianghuai	Heyue
Besturn	B50	Kia	Cerato
	B70		Kia 3
Buick	Excelle GT		Forte
	Excelle XT	Mazda	Mazda 3
BYD	F3	MG	5
Citroen	C-Quatre	Mitsubishi	Fortis
	C4L		Lancer
	c-Elysee	Nissan	Bluebird Sylphy
Changan	SX4		Tiida
	CX30	Peugeot	301
	V7		307
	Eado		308
Chery	A3		408
	A5	Qoros	Qoros 3
	E5	Senova	D50
	Banner Cloud 3	Suzuki	Alivio
Chevrolet	Cruze	Toyota	Corolla
Cross	Junjie	Trumpchi	GA3
Ford	Focus	Volkswagen	Bora
Geely	GC7		Lavida
	EC7		Santana
	SC7		Lamando
Gleagle	Yuanjing		Rapid
Gonow	Emei		Golf
Haima	Happin	Yinglun	Haijing
	Familia		
Honda	Civic		
	Crider		
	City		

Table A2. *t*-test for the Model-Free Evidence

Variables	Before Sagitar Recall		After Sagitar Recall		t-test	p-value
	Mean	S.D.	Mean	S.D.		
Total Ad	0.034	0.785	0.020	0.702	8.553	0.000
Price Ad	0.003	0.168	0.004	0.202	-2.638	0.008
Quality Ad	0.029	0.711	0.018	0.722	5.746	0.000
Brand Ad	0.000	0.013	0.000	0.008	0.431	0.667

Table A3. List of Models that are Substitutes of Cadillac SRX

Manufacturer	Model	Manufacture	Model
Acura	RDX	Kia	Sorento
BMW	X3	Land Rover	Evoque
	X4	Lanwind	X8
	X5	Lexus	NX
	X6		RX
Buick	Envision	Luxury	7
Chevrolet	Captiva	Mercedes-Benz	GLK-Class
Ford	Territory		G-Class
GAC	GS5		ML-Class
Geely	Haoqing	Mitsubishi	Pajero
Hover	H8	Nissan	X-Trail
Infiniti	QX60	Roewe	W5
	QX70	Toyota	Highlander
Jeep	Grand Cherokee		Fortuner
	Cherokee	Volkswagen	Touareg

Appendix B: Technical Detail on RDiT

The RDiT method allows one to accurately estimate treatment effects in nonexperimental settings under two specific conditions: (1) the treatment occurs on a precise date (*cutoff*), and (2) the treatment does not vary across cross-sectional units.[27] At its core, the RDiT method capitalizes on a foundational concept: observations pertaining to a particular unit ($i \in N$), just preceding the temporal threshold ($t <$ *cutoff*), provide reliable counterfactuals for those situated just past the threshold ($t >$ *cutoff*). Thus, the RDiT design leverage two sources of variation to measure treatment effect: the time-series variation (asymptotics in T) and the cross-sectional variation (asymptotics in N). Therefore, RDiT presupposes the absence of the time-varying unobservable factors that could distinctly and abruptly alter the outcome variable at the temporal cutoff.

In our empirical context, the RDiT method estimates a substitute car model's *counterfactual* ad spending—that is, in the absence of the Sagitar recall—based on a narrow time window before the recall event. Stated differently, a substitute's ad spending preceding the Sagitar recall serves as an appropriate counterfactual comparison to the substitute's ad spending right after the Sagitar recall. Consequently, the average differences in ad spending between the pre- and post-time windows around the recall event provide a consistent estimate of the average treatment effect of the Sagitar recall.

However, we must account for the challenges stemming from the use of time-series variation. Therefore, we include additional time-varying covariates related to: (1) news about the substitute model, (2) buyers' interest in the substitute model, (3) social media generated by the substitute model's dealers and manufacturers and followers' engagement to these media, and (4) substitute model's ad spending on nonprint media. In addition, we include FEs at three levels: model ($\boldsymbol{\theta_i}$), week ($\boldsymbol{\pi_w}$), and prefecture ($\boldsymbol{\mu_p}$). Model-specific FEs $\boldsymbol{\theta_i}$ allow us to account for the model-specific time-invariant unobservables (e.g., the model's manufacturer). Week-level FEs $\boldsymbol{\pi_w}$ help us control for the intertemporal differences that do not vary across models. Further, we control for prefecture-specific unobservables with the vector of prefecture-level FEs $\boldsymbol{\mu_p}$.

[27] The Difference-in-Differences method requires the treatment to vary across cross-sectional units.

Appendix C: Concerns about Endogenous Control Variables

Table C1. Replication with the Exclusion of Additional Variables

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.014**	0.007***	-0.021***	-0.000
	(0.007)	(0.002)	(0.007)	(0.000)
Model Fixed Effects	Y	Y	Y	Y
Prefecture-level Division Fixed Effects	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y
Model	62	62	62	62
Prefecture-level Division	308	308	308	308
Week	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R-Squared	0.058	0.008	0.049	0.001

Note. ***p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are reported in parentheses.**

In addition, following extant literature (Anderson & Hsiao, 1981; Blundell & Bond, 2000, Todd & Wolpin, 2003), we employed one-period lagged values for the additional variables as instruments, meeting the relevance and exclusion restriction conditions. First, regarding the relevance criterion, research has indicated a correlation between ad spending for the same category (e.g., Internet advertising spending) in the previous period (Aravindakshan et al., 2012; Ashley et al., 1980; Kireyev et al., 2016) and ad spending in the current period. Consequently, lagged values of additional variables from one period should be positively associated with current values. Second, regarding the exclusion restriction, one-period lagged values for the additional control variables (e.g., Internet ad spending) are unrelated to the print ad spending variable. Indeed, research has concluded that print ad spending had insignificant effects on other ad spending types, such as search engine advertising (Olbrich & D. Schultz, 2014). This is due to the high demand from advertisers to convey multiple messages to a broad consumer base. Advertising agencies tend to segment consumers based on their channel preferences, accommodating diverse messaging needs across various segments (Evans, 2009). As additional evidence, Sridhar & Sriram (2015) have discovered that print advertising expenditure exhibits a general downward trend, even in cases where advertisers have not invested in online advertising. Therefore, we used the one-period lagged values for the additional variables as instruments to replicate the main analyses and obtain consistent results (Table C2).

Table C2. Replication with IVs for the Additional Variables

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
After Sagitar Recall	-0.012*	0.007***	-0.019***	4.96e-06
	(0.007)	(0.002)	(0.007)	(0.000)
Controls	Y	Y	Y	Y

Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Week-FEs	Y	Y	Y	Y
Models	62	62	62	62
Prefectures	308	308	308	308
Weeks	31	31	31	31
Observations	591,976	591,976	591,976	591,976
R^2	0.065	0.033	0.056	0.002

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

References

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76(375), 598-606.

Aravindakshan, A., Peters, K., & Naik, P. A. (2012). Spatiotemporal allocation of advertising budgets. *Journal of Marketing Research*, 49(1), 1-14.

Ashley, R., Granger, C. W., & Schmalensee, R. (1980). Advertising and aggregate consumption: An analysis of causality. *Econometrica*, 1149-1167.

Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: an application to production functions. *Econometric Reviews*, 19(3), 321-340.

Evans, D. S. (2009). The online advertising industry: Economics, evolution, and privacy. *Journal of Economic Perspectives*, 23(3), 37-60.

Kireyev, P., Pauwels, K., & Gupta, S. (2016). Do display ads influence search? Attribution and dynamics in online advertising. *International Journal of Research in Marketing*, 33(3), 475-490.

Olbrich, R., & D. Schultz, C. (2014). Multichannel advertising: Does print advertising affect search engine advertising?. *European Journal of Marketing*, 48(9/10), 1731-1756.

Sridhar, S., & Sriram, S. (2015). Is online newspaper advertising cannibalizing print advertising?. *Quantitative Marketing and Economics*, 13, 283-318.

Todd, P. E., & Wolpin, K. I. (2003). On the specification and estimation of the production function for cognitive achievement. *The Economic Journal*, 113(485), F3-F33.

Appendix D: Estimates from 2SLS Method

Table D1. Relation Between *Number of New Ad Firms* and *All New Firms*

DV =	All New Firms
Number of New Ad Firms	0.015 (0.019)
Prefectures	308
Months	7
Observations	133,672
R^2	0.000

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.

Table D2. Estimates from the First-Stage Regression of 2SLS

DV =	Total Ad	Price Ad	Quality Ad	Brand Ad
Number of New Ad Firms	117.637*** (9.775)	3.559** (1.707)	64.431*** (7.672)	0.103* (0.060)
Controls	Y	Y	Y	Y
Model-FEs	Y	Y	Y	Y
Prefecture-FEs	Y	Y	Y	Y
Month-FEs	Y	Y	Y	Y
Prefectures	308	308	308	308
Months	7	7	7	7
Observations	133,672	133,672	133,672	133,672

Note. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors are reported in parentheses.