Do multinationals discriminate? Information disclosure and product recalls in China's automobile market *

Hao Geng †
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Ce Matthew Shi‡

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Abstract

This study examines product quality and regulation in the automobile industry, focusing on the recall practices of defective vehicles in China, the world's largest automotive market. Through theory-guided empirical analyses, we document the inadequately low number of vehicle recalls in China using text analysis tools and explore the determinants and consequences of insufficient recall actions.

Our theoretical model highlights the critical roles of government regulation and consumer responses in influencing recall decisions. Stronger regulatory measures are shown to unambiguously increase the likelihood of recalls, while the impact of market factors depends on the probability of defect detection, which is crucially influenced by information provision.

Guided with theoretical predictions, we empirically examine the differences in vehicle recall practices of multinational manufacturers in China compared to the United States. Leveraging a variety of data sources, including the universe of car models and recall announcements in China and the U.S., we compile a novel dataset on automobile recall differences from 2004 to 2020. Using state-of-the-art text analytic tools, we classify vehicle recalls by the severity of defects, a task that manual methods find challenging due to the complexity of safety criteria. Controlling for the year and model fixed effects, we find that for car models available in both China and U.S. markets, manufacturers are significantly less likely to initiate a defective vehicle recall in China. On average, only 12%-13% of defective car models reported in the U.S. are recalled in China. Models with safety-related defects are more likely to be recalled in China. Heterogeneous results reveal that the China-U.S. recall differences vary across brands from different countries of origin and are larger for domestically manufactured models than imported models. Recall differences diminish when U.S. recalls are covered in official Chinese news. The introduction of a 2012 regulation mandating greater recall transparency has significantly reduced these differences, suggesting that increased regulatory pressure can mitigate insufficient recall practices.

We explore consumer responses to vehicle recall news in China and the associated welfare implications. Linking vehicle recall records to detailed car sales data from 2017 to 2020 and applying a

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†Department of Economics, The Chinese University of Hong Kong. E-mail: *isaacgeng@link.cuhk.edu.hk*

‡Department of Economics, The Chinese University of Hong Kong. E-mail: *shice@cuhk.edu.hk*

micro-founded discrete-choice framework, we find that Chinese consumers are generally unresponsive to vehicle recall events, a finding consistent with previous research on U.S. markets. However, they significantly reduce car purchases when U.S. safety-related vehicle recalls are reported in official news outlets. A counterfactual analysis based on estimates from the structural model indicates that an information disclosure policy designed to improve consumer awareness of known safety-related defects would increase consumer welfare by 2.1%.

1 Introduction

Product quality differences are prevalent in international markets and widely documented by news, leading to major controversies and policy debates. In non-durable goods markets, Johnson & Johnson is reported to sell shampoos with harmful chemicals in the U.S. and China, but not in the U.K. and Japan.[1] A scandal of "food apartheid" hit Europe as multinational firms are discovered to sell the same products at lower quality in Eastern EU markets. This scandal results in a large policy debate in the EU and ultimately culminated in a total ban on "dual quality" food in 2017/2018.[2] Brazil and Kenya find that Coke products contain harmful chemicals.[3] In durable goods markets, the infamous Volkswagen emission scandal is exacerbated by the differential service plan in terms of post-scandal compensation, where U.S. consumers are offered better compensation plans than their Korean counterparts.[4] In China, regulators often complain about disparate treatment across different markets, including automobiles, electronics (e.g., the Samsung phone battery scandal), and genetically modified food. Cross-country differences in product recalls, which are essential to consumer protection and safety, are also commonly covered by news. For example, IKEA, the world's largest furniture company, is reported to adopt a "double" standard on product recalls in China.[5]

Despite the wide coverage on differences of product quality and recalls in international markets, systematic empirical evidence is scarce to support such claims. One possible reason is due to the difficulties to collect data on non-price quality-related variables, especially in international markets. Therefore, authorities often have to implement regulation on a case-by-case basis.

Despite the difficulties faced, understanding the difference in product quality is vital from various perspectives. First, from a legal perspective, disparate treatment often comes with adverse impacts and is thus considered illegal in many cases. From the economics point of view, maximizing profits through product differences would likely harm the consumer welfare. Second, the regulation on product quality differences would also affect innovation and social welfare through the cost of firms (Chen and Hua 2023). Finally, investigating product differences would be helpful to understand how multinational firms function in international markets.

We use vehicle recall texts to document cross-country product differences in terms of product recalls.

1. See reports by Daily News in 2011, https://www.nydailynews.com/life-style/health/consumers-lash-johnson-johnson-harmful-chemicals-baby-shampoo-article-1.970600
2. See reports by the Guardian, https://www.theguardian.com/inequality/2017/sep/15/europes-food-apartheid-are-brands-in-the-east-lower-quality-than-in-the-west
3. See report by Reuters, https://www.reuters.com/article/cocacola-caramel-chemical-idUKL2E8HQFDI20120626/
4. See https://www.koreaherald.com/view.php?ud=20160802000903
5. See https://www.chinadaily.com.cn/opinion/2017-11/30/content_35130180.htm

We focus on the automobile market due to its severe information problem, which make this market the center of controversies. We gather the universe of vehicle recall texts in China and compare it with that in the U.S., thus covering the two largest automobile markets in the globe. We initially explore the recall rates in China by components given a recall in the U.S. within one year. We find that the recall rates in China is less than 30% given a recall in U.S. for most components in the recall texts. If the recall in China is from the same component in the U.S., the recall rate is less than 20% in most of the component categories. After controlling for potential confounding factors, our regression shows that the correlation between recalls in China and the U.S. is about 12%-13% on average, indicating a systematic product difference. Compared with Taiwan region, where foreign recalls applicable must also be recalled in Taiwan, the recall rate is larger than 74% from 2008 to 2016. We also extract severity degree information using text analysis methods and look into the heterogeneity result. We record an 11.2% recall rate for Chinese recalls with safety-related defects versus 2.2% for recalls with non-safety-related defects. We also look into heterogeneity by country of origin and by whether the car manufacturer is a joint venture SOE. We observe heterogeneous results for brands of different origin countries. We also find that SOE joint venture models are more unlikely to be recalled in China, thus highlighting the potential political connection of SOEs.

We then explore the role of information in product recalls. To understand the role of information in consumer side monitoring, we gather foreign recall news in China and explore its effect on recall probabilities in China. To explore such role of information on regulatory monitoring, we investigate the effect of the 2012 reform in China on recall probabilities which requires car makers to report foreign recall histories to Chinese regulators. We find that information played an important role in both channels.

The remainder is structured as follows. Section 3 presents the model. Section 2 thoroughly reviews the literature on multinational companies in host countries, product quality and consumers, and service discrimination and product recalls. Section 4 describes the institutional background. Section 5 summarizes the data and variable construction process using text analysis. Section 6 illustrates the empirical strategy followed by discussions on the results. Section 8 concludes.

2 Related literature

Recall decisions by firms Our theoretical model is related to research on factors and their effect on the recall decision by firms. Cho et al. (2021) investigate how the interaction between automakers and regulators affect the firm's cover-up decisions for vehicle defects with a different level of consumer responses. They find that the manufacturers have an incentive to cover up a highly likely existed defect with a moderate harm level. They also find a heterogeneous effects on cover-ups based on different consumer responses. We build our model based on the one in Cho et al. (2021) , except we assume the regulator as exogenous.

Colak and Bray (2016) investigate the reasons behind voluntary recalls using a dynamic model with interactions between firms and government as well. However, their empirical results suggest that government recall decisions are independent to firms, supporting our modeling choice. They find empirically that consumer complaints are indicative of manufacturers' recall decisions. Our study differs from Colak and Bray (2016) in highlighting the role of consumer demand response and information on recalls.

By focusing on the automotive recalls in China and U.S., our empirical study contributes to the broad economics literature on product recalls. Among the recall and quality literature, scholars in law and economics investigate the effect of liability and the social optimal judgment rule on recalls. For instance, Simon (1981) and Polinsky and Rogerson (1983) models the effect of different liability rules on product quality and social welfare. Strict liability rules with buybacks would impede the firms' incentive to design safe products (Spier 2011), disclosure information, and make recall decisions (Daughety and Reinganum 1995, 2008a, 2008b; Hua 2011). Firms' incentives on reputation (Welling 1991) and payoffs under heterogeneous liability rules (Marino 1997) may lead to different recall levels. In line with these studies, we also investigate the role of information disclosure and how it can reduce difference on product recalls.

Multinational enterprises in host countries Our study is related to multinational firms, especially its consumer policy and quality management policy and the associated effect on consumers in host countries. We find no direct related literature studying multinational firms from a similar viewpoint. Hazell et al. (2022) examine how multi-establishment firms set wages across spaces within a country. Combining job-level vacancy data with survey data of HR managers, they find that most multi-establishment firms give their employees the same wage despite the location differences in average wage levels. Unlike their findings, our results suggest that multinational firms impose a non-uniform strategy in terms of consumer service like product recalls across countries.

Product quality and consumers Our study also adds to the literature that studies product quality and consumers. Information problem is a major issue faced by consumers in many industries. Chen and Hua (2023) shows that if consumers are permitted with with full information, there is no need for a product liability system regulating defective products.

Given the information problem, many research focus on how to perform effective regulations, especially on information awareness. For example, Noll (2004) compares the effectiveness of warranties to that of advertisement or reputation on informing consumers about product quality from a theoretical perspective. They emphasize the importance on tools provide information to consumers as well as incentives to firms. Few research empirically examines the relationship between product quality regulation and consumer responses. One exception is De Paola and Scoppa (2013), who investigate the impact of media attention on a scandal related to product defects on consumer behavior, using a widely covered quality scandal in the Italian cheese industry as a shock. They find a long-lasting effect that consumers significantly reduced their purchases of brands involved in the scandal and increased demand for uninvolved brands. We also find the importance of media coverage in consumer responses: our results show Chinese consumers would only respond when safety-related defects are media covered. We contribute to this stream of literature by providing a novel evidence on systematic discriminating behaviors of multinational firms, examining how to regulate, and measuring consumer welfare of a information regulation policy.

Service differentiation This paper contributes to the literature on the differential service provision by exploiting the effect of information regulation policy on the aforementioned difference in service. While there is no existing empirical evidence to our knowledge of service differentiation, Ukanwa and Rust (2018) theoretically analyze service differentiation to consumers finding that service differentiation could appear from seemingly rational and non-prejudiced decision-making by firms. In the context of network neutrality, many researchers have discussed the non-discrimination rules for the internet content providers (see e.g., van Schewick (2015)). In this paper, we provide the first evidence to our knowledge supporting the existence of service differentiation. Using a novel design for identification, we find causal evidence of systematic difference in automobile recalls between China and the U.S. We also contribute to the related literature on labor market discrimination on employees (pioneered by Becker (1971)) by studying market-wise differentiation to consumers.

Consumer responses to product recalls Consumer responses are key to estimating consumer welfare effect of product recalls. To this end, our study is related to the literature studying effects of product recalls on consumer safety and consumer demand (e.g. Wynne and Hoffer 1976; Crafton et al. 1981; Reilly and Hoffer 1983; Rhee and Haunschild 2006).

Wynne and Hoffer (1976) examines whether product recalls have any effect on product market shares. Using monthly make-level data from 1971 to 1973, time-series regressions for each make fails to find any significant relationship between recalls and market shares. Crafton et al. (1981) expand the study of Wynne and Hoffer (1976) by using refined and new data. Using monthly model data ranging from 1970 to 1978 and data on defects severity, a blocked pairwise comparison on sales growth rate by the "recalled group" and the "unrecalled" group implies a significant negative effect, and it is more prominent for more severe defects. Reilly and Hoffer (1983) revisits the question of whether recall announcement has any effect on consumer response. They find similar results that recalls, especially severe ones, have a significantly negative effect on consumer demand.

Consumer response is one of the key factors that drive firms to make recall decisions.[6] To this end, our work is related to the stream of literature on those factors that contribute to product recalls. Few previous studies has investigated consumer responses as a driver of product recalls with the exception of Liu and Shankar (2015) and Colak and Bray (2016). Liu and Shankar (2015) explore how recalls impact consumer on brand preference and advertising effectiveness over time, and what role do media coverage, recall severity, and brand quality expectations play in the impact of product recalls? Using a state-space model that combines a random coefficient demand model, they find that product recalls negatively affect brand preference, with media coverage and perceived quality exerting a greater impact.

We add to these various pieces of literature in four distinct ways. First, our detailed model-level recall data in China and U.S. allows us to identify the degree of recall discrimination at the model level. Second, we add to the literature on non-price service discrimination by empirically quantifying the post-purchase period unequal treatment in the auto market. Third, by studying recall regulations in China, we add to the literature on regulation using information by estimating its effect empirically on reducing the discrimination on quality management. Fourth, we add to the auto-recall, or more broadly the product recall literature, by thoroughly comparing the two of the world's largest auto markets.

3 Theoretical analysis on product recalls

We consider a model in which a firm's product may contain a defect that brings harm to consumers. The firm decides whether to recall this product or cover up the defect. If the firm voluntarily recalls, then consumer demand would decrease depending on the degree of harm and consumer responsiveness, and the firm needs to pay a unit recall cost. If the firm covers up the defect, then there is a probability that the cover-up may be revealed by regulator monitoring or consumers. If the cover-up is not revealed, the firm would avoid the penalty from regulators and the demand for the defective product would remain the same. However, if the cover-up is revealed, not only would the firm face recall cost and forfeit, but the consumers would also react to the cover-up by further reducing their demand. Obviously, there is a

6. The other factor is government regulation. See Section 3 for a model capturing both consumer monitoring and chapter 2 for estimating two channels on recall differences in China and U.S.

trade-off between cover-up and voluntary recall.

We begin by characterizing how regulatory monitoring shifts the firm's optimal recall decision. Intuitively, increasing the monitoring intensity or the penalty would increase the chance of voluntary recalls because these factors would increase the cost of the firm's cover-up behavior.

We next address how consumer response and information affect the optimal recall decision of firms. We assume that more harmful defects would be more likely to be noticed by consumers. First, we show that if the product defect leads more consumer harm, the optimal recall probability would be higher conditional on that the defect would be find out by either the government or the consumers. The intuition behind this argument is that given the high probability for a cover-up to be revealed, the firm would prefer voluntarily recalling its products to avoid further losses due to mandatory recall. Second, if the consumers are more responsive to the recall announcement, then the recall probability would be higher conditional on that the defect would be find out by either the government or the consumers. The intuition behind this argument is similar to the previous case. Specifically, with more severe harm level to the consumeres, the losses resulting from the revelation of a cover-up would be even larger given the intense consumer response.

3.1 Model

The product is sold on price p with associated demand d. We set marginal cost to 0 without loss of generality. The timeline works as follows. When $t = 0$, nature decides the product state: defective with probability ϕ_j, and non-defective with probability $1 - \phi_j$. If the product is non-defective, we assume that firms would not report and regulators would not investigate. If the product is defective, the firms' behavior would be determined by the expected profits given reporting and no reporting (cover-up). We discuss two cases in the following text.

If the firm reports to government and recalls the defective product following the law, the profit it earns would be $pd(p, h) - rd(p)$ where $d(p, h)$ represents the demand and is affected by the severity of the potential harms h that the defects may cause, and r is the unit recall cost. For simplicity, we assume that the $d(p, h) = d(p) - h$. If the firm chooses to cover up, with probability θ, the regulator issues an investigation and finds a defect. A proportion γ of consumers could find the defect after purchasing the product. We assume defects causing more serious harm h would result in a higher proportion of consumers noticing the defect. That is $\gamma = \gamma(h)$ and $\gamma'(h) > 0$.

The profit that is conditional on firms cover-up and then avoid the penalty is given by $pd(p)$. If the firm's cover-up is revealed, then we assume that in addition to the recall cost, the manufacturer has to pay a fixed punishment K. We use $\psi \in [0,1]$ to denote consumer responsiveness. Therefore, conditional on the firm chooses covering up the defects and getting caught, with probability $\theta + \gamma(h)$, the conditional profit is

$$pd(p) - p\psi h - rd(p) - K.$$

With probability $1 - \theta - \gamma(h)$, the firm can escape from punishment from the government. Conditional on the firm covering up defects and getting away, the conditional profit is $pd(p)$. Thus, the expected profit conditional on the firm's cover-up π_{NR} is

$$\begin{aligned}\pi_{NR} &= (1 - \theta - \gamma(h))pd(p) + (\theta + \gamma(h))(pd(p) - p\psi h - rd(p) - K) \\ &= pd(p) - (\theta + \gamma(h))(p\psi h + rd(p) + K).\end{aligned}$$

The expected profit by firm conditional on the firm choosing to recall is

$$\pi_R = pd(p) - p\psi h - rd(p).$$

So, The expected profit by firm if the firm reports the defects to the regulator is π_R, and it is π_{NR} if the firm chooses to cover up. The difference between π_R and π_{NR} represents the trade-off between the cost when covering up and being caught and the cost of reporting.

We write the trade-off as follows:

$$\pi_R - \pi_{NR} = (\theta + \gamma(h))K - (1 - \theta - \gamma(h))(p\psi h + rd(p)).$$

The firm then makes the decision on whether to report defects to regulators based on whether the term is positive or negative. We assume that θ is decided by national regulators and thus varies across countries. We use superscripts C and A to denote China and the U.S., respectively. Therefore, the country-specific probability of being investigated and finding a defect in China (the U.S.) is θ^C (θ^A). We further assume that the regulator's punishment K is also determined nation-wide, leading to the notations of K^C and K^A to represent the punishment levels in China and the U.S., respectively. We assume that the other variables are set by firms at the product level, so we denote these variables with subscript j. The probability of getting a report in China (C) is given by

$$Pr(R^C) = \mathbb{P}\{\theta^C K^C + \gamma_j K^C - p_j \psi_j h_j - r_j d_j + (\theta^C + \gamma_j)(p_j \psi_j h_j + r_j d_j) \geq 0\} \tag{1}$$

while the probability for the U.S. is obtained by simply substituting C with A.

We assume a linear probability model, where we can easily see that $\theta^C K^C$ would be absorbed by year fixed effects as it does not vary with time. We control for $r_j d_j, p_j \psi_j h_j$ by adding model-level fixed effects. However, the interactive effect of the country-specific law enforcement level (θ^C) and model-level variables ($r_j d_j, p_j \psi_j h_j$) cannot be easily controlled by adding fixed effects.

3.2 The effects of regulatory and consumer monitoring

We then investigate how the optimal recall probability in each country may respond to changes in regulatory monitoring θ, K, consumer monitoring ψ, and the harm of defect h.

Using Equation (1), we have

$$\begin{aligned} \frac{\partial Pr(R^C)}{\partial \theta^C} &= (K^C + p_j \psi_j h_j + r_j d_j)\mathbb{P}' > 0 \\ \frac{\partial Pr(R^C)}{\partial K^C} &= (\theta^C + \gamma_j)\mathbb{P}' > 0 \end{aligned} \tag{2}$$

Equation 2 presents the comparative statics of the optimal recall decision with respect to the regulatory monitoring changes. Both comparative statics show an unambiguous positive sign. The upper equation shows that the firm's optimal recall probability will increase given an increase in θ, which represents the intensity of regulatory monitoring. In other words, if the government would increase the intensity of investigation on product defects, firms would always increase their recall probability. The lower equation shows that given an increase in the forfeits of product defects discovered by the government, firms would also increase their recall probability. The intuition behind Equation 2 is straightforward, that is, increasing regulator monitoring would unambiguously lead to firms increasing their recall probability, because the expected losses from not recalling (government forfeit and demand loss) would increase due to either the larger probability of being found out (θ) or the larger punishment (K).

For the consumer monitoring side, we have

$$\begin{aligned} \frac{\partial Pr(R^C)}{\partial \psi} &= (\theta^C + \gamma_j(h) - 1)p_j h_j \mathbb{P}' \\ \frac{\partial Pr(R^C)}{\partial h} &= [(\theta^C + \gamma_j(h) - 1)p_j \psi_j + \gamma_j'(h)(K^C + p_j \psi_j h_j + r_j d_j)]\mathbb{P}'. \end{aligned} \tag{3}$$

These comparative statics show the effect of consumer responsiveness ψ and defect harm h on the firm's recall decision. We find that both partial derivatives have an ambiguous sign depending on whether $\theta^C + \gamma_j(h) - 1$ is positive or not. Recall that θ captures the probability that regulator finds the defects and that γ denotes the probability that consumers finds these defects. This condition illustrates that the effects of consumer responsiveness and defect harm are dependent on whether the consumers or government could *surely* find out the defect or not. If not (i.e., $\theta^C + \gamma_j(h) < 1$), then an increase in the degree of consumer response would definitely lead to a lower recall probability, that is, the firm would more like to cover up. The intuition is that given the chance for firms to get away from the cover-up, the expected benefit of cover-up would increase if consumers would react with a fiercer response. By the same logic, the effect of defect harm level to consumers h is more likely to be positive than that of consumer response ψ that is, given a chance that the firm could get away, a higher defect harm level would increase the benefit of cover-up. In other words, given a chance of getting away, a firm would face an increase in punishments due to the higher harm level h should this firm decides to recall.

Given that $\gamma'(h) > 0$, we assume that there exists h^+, where $\theta^C + \gamma_j(h) - 1 > 0$ for all $h > h^+$. Then, $\frac{\partial Pr(R^C)}{\partial \psi} \geq 0$ and $\frac{\partial Pr(R^C)}{\partial h} \geq 0$. That is, given that the defect would always be found out by either the consumers or regulators, the firm would be more likely to recall the product if the consumers would react more actively to the defect by altering their demand (ψ). The firm is also more likely to recall those products with more harmful defects comparing to products than those with minor harmful defects (h) because a more harmful product would be more likely to be found out, thus increasing the firm's losses from covering up the harmful defect.

In summary, we model the optimal recall probability as a function of government-side (regulatory monitoring) factors and consumer side factors. On the side of regulatory monitoring, increasing regulatory monitoring parameters would unambiguously increase the recall probability by manufacturers because the expected punishments faced by the firm would unambiguously increase as the government intensifies their monitoring or punishments. On the consumer side, the effect depends on whether the firm would escape from being found out. Given a chance of getting away, a higher level of consumer response or higher defect harm may induce the firm toward covering-up the defects. Given that the defect would eventually be found by either of the two parties, we find that an increase in consumer response or defect harm would increase the firm's recall probability. Given a sufficiently harmful defect, we assume that the defect would surely be discovered by either government or consumers. In this case, higher consumer harm or higher responsiveness leads manufacturers to increase their optimal recall probability.

Overall, our findings in this Section guide us towards the findings in Section 6 and 7 which also retrospectively support the findings in this section. The theoretical analysis assists us in crafting a research design to identify the cross-country difference in product recalls in which many factors would be absorbed by fixed effects, revealing unexplained differences in product recalls. It also helps us develop potential regulatory policies and estimate their respective impacts. On the side of government, a reform on information disclosure policy increases the intensity of monitoring and thus increases the recall probability. On the side of consumers, increasing information by means of the aforementioned policy reform or increased news coverage would make it more unlikely for firms to successfully hiding the defects, which in turn increases the likelihood of initiating recalls, especially for models with safety-related defects.

4 Industry background

4.1 China's automobile industry

China's automobile industry experienced rapid growth from 2000 to 2020, with an annual growth rate of about 15% (McKenzy). In 2009, China has surpassed U.S. as the largest automobile markets and Japan as the largest automobile producer. During our sample period from 2004 to 2020, models selling in China belong to one of the three categories: models produced by joint-ventures, the imported models, and domestic only models. The joint-venture model has been dominant in sales during our sample period. For example, the joint-venture sales account for 70% of total sales in China in 2009.[7]. Most of the sales are contributed by sales of joint venture brands like FAW-Volkswagen, SAIC-Volkswagen, and SAIC-GAW. The development of joint ventures in China's automobile industry could be traced back to the 1980s. Guided by the principle of "market access in exchange for technology", China set up joint ventures with foreign brands while setup strict restrictions on imported models. The first two joint ventures,Beijing-AMC and SAIC-Volkswagen, are setup in 1983 and 1984, respectively. In 1994, the "Formal Policy on Development of Automotive Industry" is issued, which formally allowed the setup of joint ventures and imposed restrictions: foreign companies are not allowed to establish more than two joint venture or cooperative enterprises for the same type of vehicle product in China; and in Sino-foreign joint ventures, the Chinese party must hold no less than 50% of the shares. This restriction is valid until 2018. In practice, all Chinese party in the joint ventures are SOEs because of the entrance restrictions on private capital in China. The domestic firms also grow over the sample period: the market shares grow from 19.67% in 2004 to 41.96% in 2018.

The imported car in China takes up a relatively small share (around 3%-4% of total sales) due to the

7. See data from China Association of Automobile Manufacturers (CACC), available here.

high prices and tariffs and the import quota. Before China joining WTO in 2001, the tariff for imported cars could take as high as 220%. In alignment with the requirements of WTO, the tariffs decreased to 28% in 2006. The import quota is abolished alignment of the requirements of WTO, after which is replaced by the restriction that each imported brand should be selling in China via a sole dealer authorized by government.

One important feature of the automobile market in China is the high prices of JV models compared to the prices in US. Actually, the prices in China are claimed to be the most expensive for imported cars.[8] This excludes the possible argument supporting a "price-in" interpretation, that is, the systematic differences in product recalls is justified by the fact that US consumers paid higher price and thus should receive better service. We present below a list of popular car models, which shows that Chinese consumers pay a higher price than their U.S. counterparts. This price gap is larger for luxury vehicles.

[Table 1 about here]

4.2 The liability system in China's automobile market

4.2.1 Liability rules in the U.S. versus China

Table 2 compares the liability rules for the U.S. and China regarding vehicle safety regulations. China established the liability system following the one in the U.S. The law in the U.S. is based on the National Traffic and Motor Vehicle Safety Act (Title 49, Part C) of 1966 and the TREAD ACT of 2000, while the law in China is based on the Provision from 2004 and the Regulation from 2012. China's liability system shares similar rules on regulators, purpose, range, agent, recall procedures/obligations, information system, and media+info disclosure. However, in some other dimensions, China has slightly weaker rules. For example, China did not mention the protection of whistle-blowers in its liability system, and such China's liability system involves no criminal penalty. Overall, China's liability system closely imitates the one in the U.S. while being slightly weaker in some dimensions. This situation provides the legal foundation for us to compare the recall probability between China and the U.S. and helps us to understand the product difference we observe in later parts of this chapter. In the next subsection, we describe evolution of the China's liability system and document the information policy change in the 2012 reform, which we adopt as a policy shock to examine the effect of information on recall probability.

[Table 2 about here]

8. See news report from ifeng.com, available here.

4.2.2 Liability rules in China: 2004-2012

The recall legislation is tightly connected to the consumer complaints on unequal treatment by foreign and joint-venture firms. The recall legislation in China could be traced back to the Mitsubishi Pajero Oil Leak scandal in 2000 when Mitsubishi acknowledged its long-lasting cover-up on vehicle defects. Mitsubishi initiated recalls of large volumes of vehicles all over the world (Watts 2000). However, China was excluded from these recalls due to its lack of legislation. This scandal thus accelerated the enactment of regulations for auto recalls in China. In 2004, the Provisions on the Administration of Recall of Defective Auto Products (henceforth *Provisions*) was issued collectively by four departments under the State Council.

The *Provisions* formally assign the power of regulating the quality of automotive products to the General Administration of Quality Supervision, Inspection and Quarantine (AQSIQ) [9]. The show up of formal regulations brings hope to consumers in China. However, the *Provision* also has its limitations. First, the *Provision* is a government rule rather than a law, and thus has limited legal effect in China's legal system. Second, there are no specific discourses on the duty of firms in information disclosure, particularly the their history of recalls abroad. Third, there is no discourse on the duty of firms to compensate consumers in any case. Fourth, the penalty to firms is very restricted as a result of point 1, at most 30,000 RMB, which is even lower than the price of a car.

As a result of these drawbacks, the post-*Provision* period sees persistent discrimination against consumers in China from big brands, such as Toyota and Volkswagen. In 2010, the infamous Toyota Brake Pedal Scandal resulted consumer outrage in China. Not only did Toyota recalled a limited number of cars and distinct models but also neglected to compensate the Chinese consumers as they did in the U.S. (China Central Television 2015). In 2012, the long-lasting complaints on the direct shift gearbox (DSG) problem received notice from AQSIQ. However, Volkswagen replied that the DSG problem is not related to vehicle safety so it would not make a recall (Ning 2012). By contrast, when the same problem received complaints in the U.S. in 2009, Volkswagen initiated recalls (Jensen 2009).

4.2.3 The 2012 information disclosure reform to liability rules in China

The regulation on information in *Provisions* is permissive. Information from firms is crucial for classifying the defects to a recall as AQSIQ has limited ability to identify and assess the defects from a volume of complaints. After 2004, consistent with the *Provision*s, AQSIQ has established an information collection system on the sides of consumers and firms. After the acquisition of filtered complaints, AQSIQ would

9. The institution is renamed as State Administration for Market Regulation (SAMR) after 2018

send these complaints to firms to probe into the defects, and then these firms would send their feedback to AQSIQ whether they think these defects are serious enough for a recall. However, given that the *Provisions* have not clarified the necessary information to be provided, most foreign car manufacturers would not enlist its recall history and the technical configurations of its new models, and such information is crucial for classifying the defects (Ma and Fan 2009).

After the infamous Toyota Pedal Scandal in 2010, the State Council released the *Regulation on the Administration of Recall of Defective Auto Products (Consultation Paper)* (henceforth *Regulations*), and usually, which would be in effect after a year. Although the actual enactment date is postponed to January 1st, 2013 for further revisions, the expectation was already formulated, and the the law was already being enforced. We thus use 2012 as the policy start year.

The differences between the *Provisions* and the *Regulations* are mainly related to information management. In fact, there is a newly added "Information Management" chapter in the second committee draft of the *Regulations*. These differences include the following. First, *Regulations* explicitly require firms to report any recalls abroad (Article 10, *Regulation*s). Second, *Regulations* empower AQSIQ to initiate investigations after receiving consumer complaints. Third, *Regulations* require AQSIQ to build a defects information collection system where consumers or institutions could submit complaints on defective automobiles.

In light of the institutional changes, we investigate whether there exists differences in automobile recalls . After conforming the existence of systematic differences, we estimate the effect of *Regulations*, which features an information disclosure reform.

5 Data

5.1 Data sources of cross-country recall difference

[Figure 1 about here]

This section describes our data sources. Figure 1 presents a Venn diagram showing our data sources and their relations. The green circles denote the data from China, and the red one denote the data from the U.S. We gathered the "universe" of models being sold in China and the U.S. during the sample period from 2004 to 2020. These models are defined as a triple tuple of brand, series, and model year (e.g., Toyota Camry 2015). We then identify the common car models in both countries, note that these models in China are either being produced domestically by joint venture firms or imported abroad. We also collect the recall announcements in China and the recall records in the U.S. and extract from them the useful recall information, including car model, component, severity, and time by extensive data cleaning and text analysis methods. The recall records in China from 2004 to 2020 comprises 1,574 recall announcements that cover more than 3,000 car models. We then merge the recall records in both countries to the universe of models in China. This merged dataset enables us to investigate systematical differences in product recalls while comparing the same model and controlling for possible confounding factors by adding model and time level fixed effects.

5.1.1 The universe of car models in China and U.S.

Our goal is to detect systematical differences in vehicle recalls in China and U.S. To form a comparable set between China and the U.S., we construct a universe of car models in China. We scrape all the models from 2004 to 2020 from autohome.com which contains information on all available car models in China and is widely used by industry practitioners or academic researchers. This website contains information on car brand, series,manufacturer, and model year. In China, manufacturers of foreign models, such as the Toyota Camry, could either be foreign or domestic, where the latter represents a joint-venture firm with a local SOE. For example, the Toyota Camry is being sold in different versions, such as the imported Toyota Camry and the FAW Toyota Camry, where the latter is manufactured by the joint venture firm FAW Toyota. We do not consider a more detailed categorization since the recall records do not contain further information, such as whether the car is a sports version or a family version. We also scrape all the car model data in the U.S. from 2004 to 2020 from Cars.com, which is one of the most popular automobile information website in the U.S.

5.1.2 Recall records in China and U.S.

[Figure 2 about here]

We use our newly collected data on automobile recalls in China and the U.S. to investigate systematic product/service differences between two countries. After receiving consumer complaints and/or the investigation by the regulator, automobile recalls are initiated, where firms are required to announce remedy the identified defects.[10] We initially examine the recall records in China, where recall announcements come from the Defective Product Recall Technical Center (DPRC) under the State Administration for Market Regulation (SAMR, formerly AQSIQ). Since the issue of the *Provisions*, the DPRC has published all automobile recall announcements through its official website.[11] We thus scrape our recall

10. See https://www.nhtsa.gov/recalls
11. https://www.qiche365.org.cn/

anouncement data from the DPRC website. After extensive data cleaning, we obtain 1,574 recall announcements in China. Each recall announcement may contains recall information involving multiple car models under same or different brands. In each recall announcement, we check for the manufacturers, recall date, model, and text information, such as defect description, consequences of the defect, and corrective actions. We use the series name and model year to identify the model(s). We use manufacturer name to identify the type of ownership (SOE, domestic private firm, or foreign firm). We also classify the severity of the related recall texts.

For the U.S. data, we directly acquire model-level observations from the publicly available recall records published by the U.S. regulator, the National Highway Traffic Safety Administration (NHTSA), on its official website.[12] The data structure are the same as that of the Chinese recall data.

5.1.3 News coverage of U.S. recalls

[Figure 3 about here]

We collect the selective "foreign recall news" published by DPAC with missing data from 2016 to 2018. Figure 3 shows the source webpage, where we identify the involved car models and defect descriptions from the text. Afterward, we match the recall announcement data with the news coverage data by hand to generate the dummy variable indicating whether the U.S. recall announcement is mentioned in the news.

5.2 Measuring recall differences

Our data contain the model-level recall records of all models in the Chinese market and their counterpart U.S models from 2004 to 2020. As our primary data source, we use the recall announcements data in China from 2004 and 2020, which contain information on the brand, series, and model year of the models involved and text descriptions for the defects and their potential consequences. We only use data from 2004 because the first law on recall in China was enacted in 2004. We then augment our main data into the car models universe data by using the Autohome.com dataset to pin down the range of the models in the market.

We construct our key dependent variable *CNRecall*, which equals 1 if there is at least one announcement in year t and equals 0 otherwise. As for the total number of recalled units, given that related data are not available at the model level but all models' total units are included in one announcement, we

12. https://www.nhtsa.gov/nhtsa-datasets-and-apis

cannot utilize such information. Moreover, even if the numbers are available, their magnitude is likely to be correlated with sales, which is also difficult to obtain.

We then construct our key variable in the DID regression, *USRecall*, by augmenting the U.S. recall and the data of the universe of car models. First, we filter the series in the Chinese market that has a corresponding "twin" series using the U.S. universe dataset. Second, we match the recall records of the corresponding U.S. "twin" model with the models in China. If there exists a recall record of its "twin" model within one year of the earliest recall records of the model in China, then we define *USRecall* as 1.

For the triple difference variable $USRecall \times Post2012$ analyzing the regulation's effect on the DID estimator, we define it as to be one if the *USRecall* is 1 and the recall happened after/on the release of the new *regulation*.

5.2.1 Text as data: Classifying severity of defects

Every recall announcement by the regulation authority in China contains texts describing the defects of the product being recalled. These texts comprise three parts: a description of the defect, potential consequences of the defect, and the corrective action taken by the manufacturers.

The crucial aspect of our empirical analysis involves transforming these recall announcements into a dataset to help us observe the evolution of manufacturers' recall decisions in relation to the defect's severity. Before addressing the conceptual challenges, we outline the initial steps. Our process begins with text tokenization. For Chinese texts, which lack natural delimiters unlike English, we employ the *jieba* Python library, which is renowned for its efficacy in Chinese text tokenization.

To categorize the recall announcements by the severity of related defects, we build a "search engine" -like database on the textual variables. Afterward, we construct a proper query to filter out the announcements with severe defects. We employ techniques in information retrieval (Manning et al. 2008) to construct this database. The database is structured as a triple tuple: Word-Records-StartAndEndPositions. For instance, the word "Engine" is represented as a nested list: "Engine-[{1:[5,6]}, {2:[9,18]},{4:[3,7]}]. The first element {1:[5,6]} indicates that the word "Engine" is in file 1 at positions 5 and 6. We then construct a module to return the list of files containing (or not containing) a set of words.

After constructing a structured database that links the words to the files in which they appear, we start constructing the query. Unlike many text-as-data applications in Economics (e.g., Aryal et al. 2022) that have a simple and clear coding scheme, our application requires an objective coding scheme to identify severe safety-related defects among all defects in recall announcements. Given that Chinese authorities have not issued classification standards, we turn to U.S. regulators. One natural candidate is the Federal

Motor Vehicle Safety Standards (FMVSS) issued by the NHTSA to implement laws from the Congress. However, this approach is very costly and infeasible given the 171 regulations related to different car parts (e.g., airbags, tires, electronic stability control), and the lengthy docs (e.g., 172 pages of Standard on Tire Pressure Monitoring Systems). We then consider using the rules and examples listed in the NHTSA's reference brochure for car owners to discriminate between safety-related defects and non-safety-related defects [13]. This approach is much more clear and concise for researchers who are not familiar with legal terms. However, this alternative approach may add more measurement errors to our text-generated variable. To alleviate this concern, we combine the information retrieval's keyword query method with the manual review to find the optimal queries that are most consistent with manual classification results. After classification, we construct our queries as three sets of keywords linked with "OR" conditions. The first set of keywords are similar to "Fire" or "Ignition," which indicate that the defect has a potential to start a fire. The second set of keywords are words related to personal safety in cars, such as "Passengers" , "Personal" , "Body harm" , "Personal Safety" , while the third set of keywords describe the key components that may lead to safety defects, such as "Engine" and "Steering system," together with words indicating the malfunction of these components, such as "break down" and "cracked." We also include a set of excluding keywords to avoid misclassification based on our manual reviews. These words include negative words, such as "No cases" , "[Defects] can be excluded," or quantifiers indicating that the defect is not severe, such as "slightly." The classification using these optimized set of query keywords generally agrees with the manual classification results. By using manual review as a benchmark, our keyword classification results obtain an 83.9% precision rate (ratio of true positive to all positives), 90% recall rate (ratio of true positives to true classifications) and 80% accuracy rate (ratio of all true results to the entire classification sample). This set of keywords also echo the principles of the NHTSA. For instance, our set of keywords related to risks of starting a fire or broken critical components reflect the principle: "Moreover, a defect may be considered "per se" safety-related if it causes the failure of a critical component; causes a vehicle fire; causes a loss of vehicle control; or suddenly moves the driver away from steering, accelerator, and brake controls—regardless of how many injuries or accidents are likely to occur in the future." (NHTSA, 2016)

5.2.2 Country of origin

We determine the country of origin based on the brand information of the car model. For example, Toyota brand models (whether produced by its domestic joint venture firm FAW or not) shares Japan as

13. See https://www.nhtsa.gov/document/motor-vehicle-safety-defects-and-recalls

their country of origin. We use such information to see whether heterogeneity is present when it comes to product recall differences.

5.3 Summary statistics

Table 3 provides the summary statistics of the 6,033 models among 155 brands and 1,839 series. All observations are at the model-year level. We have 44938 observations from 2004 to 2020, and over 5.5% of these observations have a recall in that year (*CNRecall* = 1). Among all models (including JV models and local Chinese models), 6.7% of them have been ever recalled in the U.S. For those models ever recalled in U.S., most (6.6%) of these models have an recent recall in U.S within one year.

[Table 3 about here]

5.4 Data sources of consumer responses estimation

[Table 10 about here.]

We combine five sources to construct our data. First, we gather monthly sales data in each city for each car series in China from January 2017 to July 2022. We aggregate the city-level sales data into national level. For example, our data includes the national monthly sales for car series such as Toyota Camry from January 2017 to July 2022. Second, we collect the recall records data in China and the U.S. from 2004 to 2020. We also classify the recall into safety-related recalls and non-safety-related ones using a text analysis method. For detailed descriptions on the text analysis method we adopt, readers may refer to subsection 5.2.1. Third, we construct the universe of car series in China in each year by scraping the website Autohome.com.cn, which is the largest automobile information website in China. We then merge the sales data and the recall records data in China and the U.S. into the universe of car series data in China. Fourth, we collect the news coverage data from the "foreign recall news" section in the DPAC website using a web scraper. The news coverage data span across from 2009 to 2019, with data missing in 2016, 2017, and 2018. We use the data in 2019 as it is the only overlapping year with our sales data which ranges from 2017 to 2022. The recalls in the U.S. that covered in this section are considered as covered in news reports. We manually search for recall announcements that covered in this section. Finally, we scrape the product characteristics including listed prices, height, length, and width of the car series from PCAuto.com.cn, which is another major automobile information website in China.

Table 10 presents the summary statistics of the variables by month level. We aggregate the sales up to the national level. Monthly sales ranged from 0 to more than 70 thousand while market shares ranged from 0% to 2.9%, indicating a relatively not concentrated market. *USRecall (3m)* denotes a dummy indicating whether there is a recall in the U.S. from $t - 3$ to t. *News (3m)* denotes a dummy indicating whether the associated recall in U.S. within the time window is posted on the "Foreign Recall News" section of DPAC's website. *Severe (3m)* indicates whether the defect of the recall in U.S. is safety related. Approximately 5%-6% of the collected series had a U.S. recall from January to October 2019.

6 Do multinationals discriminate? Evidence on China's automobile market

We present evidence of discrimination by multinational automobile companies in consumer policy on product recalls. Our descriptive evidence shows only 30% of JV models are also recalled in China. The number is even smaller for recalls out of same defective components as in the U.S. We then construct a novel data on automobile recalls in the U.S. and China, merging them with the universe of cars sold in the Chinese market. We then construct a measure of differential treatment in terms of product recalls, an integral part essential in product quality management practices by multinationals. Our newly constructed data containing detailed model-level (e.g., Toyota Camry 2015) information allows us to add the model level fixed effects which controls for potential quality differences. We first show the insufficiently low recall probability in China given the defect is recalled in the U.S. in the following year. We then conduct a non-parametric event study to examine the dynamics of recall responses and perform robustness tests to validate our results. We also present a series of heterogeneous results by brands of various country-of-origins and by local models versus imported models. Following our analysis verifying the discriminatory behaviors by multinationals, we investigate the mechanism behind. We find that, consistent with our theoretical predictions, products with safety-related defects would have a higher recall probability. Finally, we show a regulation improving information transparency decreases such recall differences, which is echoed by similar effect of news coverage.

6.1 Descriptive Evidence

Figure 4 provides descriptive evidence on the cross-country recall difference between China and the U.S. The first left blue bar represents the total number of recalls of JV models in each year . The second left bar in red depicts the number of joint recalls in two countries of JV models in each year. The third green bar represents the number of recalls that is in China but not in U.S. of all models in each year.

Figure 4 first shows the overall growth trends for recall numbers of JV models in the U.S., in both countries, and for the recall numbers of all models only recalled in China. The trend represented by the blue bar indicates a large growth in recalls in the U.S. The trend behind the red bars shows for the JV models recalled in the U.S., the recall number is also increasing in China. The trend of green bars shows the largest increase among all three bars, indicating a large increase of increase of recalls of local models in China. By comparing the blue bar and the red bar, we could see that the proportion of JV models recalled in both countries remains small throughout the sample period. However, there is an increasing trend, in particular from 2012. We show later on that in 2012, there is an information disclosure reformation in China that requires multinationals to report foreign recall histories to Chinese regulators. We could also notice that for the green bar, the increasing momentum further strengthened after 2012.

[Figure 4 about here]

Joint recalls by components. Table 4 presents the joint recall rates by components in U.S. recalls. The left panel (the left three columns) show the joint recall rates of the safety-related components in recalls in U.S. Column 2 shows the joint recall rates where the recall is due to defects at the related components. Column 3 shows the joint recall rates with an additional restriction that the recall in China is also due to the defects in the same components as that in the U.S. For simplicity, we would refer to this conditional joint recall probability as the joint recall rates conditional on same component. For example, cell at line 1 and column 2 shows the joint recall rates of models where recalls in the U.S. is due to defects in air bag systems. Cell at line 1 and column 3 shows the joint recall rates where the recalls in two countries are both due to defects in air bag systems. The right panel (column 4-6) shows the joint recall rates of the unsafety-related components in recalls in the U.S. Column 5 contains the same information as column 3. Column 6 contains the same information as column 4.

By looking at the joint recall probabilities (column 2 and column 5), we could see more than two thirds of them are below 40%. The number is interpreted as low comparing to the joint recall rates of larger than 70% in Taiwan region where the institution requires the eligible models be recalled in Taiwan if it is recalled in foreign countries such as in the U.S. The joint recall rates conditional on same components at column 3 and column 6 is significantly lower than the unconditional joint recall rates. This further validates the systematic recall difference between China and the U.S.

Comparing the joint recall rates of safety-related components with those of unsafety-related components, the former ranges from 32%-41% and the latter ranges from 0% to 55%. However, one may note that for two thirds of unsafety-related components, the joint recall rates are below 38%. For safety-related components, two thirds of them are higher than 38%. Similar patterns exist for joint recall rates conditional on same recall components. There are 6 unsafety-related component categories with 0 joint recall rates conditional on the same components.

Overall, these descriptive statistics show preliminary evidence on two points. First, there exists recall difference between China and the U.S., and the difference is larger if we further restrict the joint recall is due to defect of same component. Second, the joint recall rates are higher for safety-related recalls in China compared to unsafety-related recalls.

[Table 4 about here]

6.2 Baseline results

Our previous descriptive statistics suggests a large recall difference between China and the U.S. from the time dimension as well as the component dimensions. However, these descriptions do not account for the impact of possible confounding factors. These factors may include persistent differences in product quality (e.g. Toyota Corolla has slight differences in interior designs in China and the U.S.) and evolving institutions between two countries. We further controlled for these confounding factors by adding the year fixed effects and model level fixed effects.

We use the following baseline specifications to test the associations of the recall rates between China and the U.S.:

$$Y_{it} = \alpha + \beta USRecall_{it} + \mu_i + \lambda_t + \epsilon_{it}. \tag{4}$$

In Equation 4, i and t are the model and year subscripts, respectively. The dependent variable is whether model i is recalled in China in year t. The main explanatory variable, $USRecall_{it}$, equals 1 if the model is recalled in the U.S. before within one year to the current t period. μ_i and λ_t captures model-fixed effects and time-fixed effects respectively. The model fixed effects could control possible product quality differences that do not vary between years. One example is the aforementioned interior design difference in Toyota Corolla in two countries. The year fixed effects could control possible institutional differences between two countries that supposedly do not vary between models. We include the non-JV models where $USRecall_{it}$ equals to zero by definition to control for possible recall trend that is not explained by recalls in the U.S. Standard errors are clustered at the model level.

Table 5 reports the baseline DID results from Equation 4. The coefficient on $USRecall_{it}$ is positive and highly significant (at the 1 percentage level). The coefficient represents the association of recalls in U.S. and China controlling for the possible quality differences and institutional differences. Our estimates show that if the corresponding model in the U.S. is recalled, then the probability that the model is recalled in China in the following one year would be about 13.5%. In column 2, we add the model specific year trends to control for trends specific to models. The R^2 increased from 0.256 to 0.355 after adding the model-specific year trends. The coefficient remains robust. The estimates with model-specific year trends show an association of 12.5% and the estimate is significant at the 1 percentage level. The estimates provide evidence of recall difference between China and the U.S. conditional on same car models. Empirically, Taiwan region with a similar legal system as mainland China has a joint recall rate larger than 70%. The key institutional difference besides the overall similarities shared between mainland China and Taiwan region is the requirement in Taiwan region to recall eligible car models given recalls in foreign countries or regions. So ideally, we would expect that the association between recalls in China and the U.S. be larger than 70%. The estimated association rate at 13.5% indicates the existence of recall difference between China and the U.S.

The year and model level fixed effects help us to control for a large set of possible confounding factors. The year fixed effects would control for model-invariant factors that varies with time. These factors include all government level factors in China and the U.S. which are not model-specific and varies by years. The model level fixed effects would control for all time-invariant model level factors. For example, the possible interior design differences or car quality differences in China and the U.S. that do not vary between years. The model specific year trends would control for some of the uncontrolled model specific factors with a linear time trends. By adding the two fixed effects and model-specific year trends, we believe our estimates showing causal evidence on recall differences in China and the U.S.

We would further address some of the possible identification concerns in the following robustness checks. First, we would exclude the existence of the pre-trends of our association rate. Second, we run a country-of-origin heterogeneity test to show that our results is not driven by a small subset brands. Third, we rerun our main regression using a sub-sample of JV models only to exclude possible bias from recalls of domestic only models. Finally, we perform a set of placebo tests by randomly assign the $USRecall$ variable. We show the estimates from the "fake" samples are normally distributed around zero and far from the true estimates. These robustness checks strengthen the causal interpretation of our association between China recalls and U.S. recalls.

Our estimates emphasize the need of effective regulations to reduce the recall difference. In the following sections, we would explore the role of information as regulation tools on recall associations. Theoretically, the role of information is highlighted in our models. Information would possibly affect the government investigation efficiency, represented by the investigation probability θ. Information would also possibly affect consumer's responsiveness ψ. Another reason is that information regulation would not distort the firm's behavior to the extent of more intense regulations (e.g. mandatory recall given a foreign recall like in Taiwan region). Chen and Hua (2023) highlights that strict liability rules could also affect the supply quantity and innovation. Information regulation, however, would likely be prone to such drawbacks.

[Table 5 about here]

6.2.1 Parallel trends on the DID setting

One concern that threatens our estimates on association of recalls is that the estimates reflects the effect of China's recall on following U.S. recalls. To verify the pre-trend assumption needed for valid identification, we perform a non-parametric event-study analysis of the dynamics of the impact of the research exemption. Formally, we run the following regression:

$$Y_{it} = \alpha + \sum_{k=-3}^{k=3} \beta_k USRecall_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \tag{5}$$

where k denotes the leads and lags. $USRecall^k$ is defined as 1 if $USRecall$ at $t-k$ period is 1. Given that there exists multiple recalls for a model across this period, we exclude those observations where $USRecall = USRecall^k$ for all k.

Figure 5 provides the coefficient dynamics 3 years around the date of recall in the U.S.We use 1 year before the current period as the reference period. If the regression coefficients β_{-3} and β_{-2} are significant from 0, then the parallel trends assumptions tend not to hold. Instead, we find β_{-3} and β_{-2} are not significantly different from 0, where β_1 to β_3, which captures the post-recall effects, are significantly positive. Our event-study analysis provides additional support for causal interpretation of our main findings: the results exclude the interpretation that the association reflect the effect of China's recalls on following-up U.S. recalls.

Our event study also alleviates the concern that our estimates are driven by other factors, which is likely to occur when the recall is conducted in China. The figure showing no significant coefficients of $USRecall$ variables for $k = 1, 2, 3$ tend to reject such a concern. Furthermore, this event study also indicates how long lasts the effect of recall in U.S. on the recalls in China. The post-treatment coefficients $(k = -1, -2, -3)$ are positive and significant indicating that the effect lasts for about two years after the recall in the U.S.

[Figure 5 about here]

6.3 Heterogeneity results

Country of Origin We then examine the heterogeneous recall associations on the country-of-origin of brands. Figure 6 reveals that French brands show the highest recall association rate compared to brands from other countries. Korean brand cars, by contrast, demonstrate the lowest recall association rate.

Brands originating from Japan, the U.K., and the U.S. have similar recall probabilities, falling within a relatively narrow range and closely aligned with each other.

Overall, our regression analysis points to a distinct pattern regarding the recall probabilities of brands from different origins in China. While French manufacturers tend to recall products more frequently, Korean brands demonstrate a lower likelihood of recalls. Meanwhile, Japanese, U.K., and U.S. brands occupy an intermediate position, indicating a similar level of commitment to addressing potential product issues in the Chinese market.

[Figure 6 about here]

Domestic vs Import Models JV models consist of domestic produced models by joint ventures (henceforth domestic JV models) and imported models. Before 2018, all domestic partner of joint ventures producing the domestic JV models are SOEs. Given widely documented political connections between SOEs and the government, we investigate whether the recall association is different between domestic JV models and imported models.

Table 6 presents the results on the effect of being produced by domestic joint ventures on recall probabilities in China. We add an term interacting $USRecall$ with SOE into equation 4, where SOE represents the model is being produced by domestic joint ventures whose partner is a SOE. Following equation 4, we add year fixed effects to control for factors such as cross-country law-enforcement differences which changes in years. We also add model fixed effects to account for model level demand and recall cost factors on recalling probabilities. Column 1 shows the baseline results whereas column 2 adds the model-specific linear trends. The coefficient on $USRecall$ represents the recall association between China and the U.S. for imported models. This coefficient indicates the recall association rate for imported car models in China and corresponding models in the U.S. is 14.6%-15.1%. The coefficient on the interaction term $USRecall \times SOE$ represents the effect of being produced by domestic joint ventures. The results show that being being domestically manufactured by domestic joint ventures would significantly reduce the recall probabilities in China by 3.8% to 5.6%, accounting for about 30% (3.8% / 15.1% as treatment effect) of total effect. Our estimates validates the conjecture that political connections between SOE and government would curb the recall association rate between China and the

U.S.

[Table 6 about here]

6.4 Mechanism

Safety-related vs non-safety-related recalls Our models in Chapter 1 and previous research suggests the severity degree of consumer harm is an important factor on firm's recall decision. We categorize the recalls in China into severe safety-related and non-safety-related recalls. Please refer to subsection 5.2.1 for details on text classification. Briefly speaking, our classification is to apply the information retrieval method of keyword searching to the text description fields listed in Chinese recalls. The keywords are constructed by summarizing the rules listed in NHTSA's examples on safety-related recalls. We then redo the estimation in equation 4 by replacing the dependent variable as $Y_{it} \times SafetyRelated_{it}$. Table 7 shows the heterogeneous response on safety-related recalls and non-safety-related recalls. Column 1 and 2 provide the results for safety-related recalls while column 3 and 4 present the result for non-safety-related recalls.We added model-specific fixed effects to capture possible time invariant model specific confounding factors including quality differences in the JV models between China and the U.S.. We also add time-fixed effect to control for model invariant time varying confounding factors such as institutional factors including the investigation probability (θ in model in Chapter 1) in two countries. In column 2 and 4, we added model-specific year trends to account for further confounding factors that are model specific and following a linear time trend.

In column 1, for safety-related recalls, a U.S. recall would be associated with a 11.2% probability of recalls in China in the following year. The effect is statistically significant at 1% level. The result in column 2 with model-specific year trends remains quantitatively robust and statistical significant at 1% level with estimated effect to be 10.4%. Column 3 presents the effect on non-safety-related recalls as 2.2%, which is about one-fifth of the effect on severe ones. The estimated coefficient is statistically significant at 1% level. Column 4's estimate (1.9%) is quantitatively similar to column 3's (2.2%) and statistically significant at 1% level.

Summing up, our results demonstrate that most of the estimated recall associations in China is from safety-related recalls. This implies that firms particularly pay more attention on recalling products with safety-related defects than products with non-safety-related defects. Our findings is consistent with previous studies indicating that firms would respond to safety-related recalls comparing to non-safety-related ones (Liu and Shankar 2015; Crafton et al. 1981; Colak and Bray 2016).

[Table 7 about here]

6.5 Information provision and regulation

Information on consumer monitoring We then investigate whether news coverage would increase recall probability. Given that this information is made public to consumers, part of this effect could be interpreted as the effect of information on consumer monitoring.

Table 8 presents the results on the effect of news coverage on recall probability. We add a term interacting $USRecall$ with $News$ into Equation 4, where $News$ indicates that the model's associated recall in the U.S. is reported in China. Following Equation 4, we add year fixed effects to control for certain factors, such as cross-country law-enforcement differences that vary across years. We also add model fixed effects to account for model level demand and recall cost factors on recalling probabilities. Column 1 shows the baseline results, while column 2 adds the model-specific linear trends. Results show that news coverage significantly increases the recall probabilities by 4% to 5%, accounting for more than 30% (4% / 15.1% as treatment effect) of the total effect.

Figure 7 depicts the coefficient dynamics 3 years around the date of recall in the U.S. We use 1 year before as the reference period. The X axis shows the time gap between a recall in China and the associated U.S. recall, e.g., -2 denotes the Chinese recall is happened two years before the U.S. recall. All the pre-recall years' effects do not significantly different than 0 and thus exclude the pre-treatment effect.

[Table 8 about here]

[Figure 7 about here]

Information on regulatory monitoring We further explore the effect of information disclosure regulation on the DID estimator by following baseline triple difference baseline OLS model:

$$Y_{it} = \alpha + \beta_1 (Post2012 \times USRecall)_{it} + \beta_0 USRecall_{it} + \mu_i + \lambda_t + \epsilon_{it} \tag{6}$$

Post2012 is a dummy indicating whether the current year is on/post the regulation. All other settings are in line with equation 4.

Table 9 presents the additional effects upon adding the *Regulations* on DID estimator using a triple difference strategy. The additional difference here refers to the difference before and after the *Regulations* is firstly released, which is in 2012. The coefficient on *Post2012* $\times$ *USRecall* is positive and significant at the 1% level. Our β estimate indicates that the probability of recall in China would increase by about 5.7% if the model is recalled in U.S. The coefficients on *Post2012* $\times$ *USRecall* and *USRecall* add up to as nearly equal to the coefficient on *USRecall* in the DID framework. Based on the causal interpretation of our estimation, information disclosure accounts for about $0.058/(0.058 + 0.091) \approx 40\%$ of the total effects, which means that taking aside the information disclosure, a recall in the U.S. would have a 9% chance to initiate a recall in China. After the release of the *Regulations*, this probability increases by 40% to 14%. This finding highlights the role of information regulation in quality management and consumer rights protection.

[Table 9 about here]

Parallel trends test. One of the underlying identifying assumptions to provide causal interpretations for our estimates is an assumption of parallel trends. That is, the trend for those models with $USRecall = 0$ should be independent of those with $USRecall = 1$. It may challenge our conclusion if the models with $USRecall = 0$ already has an existing pattern before the release of the *Regulations* in 2012. To validate the parallel trends assumption, we provide the dynamics of the DDD estimator using the following regression:

$$Y_{it} = \alpha + \sum_{2004}^{2020} \beta_k USRecall_{it}^{k} + \mu_i + \lambda_t + \epsilon_{it} \tag{7}$$

Figure 9 plots the estimates of β_k coefficients and their 95% confidence intervals. The years on or before 2006 are omitted due to relatively small observations. The coefficient of estimators are all insignificant before 2012, showing that the effect of the recall in the U.S. is indistinguishable from those of recalls occurringprior to 2006, thus confirming the parallel trends assumptions. The parallel trends continue into the post-regulation years, but the positive difference becomes significant and persists from 2015. These results remain robust if we change our base year to 2009.

[Figure 9 about here]

Country of origin We then examine the effects of *Regulations* by country of origin. Figure 8 reveals that French brands react most actively to the 2012 information regulation compared to brands from other countries, given a recall in U.S. within before a year. Korean brand cars, however, demonstrate the lowest reaction to the information regulation.

Meanwhile, brands originating from Japan, the U.K., and the U.S. respond to the *Regulations* in similar degrees, falling within a relatively narrow range.

Overall, our regression analysis points to similar reactions to the *Regulations*.

[Figure 8 about here]

6.6 Summary

In this Section, we first present a set of descriptive evidence to show that the recall rate in China given a recall in the U.S. (hence forth the recall association rate) is low. Figure 4 shows the recall association rate is very low for JV models. Looking into each components in recalls in the U.S., Table 3 shows low recall association rates despite of recall components (reasons).

Confounding factors like time-invariant unobserved product differences or product invariant unobserved institutional differences may weaken our descriptive evidence. We thus use a DID design with two-way fixed effects to subsume such unobserved confounding factors. We find that Chinese consumers are more unlikely to receive a recall compared to the U.S. market. We present heterogeneous results for brands of different origin countries. We show also that SOE joint venture models are more unlikely to be recalled in China, indicating existence of SOE's political connection. Using text-analytic methods to classify the recalls into safety-related and non-safety-related categories, we find manufacturers are more likely to recall models with safety-related defects comparing to non-safety-related ones.

Our results also highlight the importance of information in reducing such difference. Specifically, news coverage and information disclosure regulation are effective in reducing such product recall difference. The information closure policy effect is more evident for safety-related ones as well.

7 Consumer responses to recalls in China's automobile market

Product recalls are an integral part of quality management (product risk management), and consumer response is core to recall decisions of firms. Consumer responses to product recalls are crucial to understanding the following questions: 1. what drives manufacturers to recall (see e.g. Colak and Bray 2016; Rupp and Taylor 2002), and 2. what is the welfare implication of consumer's misconception, which is key to evaluating the effect of various policy instruments for product quality regulation. Consumer response is pivotal to the recall decisions by manufacturers. It is one of the two channels driving the recall decisions of manufacturers, which is illustrated in our model in Section 3. For example, changes in consumer demand would affect profits of firms and thus shifting the recall decision by firms. Heterogeneous consumer responses on different types of recalls would also lead to different recall strategies to defects of different types. If consumers could fully perceive the quality of the products, there would be no necessity for government intervention and the recall level would be at the optimal level (Chen and Hua 2023). However, in reality, consumers often could not fully acquire information on product quality and safety due to the information problem. Therefore, consumer response is vital in driving the recall decisions by firms, and lacking response would lead to insufficient recalls which lowers consumer welfare. According to a survey on product recall by the European Union, a large proportion of consumers in Europe are either unaware of or do not believe that manufacturers are obliged to recall dangerous products. European Commission, Consumers, Health, Agriculture and Food Executive Agency 2019 However, even consumers know this obligation, inadequate response to specific recalls may still hinder firms from fully recalling products with defects. It is thus important to study whether consumers respond to recalls as well as the extent of this response.

Other studies also acknowledge the importance of consumer response. For example, Colak and Bray (2016) study whether manufacturers recall to avoid consumer complaints or to avoid government recalls. And they find that manufacturers mainly recall products to avoid consumer complaints. Rupp and Taylor (2002) study the association between recalls and owner response rate, and find that higher owner response rate is associated with hazardous and newsworthy recalls. Although consumer complaints and owner response rate are both important factors characterizing consumer response, how purchasing decisions of consumers affect recall decisions of manufacturers is less explored.

On the other hand, the possible inadequate consumer response due to information problems leaves room for government regulations and liability rules. The government could consider various regulation policies or liability rules. These policies could indirectly increase recall rate or effectiveness by increasing consumer response. Or, they could increase recall rates through investigation and associated penalties. Suggested actions on increasing consumer response include targeted awareness campaigns, learning from member states with higher recall effectiveness, and clarifying key steps in the recall process. European Commission, Consumers, Health, Agriculture and Food Executive Agency 2019 Monetizing the extent of consumer response is crucial to evaluate these policies.

In this Section, we build a demand model to estimate consumer response to product recalls and relevant defect information. We study China's automobile industry because it involves severe information problems to consumers and the product defect is important to consumer safety. We combine five data sources in automobile industry. First, we gather monthly sales data for each car series in China from January 2017 to July 2022. Second, we collect the recall records data in China and the U.S. from 2004 to 2020. And we also classify the recall into safety-related recalls and non-safety-related ones using a text analysis method. Third, we construct the universe of car series in China in each year by scraping the website Autohome.com.cn, which is the largest automobile information website in China. Fourth, we collect the news coverage data from the "foreign recall news" section in the DPAC website using a web scraper. Finally, we scrape the product characteristics including listed prices, height, length, and width of the car series from PCAuto.com.cn, which is another major automobile information website in China. We examine the following questions step by step. We first study whether consumers have enough response to recalls in general in China. Consistent with findings in the U.S. (Wynne and Hoffer 1976), we find no response to recalls in general indicating no adequate response in market. We then examine whether consumers respond to recalls of safety-related defects or recalls reported by news. Safety-related news-covered recalls would decrease the purchasing probability by 10% to 13%. This results suggest a information problem: consumers would only respond to recalls that are on news report and related to high consumer harm level. Motivated by these findings, we estimate the welfare effect of a counterfactual policy that expands media coverage to all safety-related U.S. recalls. We also utilize the welfare framework with consumer misconception developed by Train (2015) together with the estimated demand model to evaluate how releasing public information on all safety-related recalls in the U.S. would affect Chinese consumers. We find that the counterfactual policy increases consumer welfare by 46 thousand CNY per person, which is equivalent to a 2.1% increment. Overall, our results reveals that information regulation is a very effective tool for protecting consumer welfare.

7.1 Demand for Automobiles

In this section, we set up our demand model. We aim to estimate the willingness-to-pay (WTP) for public recall news by using a revealed-preference approach. Specifically, we aim to estimate the parameters in the consumer utility functions by connecting the derived demand system to product-level market share data. We build the demand system by aggregating a discrete choice model of an individual consumer. We then derive a system of equations to be applied on the data from the demand model. Similar to previous works that conduct demand estimation, we do not have data that links consumer characteristics to the product they chose. Therefore, we estimate all parameters using product-level data, which include information on prices, quantities, and observable product characteristics. We then discuss the possibility to add exogenous information on consumer characteristics distributions.

$$u(\zeta_i, p_j, x_j, \xi_j; \theta) \tag{8}$$

We first present a general utility model under our consideration. Let i, j denote consumer and product, respectively. The setup posits that the utility level that consumers derive are determined by a combination of consumer-level characteristics and product-level information. Here, p is the price of the product, and x is the observed product attributes. We denote the unobserved (for econometricians) product characteristic by ξ and let ζ denote consumer characteristics. Given that different consumers make different choices, we could derive the equation of individual optimal choice. We then integrate the choice function over the distribution of ζ to get the aggregate product-level demand. We assume that ζ follows a known standardized distribution whose standardization parameters are estimated. Specifically, we assume a standardized normal distribution where the standard deviation is the parameter to be estimated.

Given the utility in Equation 8, consumer i chooses good j if and only if

$$u(\zeta_i, p_j, x_j, \xi_j; \theta) \geq U(\zeta_i, p_r, x_r, \xi_r; \theta), \forall r = 0, 1, ..., J.$$

The outside option 0 indicates that the consumer does not purchase any products. Then, we could obtain the set of ζ that induces the consumer to choose j as follows:

$$A_j = \{\zeta : u(\zeta_i, p_j, x_j, \xi_j; \theta) \geq u(\zeta_i, p_r, x_r, \xi_r; \theta), \forall r = 0, 1, ..., J\}.$$

We let $P_0(\zeta)$ denote the population density, and we express the market share of good j as a function of characteristics of all goods:

$$s_j(p, x, \xi; \theta) = \int_{\zeta \in A_j} P_0(d\zeta).$$

We then specify the functional forms of our demand system. We first present the random utility model of differentiated products. We parameterize our model and then estimate the parameters. The estimates on price coefficient and recall news would help us recover the WTP for recall news. This information intuitively measures the consumer valuation of and responses to recall news.

Let $i \in [1, ..., I]$ denote consumer and $j \in [1, ..., J]$ denote the automobile series. In each month $t \in [1, ..., T]$, consumer i chooses the series j that gives him/her the highest utility. The consumer facing recall news may react to this news by not purchasing the product under risk. The conditional indirect utility of consumer i from purchasing the series j is

$$u_{ijt} = -\alpha_i p_j + X_j \beta + \gamma HazardNews_{jt} + \xi_j + \lambda_t + \xi_{jt} + \epsilon_{ijt} \tag{9}$$

where $HazardNews_{jt}$ indicates whether the series has been on recalled news in China because of a safety-related defect in the U.S. in month t, X_j represents the utility gained from product characteristics conditional on the purchase of series j, and p_j represents the listed price of series j, which does not vary with time in our sample period. ξ_j represents the series fixed effects or the utility gains from unobserved product characteristics, λ_t represents the month fixed effects, ξ_{jt} represents a product-month specific demand shock, and ϵ_{ijt} represents a mean-zero stochastic term. The parameter γ_i measures the marginal utility for $HazardNews_{jt}$, and α_i measures the negative marginal utility of price.

We assume the distribution of error term ϵ_{ijt} to be a type I extreme-value distribution. We estimate a standard logit demand model and a random coefficient logit demand model. The standard logit model assumes that all consumers have the same response, that is, the coefficients in Equation 9 do not vary by consumer index i. One benefit of the standard logit model is the easiness on computation, that is, one could estimate a linear equation using standard OLS regression with instruments on prices. In contrast to the standard logit model, the random coefficient model provides more flexible substitution patterns in cost of estimating a highly non-linear objective function with a specific GMM algorithm. In this paper, we adopt both approaches to estimate the WTP for recall news.

7.2 Random-coefficient Logit model

We first summarize the random-coefficient Logit model. Detailed discussions on random coefficient logit demand models are well documented in the literature (Berry et al. 1995; Nevo 2001). Here, we focus on model descriptions relevant to our empirical estimation.

We step from Equation 9 and specify the coefficient on price as a random coefficient. We model the random price coefficient as a linear function on a non-random part plus a random part depending on consumer's demographic information. Specifically, we have

$$\alpha_i \quad = \quad \alpha_0 + \sigma_e e_i$$

where e_i is standard normally distributed unobservable heterogeneities with density $P(e)$, and α_0 measure the common consumer response on price. For the random part, σ measures the unobserved heterogeneity on consumer response. We denote the utility part without consumer heterogeneity as the mean utility δ_{jt} and the random utility part as μ_{ijt} as below.

$$
\begin{cases}
\delta_{jt} = \underbrace{-\alpha_0 p_j + \beta_0 X_j + \gamma_0 HazardNews_{jt} + \xi_j + \lambda_t + \xi_{jt}}_{\text{Mean Utility Level}} \\
\mu_{ijt} = \qquad \underbrace{-e_i p_j}_{\text{Random Utility Part}}
\end{cases} . \tag{10}
$$

For consumer i, the probability of choosing j is then

$$
\frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k=0}^{J} \exp(\delta_{kt} + \mu_{ikt})}
$$

given the extreme value distribution of ϵ.

We illustrate our estimation method below. The core of the algorithm in Berry et al. (1995) is to generate the set of moments for GMM estimation. Here we provide a short description of how to generate the set of moments and estimate parameters using GMM with the generated moments. The algorithm proceeds as follows. First, we calculate the simulated market shares implied by the model. Second, we solve the vector unobservables ξ_{jt} as a function of simulated and observed market shares. Finally, we calculate the instruments and interact them with the unobservables ξ_{jt} to generate the set of moments. We then use GMM to estimate the parameters in the utility function by finding those parameters that minimize the objective GMM function.

We initially obtain the simulated market share implied from our model. The market share for series j in month t is

$$
s_{jt}(p, x, \xi, \theta, P(e)) = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k=0}^{J} \exp(\delta_{kt} + \mu_{ikt})} P(de)
$$

which is the integral over the distribution of consumers who choose product j. We approximate the integral using the following Monte Carlo integration:

$$
s_{jt} \approx \frac{1}{n_t} \sum_{i=1}^{n_t} s_{ijc} = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k=0}^{J} \exp(\delta_{kt} + \mu_{ikt})}. \tag{11}
$$

Afterward, we combine the simulated market shares s with observed market shares S to solve δ as a function of parameters θ. Given that the mean utility δ_{jt} could not be solved analytically like in standard logit case by reverting a system of equations, we use the fixed point iteration algorithm:

$$
\delta_{\cdot t}^{h+1} = \delta_{\cdot t}^{h} + \log(S_{\cdot t}) - \log(s_{\cdot t})
$$

where h denotes the iteration rounds, $S_{\cdot t}$ denotes the observed market share, and $s_{\cdot t}$ denotes the predicted market share from Equation 11. Given the estimates of δ_j, we could solve for the demand unobservable as $\xi_{jt} = \delta_{jt} - (-\alpha_0 p_j + \beta X_j + \gamma HazardNews_{jt} + \xi_j + \lambda_t)$, which represents the set of moments that we later utilize using GMM. With instruments Z_j that are uncorrelated with ξ_{jt}, we have $E[\xi_{jt}|Z_j] = 0$, and we assume that

$$E[\xi_{jt}^T \xi_{jt}|z] = \Phi(Z_j)$$

where z denotes the matrix of Z_j. Then, we could construct a proper non-linear GMM objective function

$$\xi_{jt}(\theta)^T (Z_j) \Phi^{-1} (Z_j^T) \xi_{jt}(\theta)$$

where Φ^{-1} denotes the optimal weight matrix for the GMM estimation. Given the initial guess of $\hat{\theta}$, we could update $\hat{\theta}$ by minimizing the objective GMM function:

$$\hat{\theta} = \arg\min \xi_{jt}(\theta)^T (Z_j) \Phi^{-1} (Z_j^T) \xi_{jt}(\theta).$$

We then iterate through the whole loop until we get a fixed point estimates of parameters $\hat{\theta}$.

Identification The issue of identification includes potential endogeneity of two variables of interest: $HazardNews_{jt}$ and $price_j$. $HazardNews_{jt}$ may be endogenous since it can correlate with the unobserved quality component ξ_{jt}. The panel data structure allows us to add the car series fixed effect, which captures all the factors that vary with the car series including unobserved product-specific factors.We also add time fixed effects to capture all the unobserved time-specific factors. The key variable $HazardNews_{jt}$ has variations on both the product level and the time dimension, thus helping identify its effect on consumer response as reflected in market shares.

To address the endogeneity problem of the price variable, we use the "BLP-type" instruments commonly used in the empirical IO literature. They include the the average price and average product characteristics of competitors of the same car category (e.g. SUV, MPV, etc.). These instruments satisfy instrument relevance principle because of the oligopoly market structure. Specifically, it infers that the product characteristics of competitors would affect the optimal price by the firm. These instruments are exogenous because it is assumed that product characteristics are determined before the price. Assuming a unique Nash-Bertrand equilibrium, Berry et al. (1995) argue that using the following instruments could satisfy the conditions that these instruments directly influence the costs but not price and that they are correlated with the own product cost.

7.3 Logit model

Unlike the random-coefficient logit model, the standard logit model assumes that $\beta_i = \beta, \alpha_i = \alpha$,and $\gamma_i = \gamma$ for consumer i. The market share for series j in month t is reduced to

$$s_{jt} = \frac{\exp\left(-\alpha p_j + X_j\beta + \gamma HazardNews_{jt} + \xi_k + \lambda_t + \xi_{jt}\right)}{1 + \sum_{k=1}^{J} \exp\left(-\alpha p_k + X_k\beta + \gamma HazardNews_{kt} + \xi_k + \lambda_t + \xi_{kt}\right)}.$$

The utility of outside option is normalized to 0, and

$$s_{0t} = \frac{1}{1 + \sum_{k=1}^{J} \exp\left(-\alpha p_k + X_k\beta + \gamma HazardNews_{kt} + \xi_k + \lambda_t + \xi_{kt}\right)}.$$

We could eliminate the denominator by using the difference between the log market share of j and outside option: $log(s_{jt}) - log(s_{0t}) = -\alpha p_j + X_j\beta + \gamma HazardNews_{jt} + \xi_j + \xi_{jt} + \lambda_t$. Note that $log(s_{0t})$ is captured by month fixed effects. Our estimation equation is thus reduced to

$$log(s_{jt}) = -\alpha p_j + X_j\beta + \gamma HazardNews_{jt} + \xi_j + \xi_{jt} + \lambda_t \tag{12}$$

where γ measures the willingness to pay for recall news, and α represents the negative marginal utility for price. We estimate the marginal willingness to pay for recall news by $-\gamma/\alpha$.

One potential identification problem is that with series-level fixed effects, our data do not have variations on price and product characteristics. We follow Nevo (2000) to back out α. First, we estimate β and ξ by OLS estimate equation (12). Second, we regress series fixed effects on product characteristics using IV regression with instrumental variables for price. Third, we construct the instrumental variables by using the average price and average product characteristics of competitors. We define competitors as all of those series belonging to the same car class (MPV, SUV etc.)

7.4 Empirical Analysis and Results

We present here the estimates of our random coefficient logit demand models. These estimates help us calculate the willingness to pay for recall news. We show consumers in China do not react to general recall announcements in China. We present the estimation results for consumer's willingness to pay for recall news with safety-related defects. We then show the estimation results for the random coefficient logit model.

7.5 Consumers' unresponsiveness to general recalls

In this subsection, we justify the selection of our target variable, namely recall news in China on U.S. recall announcement with safety-related defect. Following the demand model, we first estimate whether consumers in China are insensitive to general recall announcements in China. Following the literature on consumer response to recalls, we further explore whether consumers respond to safety-related recall announcements in China.

We first run the estimation on the following equation,

$$log(q_{jt}) = \alpha + \beta CNRecall_{jt} + \gamma CNRecall_{jt} \times Severe(CN)_{jt} + \xi_j + \lambda_t + \epsilon_{jt} \tag{13}$$

where j denotes the series, and t represents month. This equation is equivalent to Equation 12. Specifically, given that $s_{jt} = \frac{q_{jt}}{M_t}$, Equation 12 shows

$$log(q_{jt}) - log(M_t) = -\alpha p_j + X_j \beta + \gamma HazardNews_{jt} + \xi_j + \xi_{jt} + \lambda_t.$$

We model $HazardNews_{jt}$ using $CNRecall_{jt}$ and $CNRecall_{jt} \times Severe(CN)_{jt}$. Equation 12 then implies

$$log(q_{jt}) = \gamma HazardNews_{jt} + \xi_j^{'} + \lambda_t + \xi_{jt}$$

where $HazardNews_{jt}$ is a linear function of $CNRecall_{jt}$ and $CNRecall_{jt} \times Severe(CN)_{jt}$, and $\xi_j^{'} = -\alpha p_j + \beta x_j + \xi_j$. Therefore, the estimation Equation 13 is derived from our demand model. $CNRecall_{jt}$ equals 1 if series j has a recall announcement in China in month t and equals 0 otherwise. $Severe_{jt}$ is a dummy indicating whether the recall announcement is due to a safety-related defect. ξ_j and λ_t are series and month fixed effects that capture the product characteristics and seasonal factors influencing consumer demand, respectively. Table 11 provides the estimates. The coefficients on $CNRecall_{jt}$ are statistically insignificant and interpreted as 0 in column 1. We further add $CNRecall_{jt} \times Severe_{jt}$ following Liu and Shankar (2015), who find that the severity of defects would affect consumer response to recall. Our results show that consumers are insensitive to *general* recall announcements in China regardless of whether they are due to safety-related defects or not. This insignificant estimation is consistent with evidence from the U.S. where Crafton et al. (1981) find that U.S. consumers are unresponsive to non-safety-related cases. They attributed this result to less media coverage for those defects, thus highlighting the value of public information for product defects. Wynne and Hoffer (1976) add that recalls have no effect on market shares in the U.S.

[Table 11 about here.]

7.6 Logit model estimation

In the previous subsection, we show that consumers are insensitive to general recall announcements in China regardless of whether the recall defect is safety-related or not. Following the literature, our conjecture is that information plays a vital role here. We then investigate the role of information by adding the news coverage variable in our logit estimation.

Column 1 in Table 12 shows the first-stage regression following Nevo (2000), where we first regress the log sales on independent variables varying with month. Columns 2 to 4 of Table 12 shows the estimations obtained by using different definition of $News$ variable across different time periods, which is measured from themonth of the news release to the month of sales. All of these columns show a similar estimation. The U.S. recall announcement itself and the news coverage on recalls are not strong enough to induce consumer response. If the U.S. recalls due to safety-related defects are reported on news, then consumers on average would reduce their purchasing probabilities by 10% to 13%, which is a considerable amount. The coefficients on prices and product characteristics in Table 12 show the results of the second-stage regression, where we run an cross-section regression of the estimated series fixed effects in the above panel data regression on prices and product characteristics. Consumers on average would decrease their purchase probabilities by 9% for every 10 thousand increase in price. By combining these estimates, we could infer that the provision of safety-related recall news accounts for a12 thousand increase in car series price. Given the average price of 140.68 thousand RMB in our sample, the announcement of recalls accounts for an 8.5% increase in price.

[Table 12 about here.]

[Figure 10 about here.]

7.7 Random-coefficient logit model estimation

Although a standard logit estimation provides a simple starting point since it could be estimated using a simple IV regression, it restricts that consumers are homogeneous in terms of their responses to prices and other variables. In this section, we relax the restriction on consumer homogeneity. Specifically, we allow the consumers' response to the price variable to be heterogeneous.

Table 13 shows the result of the random coefficient logit estimation. The price coefficient is -1.043, indicating that a 1,000 increase in price would decrease the purchasing probabilities by 10.04%. However, consumers responses are highly heterogeneous, and the standard deviation of the coefficient σ_u is 2. The interaction term of recall on *News* and *Safety-related* is significant with coefficient of -12.4, which suggests that when given a safety-related news, this news accounts for about 120 thousand CNY of price increment, which is almost the average car's selling price. We later use these estimates to derive the counterfactual welfare effect given a policy to publicly reveal all safety-related recalls in the U.S.

[Table 13 about here.]

7.8 Welfare Estimation

We present here our framework for estimating consumer welfare. Specifically, we estimate the welfare effect of an information policy, that is providing information on U.S. safety-related recalls to Chinese consumers.

Perceived utility v.s. decision utility Suppose that consumers choose product $j \in [1, ..., J]$ among J products. They would realize the true quality of this product only after a period after its purchase. The utility they actually obtain after purchasing the product is U_j, which is called "actual utility" (Train 2015) or "experience utility" (Allcott 2013). These consumers choose among alternatives based on the "anticipated utility" (Train 2015) or "belief utility" (Allcott 2013), which is indicated by W_j. Consumers choose j if for all $k \neq j$, we have $W_j > W_k$.

[Figure 11 about here.]

Measuring the welfare under imperfect knowledge We follow Train (2015) to measure the welfare under imperfect knowledge. One source of welfare loss (gain) is imperfect knowledge. We measure this welfare change as the difference between the decision utility and experience utility following Train (2015): $d_j = U_j - W_j$. When the "true" or experience utility is higher than the decision utility, $d_j > 0$, and vice versa.

We denote by j^* the alternative from which consumers acquire the highest utility when they are facing imperfect knowledge where $W_{j^*} > W_j, \forall j \neq j^*$,and we use k^* to denote the alternative from which consumers acquire highest actual utility without imperfect knowledge where $U_{k^*} > U_k, \forall j \neq k^*$. We assume that $j^* \neq k^*$ and that consumers would incur a loss when they found the defect from recall news, thus $d_{j^*<0}$. The loss due to imperfect knowledge in terms of experience utility is

$$U_{j^*} - U_{k^*} = W_{j^*} - W_{k^*} + d_{j^*} - d_{k^*} \tag{14}$$

Under the random coefficient logit model, the welfare is measured by

$$\begin{aligned} CS &= \int E(U_{j^*})/\alpha f(a)da \\ &= \int E(W_{j^*} + d_{j^*})/\alpha f(a)da \\ &= \int [ln \sum_j \exp(-\alpha p_j + X_j\beta) + \sum_j S_j d_j]/\alpha f(a)da \end{aligned} \tag{15}$$

where $f(a)$ is the distribution of the random price coefficient, and S_j denotes the choice probability of product j. We could then obtain the loss from imperfect knowledge as

$$\begin{aligned} \Delta CS &= \int [E(U_{j^*})/\alpha - E(U_{k^*})/\alpha] f(a)da \\ &= \int [E(W_{j^*} + d_{j^*})/\alpha - E(U_{k^*})/\alpha] d\alpha \\ &= \int \frac{1}{\alpha}[ln \sum_j \exp(-\alpha p_j + X_j\beta) - ln \sum_j \exp(-\alpha p_j + X_j\beta + d_j) \\ &+ \sum S_j d_j] d\alpha \end{aligned} \tag{16}$$

Figure 11 illustrates the welfare loss from imperfect knowledge when making a purchasing decision. Consumers having a higher anticipated utility than experience utility are denoted by a higher demand curve, while consumers having a higher experience utility than anticipated utility are represented by the lower demand curve. Optimal demand $Q^{\#}$ differs from Q^* under biased beliefs on product value. The consumer surplus under experience utility is denoted by the triangular area BCE minus the triangular area EFG. The former area represents those consumers who would purchase j^* even with a correct belief in the value of the product, whereas the latter area represents the loss in welfare of consumers who would change their choice of consumption.

Information policy. We consider a specific information policy and evaluate the welfare change between the counterfactual (where this information policy is in effect) and the reality. This policy mandates the public announcement of information about all safety-related recalls in the U.S. We focus on information policy instead of other forms of policy (e.g., a policy forcing manufacturers to recall models in China when recalled in the U.S.) because these policies may also distort the incentive of firms on innovation and production. One may note that the recall system in the Taiwan region does follow these liability rules. As argued by Chen and Hua (2023), under a strict liability rule, the regulator would face a trade-off between the welfare loss resulting from distortion on production quantity and the welfare gain from consumer protection. We leave the analysis on these recall policies for future research.

Counterfactual estimates

$$\Delta CS = 0.46/22.29 = 2.1\%$$

Given our estimates on the random coefficient logit demand model and Equation 16, we find that on average, each consumer would benefit by 46 thousand CNY. Compared with the baseline consumer surplus of 223 thousand CNY per consumer, this welfare gain accounts for 2.1% of the consumer surplus. However, these estimates are conservative because firms may recall products after releasing public information to consumers, which would lead to a larger welfare gain for these consumers.

8 Conclusion

Despite extensive media coverage, cross-country product differences are supported by limited causal evidence. Understanding these differences is crucial because it is illegal in many countries and can harm consumer welfare due to adverse impacts, while the lack of empirical research forces regulators to monitor cases individually. To the best of our knowledge, our study is among the first to provide evidence on systematic differences in vehicle recalls between China and the U.S. By combining data from four sources, including recall records and model universe data from both countries, we compile a novel model-level dataset covering the years 2004 to 2020. Descriptive evidence shows that the recall rate in China, given a recall in the U.S. (referred to as the recall association rate), is low, particularly for joint venture (JV) models. Even when considering different recall components, the recall association rates remain consistently low. To address potential confounding factors, such as time-invariant unobserved product differences or product-invariant unobserved institutional differences, we employ a Difference-in-Differences (DID) design with two-way fixed effects. Our findings indicate that Chinese consumers are significantly less likely to receive recalls compared to their U.S. counterparts. Using text-analytic methods, we classify recalls into safety-related and non-safety-related categories. We find that manufacturers are more likely to recall models with safety-related defects compared to non-safety-related ones. Additionally, we observe heterogeneous results across brands from different countries of origin, with SOE joint venture models being less likely to be recalled in China. Our results also highlight the importance of information in reducing recall differences. Specifically, news coverage and information disclosure regulations are effective in narrowing these gaps, particularly for safety-related recalls.

In Section 6, we examine how Chinese consumers react to recalls of automobile products. Our findings mirror those from U.S. studies, showing that Chinese consumers generally remain indifferent to recalls. Following the literature, we further explore whether safety-related recalls issued by Chinese manufacturers elicit a consumer response, but find no significant reaction. We then focus on the impact of media coverage. Specifically, we assess whether news reports influence consumer behavior regarding safety-related recalls. Our analysis reveals that consumers respond negatively only when both a safety defect and media coverage are present. This underscores the importance of information dissemination and the potential harm posed by defects, aligning with our theoretical framework outlined in Section 3. We estimate a random coefficient logit demand model to evaluate the potential benefits of a news release policy. Our welfare analysis indicates that consumers suffer due to insufficient information. Results show that consumers react to safety-related recalls only when they are reported in the news. Enhancing the availability of information on safety defects would improve consumer welfare. Covering all severe recalls in the news could increase consumer welfare by 2.1%. Our estimates provide a conservative lower bound for the potential welfare gains, as firms might adjust their pricing or recall strategies in response to declining consumer demand, further enhancing consumer welfare. However, our study has limitations. We did not consider the long-term effects of information, such as the impact on brand reputation. Additionally, we did not account for regional variations in our demand data, which could offer valuable insights. Lastly, our measure of news coverage may be subject to measurement errors, as it does not capture all public media sources. Future research will address these areas to refine our understanding.

Overall, our empirical findings have important implications for understanding the choices of multinational firms in providing differential products or services and for the design of product safety policies.

First, we add to the causal evidence on service discrimination by multinational firms. Second, we demonstrate that information policies have a strong effect on product recalls and consumer welfare. The lessons from China may also inform similar policy issues in other developing countries aiming to protect consumer rights.

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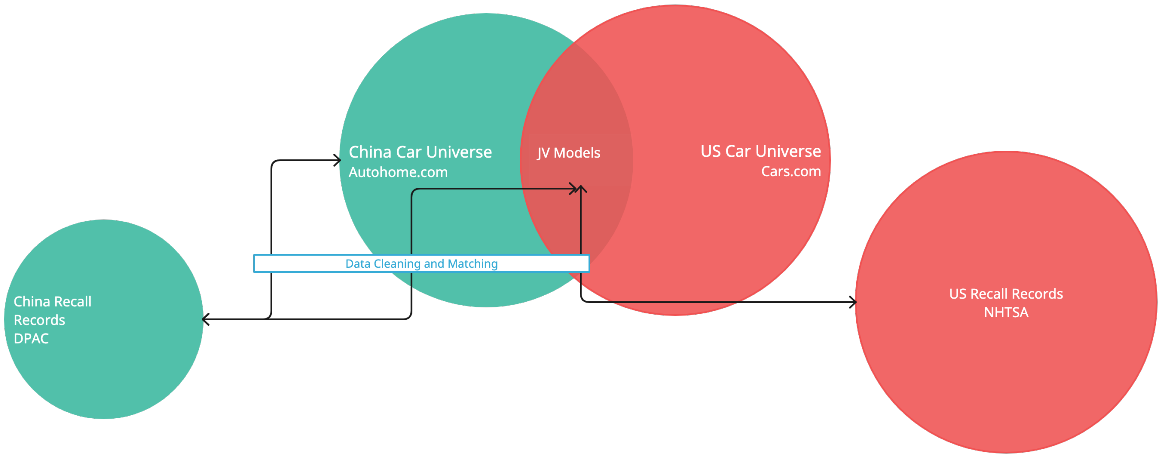
A Figures

Figure 1: Data sources



Notes: This figure shows the data sources to identify the cross-country recall differences. Green circles indicate Chinese data including recall announcements and the universe of car models in China. Red circles indicate the data in the U.S. including recall announcements and the universe of car models as well.

Figure 2: Sample recall texts in China

汽车制造商	丰田汽车		
品牌	丰田		
召回时间	2021-09-03 至 2022-09-02	召回数量	124

召回车型

车型	TOYOTASUPRA	年款	2021
型号	TOYOTASUPRA	涉及数量	124
生产起始时间	2021-03-01	生产终止时间	2021-06-21
vin码范围	起：JT2DB41A1MW043770 止：JT2DB41A1MW045793		

汽车缺陷信息

缺陷情况	本次召回范围内车辆由于发动机控制电脑的控制程序设计不当，在启动发动机后的瞬间，如进行了某种特定的操作（例如快速两次按下点火开关），可能会导致发动机曲轴反向旋转。受此影响，为制动助力装置提供负压的真空泵内的润滑油无法排出，被压缩后可能对真空泵内部零件造成损伤。在最坏的情况下，会导致助力作用下降，制动距离变长，增加车辆发生碰撞的风险，存在安全隐患。
可能后果	在启动发动机后的瞬间，如进行了某种特定的操作（例如快速两次按下点火开关），可能会导致发动机曲轴反向旋转。受此影响，为制动助力装置提供负压的真空泵内的润滑油无法排出，被压缩后可能对真空泵内部零件造成损伤。在最坏的情况下，会导致助力作用下降，制动距离变长，增加车辆发生碰撞的风险，存在安全隐患。
维修措施	免费对召回范围内车辆的发动机控制电脑程序进行升级，以消除安全隐患。
改进措施	正在生产的产品已经使用修正后的软件程序。
投诉情况	缺陷报告案例或投诉数量:0；保修或索赔案件: 0
车主通知	通知车主时间:2021-09-03至2021-09-03；通知车主方式:电话,短信,信函；服务热线（手机拨打）:400-606-2772；通知车主方式其他:
其他信息	用户也可登录中国汽车召回网（www.qiche365.org.cn）以及关注微信公众号汽车三包与召回（iautocloud365）了解更多信息。此外，也可拨打中国汽车召回网热线电话：010-65537365/010-64696365，反映召回活动实施过程中的问题或提交缺陷线索。
备注信息	应急处置方法：请不要在发动机启动后立即实施发动机熄火的操作。

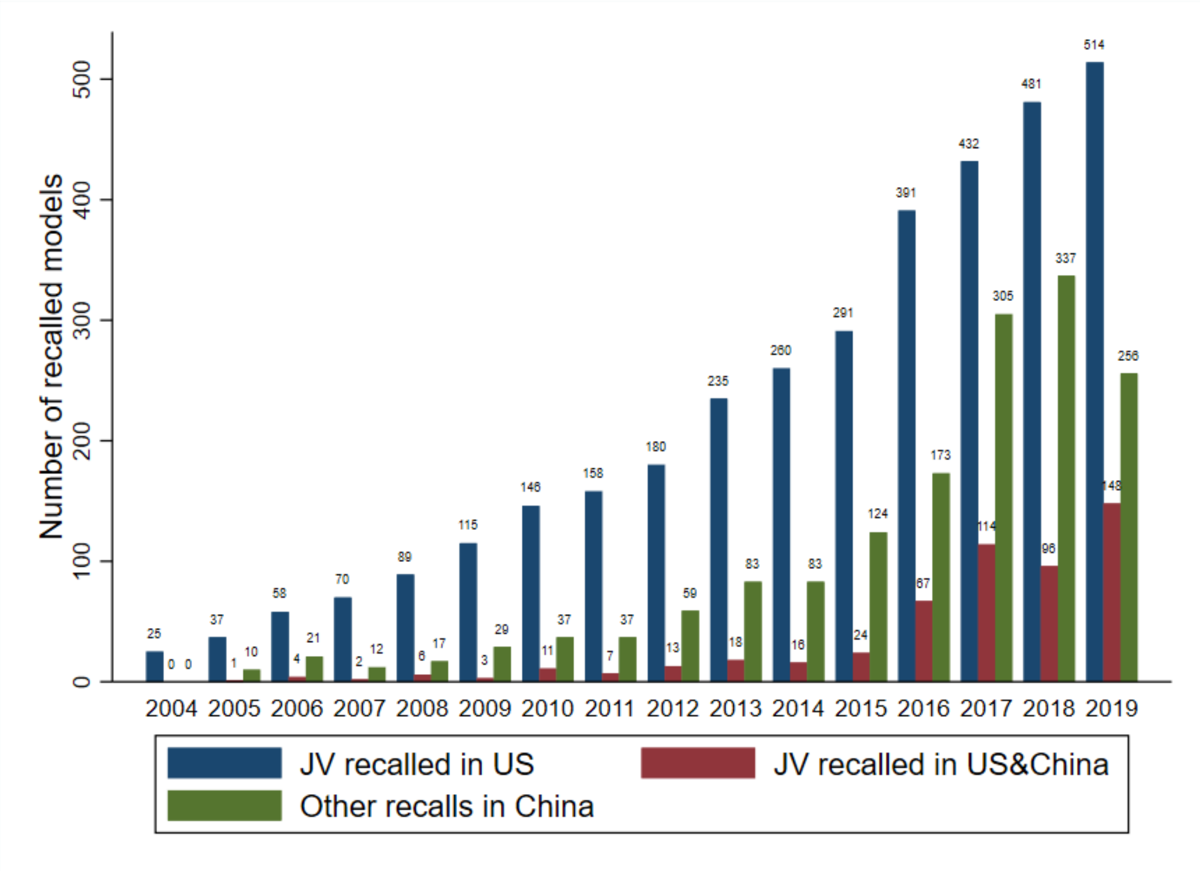
Automobile Manufacturer	TOYOTA Motor Corporation		
Brand	TOYOTA		
Time of Recall	03/09/2021-02/09/2022	**No. of Recalls**	124
Recalled model			
Series	TOYOTA SUPRA	**Model Year**	2021
Model info	TOYOTASUPRA	**No. involved**	124
Production Start Time	01/03/2021	**Production End Time**	21/06/2021
VIN Range	JT2DB41A1MW043770 - JT2DB41A1MW045793		
Auto Defect Information			
Defect Description	Due to the improper design of the control program of the engine control unit, the engine crankshaft may rotate in the opposite direction if a specific operation (such as pressing the ignition switch twice quickly) is performed at the moment after starting the engine.		
Consequences of Defect	As a result, the lubricant in the vacuum pump, which provides negative pressure to the brake booster, cannot be discharged, and may cause damage to the internal parts of the vacuum pump when it is compressed. In the worst case, it will lead to a decrease in the booster effect and a longer braking distance, increasing the risk of a vehicle collision, thus posing a safety risk.		
Repair Action	For the vehicles within the recall scope, the control program of the engine control unit will be upgraded free of charge to eliminate safety risks.		
Corrective Action	Products in production use the upgraded control program.		
Complaints	Defect report cases or complaints: 0; Warranty or claims: 0		
Owner Notification	Notification time: 03/09/2021 - 03/09/2021; Notification method: telephone, text message, letter; Service hotline (dial by mobile phone): 400-606-2772.		
Other Information	Users can log on to the China Auto Recall website (www.qiche365.org.cn) and follow the WeChat official account (iautocloud365) for more information. Users can also call the hotline of China Auto Recall website: 010-65537365/010-64696365 to report problems during the recall or submit defect clues.		
Remark	Emergency response: please do not turn off the engine immediately after it is started.		

Notes: This figure shows a sample text of recall announcement in China. Each announcement includes the information of recall models (brand, series, and model-year) and text fields describing the related defects, including the consequences of the defect, the repair or corrective actions.

Figure 3: Sample webpage of U.S. recall news coverage

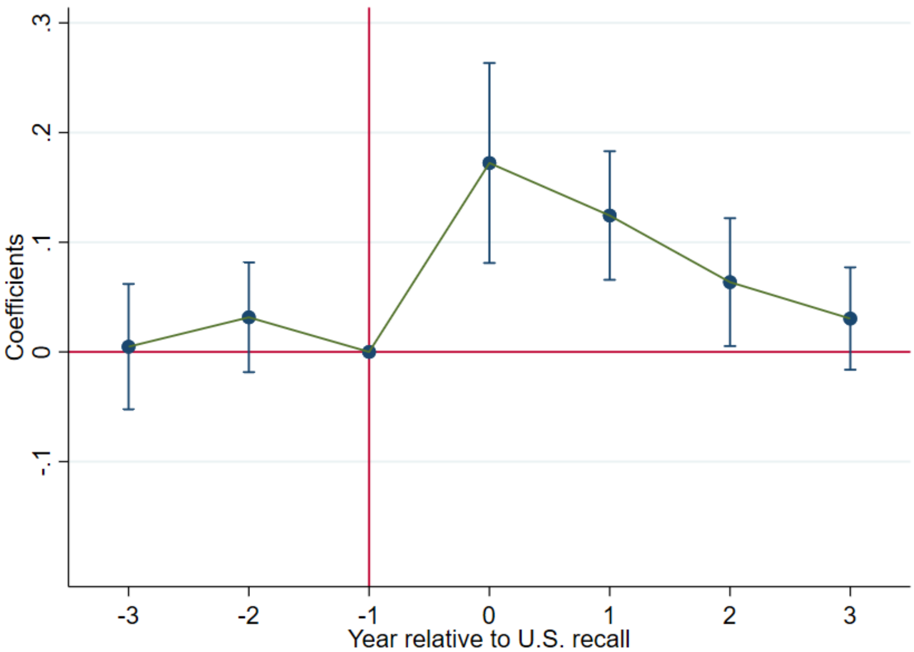
Notes: This figure shows a sample webpage of recall news in China. DPAC (Chinese regulator) would publish certain recall news in foreign countries on their website. We collect those recall news that is related to recalls in the U.S. We match the recall news to recall records in the U.S. by comparing the following information: model name, defect description, number of cars involved.

Figure 4: Numbers of models recalled in China and the U.S.



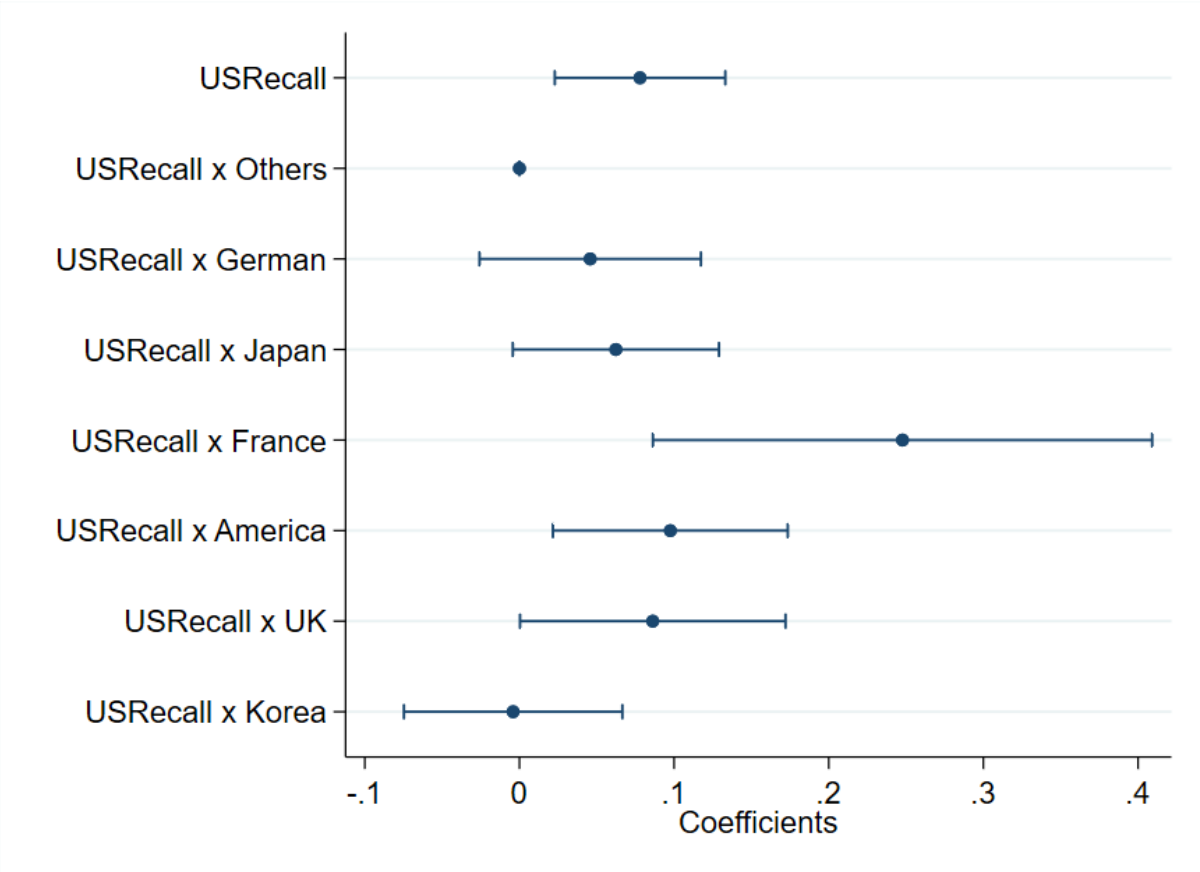
Notes: This figure shows the number of recalled models in the U.S. and China. The blue and red bar shows the number of recalled joint venture (JV) models in the U.S. and in both countries, respectively. The green one indicates the number of recalled local models in China. Comparing the red bar to the blue bar, this figures shows a insufficient number of recalls of JV models in China, and this figure shows the share of jointly recalled models to models recalled in the U.S. rises after the 2012 information disclosure regulation. There is a rising number in all three bars because of the introduction of new models.

Figure 5: Dynamic effects of recall in the U.S. on recall probability in China



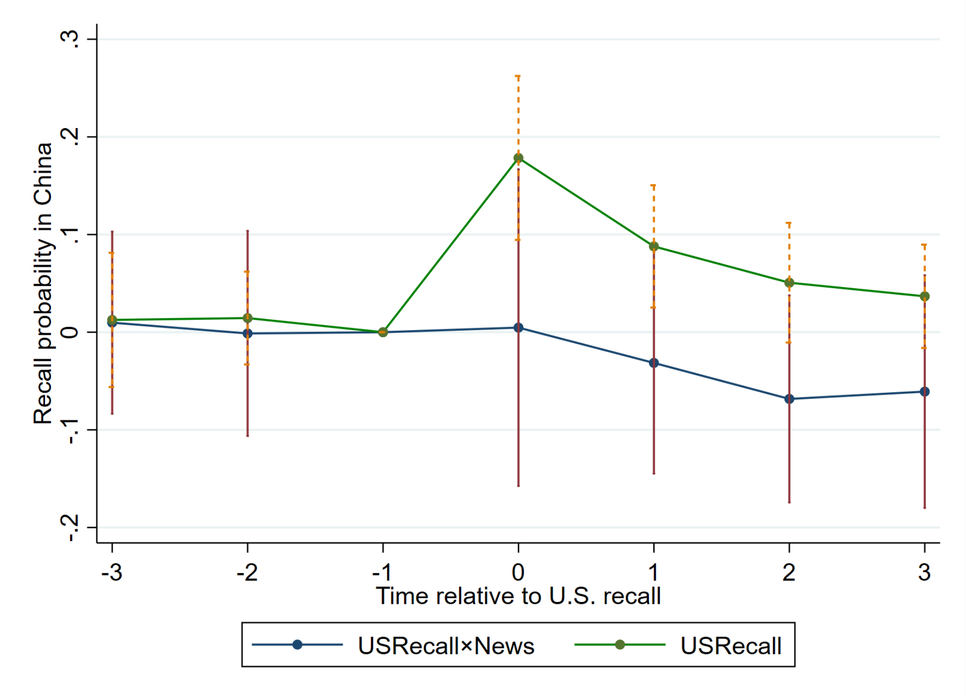
Notes: This figure plots coefficients β_k and 95 percent confidence intervals from the event study specification in Equation 5 with clustered standard errors at the model level. X axis shows periods when the year of recall in China is k years ahead or after to that in the U.S., for example, -2 means the recall in China is two years before that in the U.S. This figure indicates that our results are not driven by factors like expectations.

Figure 6: Heterogeneous effects of recall in the U.S. by country of origins



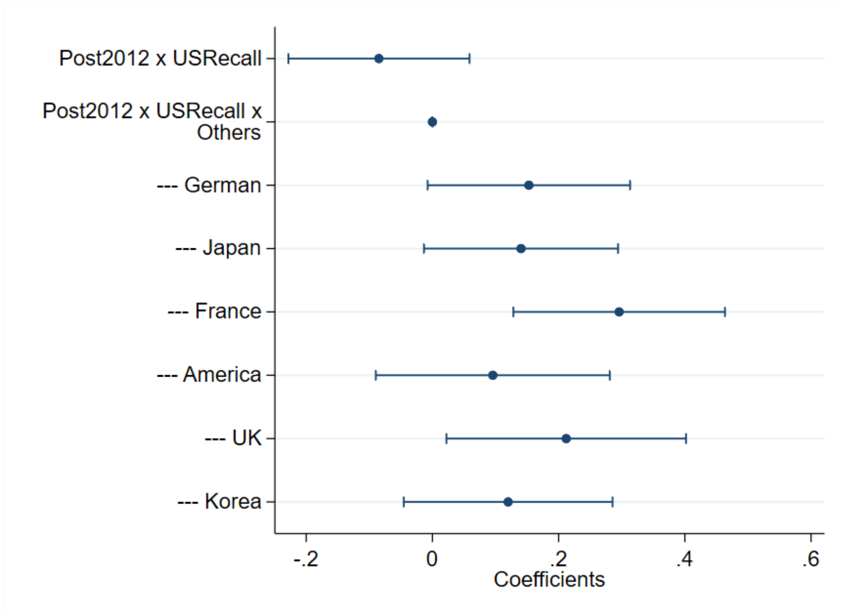
Notes: This figure plots coefficients of $USRecall_{it}$ and the interaction between $USRecall_{it}$ and dummies indicating the origin country to the brand of a model and 95 percent confidence intervals. Standard errors are clustered at the model level. This figure shows that France brands have the largest probability of issuing a recall in China given the model is recalled in the U.S. while Korea brands have a smallest probability of recalling models in China given a model recalled in the U.S. Brands from Germany, Japan, U.K. and the U.S. have similar estimates.

Figure 7: Dynamic Effects of Recall News



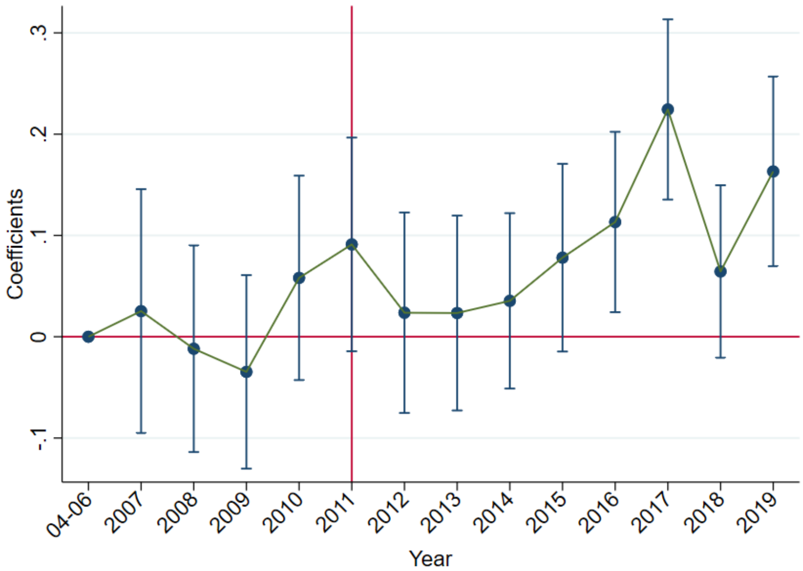
Notes: This figure plots the dynamic effects of recall news on the recall probability in China. Coefficients on $USRecall_{it} \times News_{it}$ are depicted. X axis shows periods when the year of recall in China is k years ahead or after to that in the U.S., for example, -2 means the recall in China is two years before that in the U.S. Standard errors are clustered at the model level. This figure validates there is no pre-trends in estimating the effects of recall news.

Figure 8: Heterogeneous effects of information regulation: by country of origin



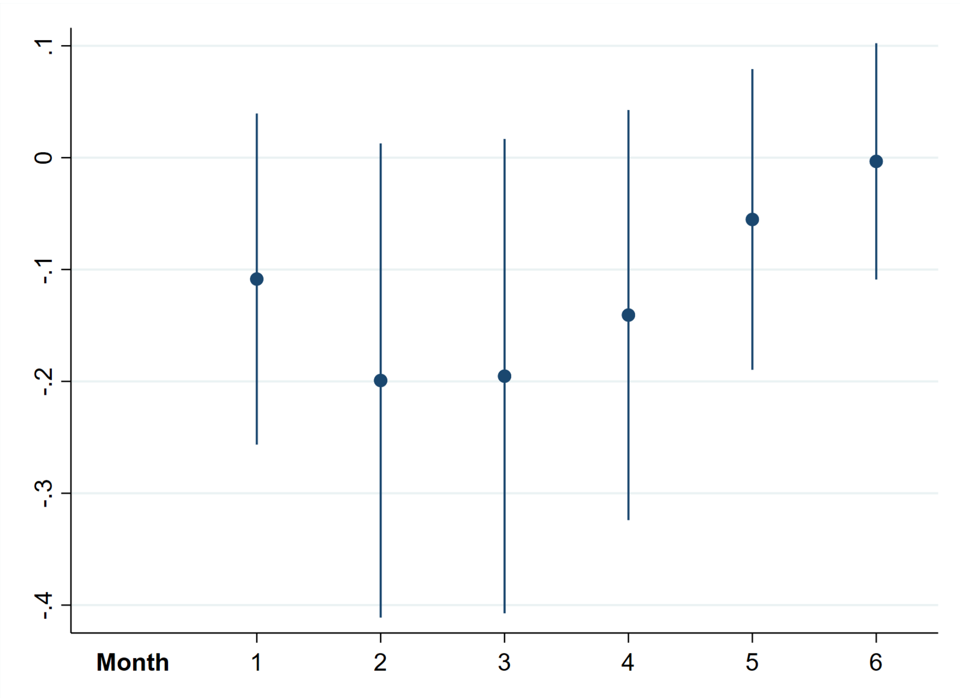
Notes: This figure plots coefficients of $USRecall_{it} \times Post2012_t$ and the interaction between $USRecall_{it} \times Post2012_t$ and dummies indicating the origin country to the brand of a model and 95 percent confidence intervals. Standard errors are clustered at the model level. This figure shows that the effect of information disclosure regulation is prominent for France brands while insignificant for Korea brands. The effect of information disclosure regulation on recall probability of other country-of-origin brands are similar.

Figure 9: Parallel trends and dynamic effects of the policy



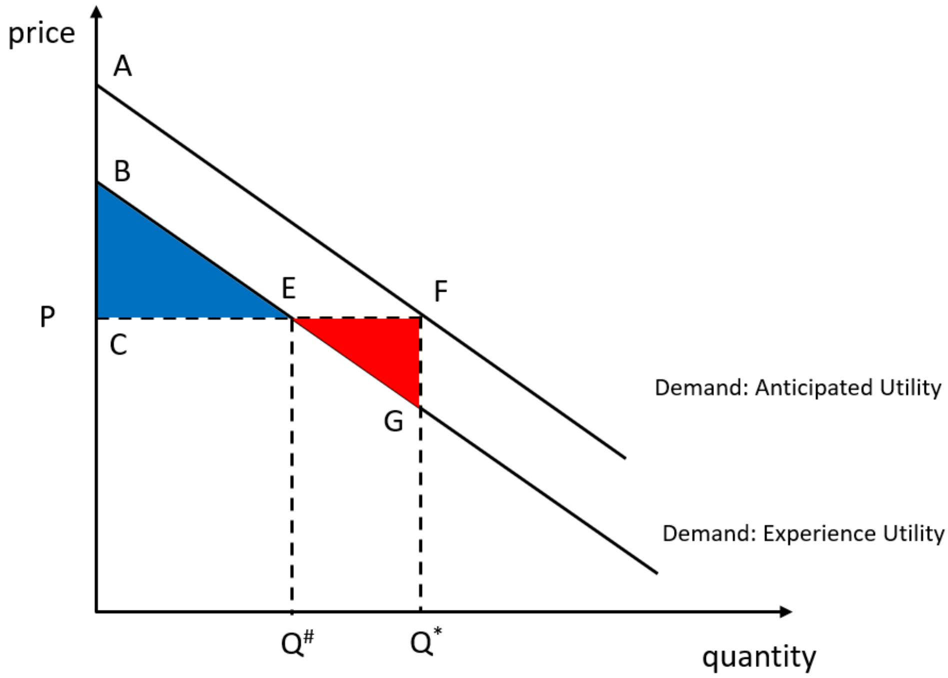
Notes: This figure plots coefficients and 95 percent confidence intervals from the event study specification. The coefficients are estimates from OLS regressions with clustered robust standard errors at the model level.

Figure 10: Dynamic effects of safety-related news



Notes: This table shows the dynamic effects of safety-related recall news on log market share.

Figure 11: Consumer surplus under imperfect knowledge about defect



Notes: The higher demand curve represents the anticipated benefits of purchasing the model with defects and the lower one represents the actual benefits. The number of people who purchase the model is Q* under their incorrect belief about the quality of the model. Consumer surplus under the actual utility is depicted as the triangle BCE minus the red triangle EFG. This combined surplus is less than consumers had anticipated receiving,by the area AFGB. The loss due to not knowing full information is measured by the area EFG.

B Tables

Table 1: Price gaps between the U.S. and China

Year	Model/Series	Listed Price in US (CNY)	China (CNY)
2008	Toyota Yaris S Sedan 2008	95K	126K
2008	Toyota Highlander 2008	176K	249K
2008	Kia Forte Ex 2008	110K	139K
2013	Volkswagen Tiguan	140-230K	200-320K
2013	CR-V	140-186K	194-270K
2013	Toyota Camry	136-169K	179-329K
2013	BMW X3	242-273K	523-725K
2013	Audi A6	258-348K	383-742K
2013	Audi Q7	287-371K	827-1339K

Notes: This table shows the listed prices in China versus that in the U.S. of a sample of popular models. Prices are in thousand (K) CNY. Data are gathered from industry news reports.

Table 2: Liability Rules: U.S. vs. China

	U.S.	China
Law	1966: The National Traffic and Motor Vehicle Safety Act (Title 49, Part C); 2000: TREAD ACT	2004: *Provision* 2012: *Regulation*
Regulator	NHTSA	Similar: DPRC
Purpose	Safety, Traffic accidents	Similar: Public Safety
Range	Cars selling in U.S.	Similar
Agent	Manufacturer, Distributor, and Importer	Similar
Service Period	No restriction	Weaker for 2004 version: 10 years for car, 3 years for tire, self-defined for wearing parts Similar after 2012 *Regulation*
Determination of Defects	Testing Authority: Violating Safety Standards Manufacturers/importer: Personal harm	Similar
Recall Procedures/ Obligations	Voluntary or Mandatory	Similar
Information System	Post 2000: Foreign recall history	Pre2012: No mandatory requirement for firms Post 2012: Similar
Media+Info Disclosure	Should publish to public media	Similar
Information Keeping	Within 5 days (TREAD ACT) reporting foreign recall history;	Slightly Weaker. 2004: No time constraint, no content specification 2012: No time constraint, Content requirement
Information provider	Safe harbor to encourage reporting and for whistle blowers	Slightly Weaker: Any human or organization
Penalty	Civil Penalty:5000 for small violation, 15 million at max Criminal Penalty: misleading information or failing to report (15 years in prison)	Weaker. Pre 2012: 5000 USD at max Post 2012: Civil Penalty of 1%-10% of revenue of defective products) *or* Prohibit selling in China
Acceleration of manufacturer remedy program	Yes	No

Notes: This table shows the comparison of liability rules in China versus the U.S. The *De Jure* regulation in China is similar to that in U.S.

Table 3: Summary statistics of the main variables

Panel A: Numbers of Brand, Series, Models in China: 2004-2020		
	Obs	Unique
Brand	44938	155
Series	44938	1839
Models	44938	6033

Panel B: Descriptive statistics for the main variables								
	obs	mean	sd	min	25%	median	75%	max
CNRecall	44938	0.055	0.229	0	0	0	0	1
HasBeenRcdUS	44938	0.067	0.250	0	0	0	0	1
USRecall	44938	0.066	0.248	0	0	0	0	1
Regulation2012×USRecall	44938	0.059	0.236	0	0	0	0	1

Notes: This table reports the descriptive statistics for the variables used in the baseline regressions. It includes the universe of car models in China and the U.S. and their recall recordsduring 2004 to 2020. Observations are at the model-year level.

Table 4: Joint recalls by components

Safety-Related Components in U.S. Recalls	*Joint Recall*	*Joint Recall, Same comp*	*Less Safety Related Components in U.S. Recalls*	*Joint Recall*	*Joint Recall, Same comp*
AIR BAGS	39%	30%	BACK_OVER_PREVENTION	18%	0%
ELECTRICAL SYSTEM	41%	7%	CHILD_SEAT	52%	35%
ENGINE	38%	24%	COMMUNICATION	0%	0%
ENGINE AND ENGINE COOLING	40%	11%	ELECTRONIC_STABILITY_CONTROL	38%	10%
EXTERIOR LIGHTING	32%	4%	FORWARD_COLLISION_AVOIDANCE	50%	0%
SEAT BELTS	35%	10%	FUEL_SYSTEM	26%	8%
SERVICE BRAKES	39%	16%	HYBRID_PROPULSION_SYSTEM	55%	27%
STRUCTURE	32%	5%	INTERIOR_LIGHTING	50%	0%
VEHICLE SPEED CONTROL	32%	0%	LANE_DEPARTURE	0%	0%
			LATCHES/LOCKS/LINKAGES	37%	5%
			OTHER	25%	9%
			PARKING_BRAKE	52%	30%
			POWER_TRAIN	38%	11%
			SEATS	30%	9%
			STEERING	30%	9%
			SUSPENSION	34%	9%
			TIRES	22%	4%
			TRACTION_CONTROL_SYSTEM	0%	0%
			TRAILER_HITCHES	23%	0%
			VISIBILITY/WIPER	42%	9%
			WHEELS	39%	13%

Notes: This table shows the recall rate in China given the model is recalled in U.S. (Joint Recall). “Joint Recall, Same comp” means the defect in recalls in both countries are also of same component.

Table 5: Effect of U.S. recall on China recall

	(1)	(2)
USRecall	0.135***	0.124***
	(0.011)	(0.012)
Constant	0.016***	0.047***
	(0.0047)	(0.001)
N	44938	44938
R^2	0.256	0.355
Model-specific Year Trends	No	Yes
Year Fixed Effects	Yes	Yes
Model Fixed Effects	Yes	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered by model shown in parentheses.

Table 6: Heterogeneous effect on differential treatment: Domestic vs imports

	(1)	(2)
USRecall	0.151***	0.146***
	(0.013)	(0.016)
USRecall $\times$ SOE	-0.038*	-0.056**
	(0.020)	(0.024)
Constant	0.047***	0.048***
	(0.001)	(0.001)
N	44938	44938
R^2	0.256	0.355
Model-specific Year Trends	No	Yes
Year Fixed Effects	Yes	Yes
Model Fixed Effects	Yes	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered by model shown in parenthesis.

Table 10: Summary statistics of sales data

	count	mean	sd	min	max
Monthly sales	99273	845.129	3223.519	0.000	73547.000
Market share	21030	0.000	0.002	0.000	0.029
USRecall (3m)	21030	0.044	0.206	0.000	1.000
USRecall (4m)	21030	0.051	0.220	0.000	1.000
USRecall (5m)	21030	0.056	0.230	0.000	1.000
News (3m)	21030	0.007	0.083	0.000	1.000
News (4m)	21030	0.008	0.087	0.000	1.000
News (5m)	21030	0.008	0.088	0.000	1.000
Safety-related (3m)	21030	0.033	0.178	0.000	1.000
Safety-related (4m)	21030	0.038	0.192	0.000	1.000
Safety-related (5m)	21030	0.043	0.204	0.000	1.000
Price (10K CNY)	39224	14.490	10.785	2.347	93.122
Length (mm)	39272	4481.359	391.417	2488.000	5299.222
Width (mm)	39272	1781.809	98.623	1405.000	2069.000
Height (mm)	39272	1625.576	150.265	1253.000	2108.762

Notes: This table plots the summary statistics of variables in the sales data. Data are on month by series level. The "3m" denotes for the time window for the variable is 3 months.

Table 7: Heterogeneous effect on differential treatment to consumers: Safety-related vs non-safety-related defects

	Safety-related		Non-safety-related	
	(1)	(2)	(3)	(4)
USRecall	0.112***	0.104***	0.022***	0.019***
	(0.010)	(0.011)	(0.005)	(0.006)
Constant	0.008*	0.036***	0.008*	0.011***
	(0.004)	(0.001)	(0.001)	(0.000)
N	44938	44938	44938	44938
R^2	0.225	0.319	0.185	0.302
Model-specific Year Trends	No	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Model Fixed Effects	Yes	Yes	Yes	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered by model shown in parentheses.

Table 8: Effect of news on recall probability

	(1)	(2)
USRecall	0.089***	0.078***
	(0.016)	(0.022)
USRecall $\times$ News	0.045*	0.050
	(0.011)	(0.031)
Constant	0.0345***	0.035***
	(0.001)	(0.001)
N	18714	18714
R^2	0.253	0.428
Model-specific Year Trends	No	Yes
Year Fixed Effects	Yes	Yes
Model Fixed Effects	Yes	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered by model shown in parentheses.

Table 9: Effect of information regulation on recall probability

	(1)
Post2012 × USRecall	0.0576***
	(0.0185)
USRecall	0.0911***
	(0.0154)
Constant	0.0208***
	(0.00429)
N	44938
R-square	0.256
Year Fixed Effects	Yes
Model Fixed Effects	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered by model shown in parentheses.

Table 11: Consumer response to general recalls

	log(sales)	log(sales)
	(1)	(2)
CNRecall	-0.032	-0.097
	(0.044)	(0.077)
Safety-related		0.077
		(0.071)
Constant	2.245***	1.866***
	(0.042)	(0.000)
N	98560	98560
R-square	0.880	0.879
Year Fixed Effects	Yes	Yes
Series Fixed Effects	Yes	Yes

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered at the model are shown in parentheses.

Table 12: Logit demand estimates

Time window	First stage	3 Months	4 Months	5 Months
	(1)	(2)	(3)	(4)
USRecall		0.034	0.012	0.020
		(0.039)	(0.055)	(0.061)
USRecall × News		0.033	0.044	0.034
		(0.058)	(0.059)	(0.058)
USRecall × News × Safety-related		-0.106*	-0.125*	-0.123*
		(0.055)	(0.068)	(0.074)
Price		0.088***	0.088***	0.088***
		(0.030)	(0.030)	(0.030)
Height	-0.013**	-0.003***	-0.003***	-0.003***
	(0.005)	(0.001)	(0.001)	(0.001)
Length	-0.002	0.001	0.001	0.001
	(0.002)	(0.000)	(0.000)	(0.000)
Width	0.057***	0.012***	0.012***	0.012***
	(0.006)	(0.003)	(0.003)	(0.003)
BLP instruments:				
- Price	0.935***			
	(0.101)			
- Height	0.013**			
	(0.005)			
- Length	0.002			
	(0.002)			
- Width	-0.054***			
	(0.009)			
Constant	-6.240	1.527***	1.529***	1.529***
	(9.898)	(0.002)	(0.003)	(0.004)
Year Fixed Effects		Yes	Yes	Yes
Series Fixed Effects		Yes	Yes	Yes
N	891	21030	21030	21030

Notes: This table shows the standard logit demand model estimates. Column 1 shows the estimates of the first stage IV regression. Columns 2 to 4 show the estimates on independent variables on time t+3, t+4, and t+5, respectively.
* p< 0.1, ** p< 0.05, *** p< 0.01.
Robust SEs clustered at the model are shown in parentheses.

Table 13: Random coefficient logit estimates

	Mean
	(1)
Constant	88.221***
	(0.389)
α_0	-1.043***
	(0.052)
σ	2.000***
	(0.048)
β	
–Length	-21.488***
	(0.103)
–Width	15.662***
	(0.408)
–Height	-10.254***
	(0.176)
–USRecall	9.040***
	(0.164)
–USRecall $\times$ News	0
	(0.000)
γ	
–USRecall $\times$News $\times$ SafetyRelatedUS	-12.423***
	(0.219)

Notes: This table shows the random coefficient logit demand model estimates on α_0, σ, and βs in Equation 10
* p< 0.1, ** p< 0.05, *** p< 0.01.
SEs clustered at models are shown in parentheses.