The Cost of Regulatory Fragmentation: Evidence from Product Quality Failures*

This Version: September 25, 2025

Md Imran Hossain
mdimran.hossain@business.uq.edu.au
UQ Business School
The University of Queensland, Australia

Dewan Rahman
d.rahman@business.uq.edu.au
UQ Business School
The University of Queensland, Australia

Suman Neupane
s.neupane@business.uq.edu.au
UQ Business School
The University of Queensland, Australia

Abstract

This paper examines whether and how regulatory fragmentation leads to product quality failures, measured by product recalls. Exploiting a hand-collected comprehensive dataset of recalls by the U.S. public firms from 1996 to 2023 and a text-based firm-specific measure of regulatory fragmentation, we provide novel empirical evidence that firms facing fragmented regulations are more likely to experience product quality failures. Specifically, our results show that a one-standard deviation increase in regulatory fragmentation is associated with approximately 516 additional recalls. Our findings are robust to endogeneity concerns, supported by a quasi-natural exogenous shock-based difference-in-difference design, as well as several robustness checks and alternative explanations. Further analyses show that the adverse effects of regulatory fragmentation are stronger for firms with broader scope, greater product market competition, and higher policy uncertainty. Finally, we document that fragmented regulations contribute to product quality failures by weakening quality culture, reducing R&D investment, and lowering patent quality.

JEL Classifications: E22, G18, G28, G31, G38, L15

Keywords: Regulation, Fragmentation, Product Quality, Quality Failure, Recall

* We thank Denis Sosyura, Nadya Malenko, Itzhak Ben-David, Ekaterina Volkova, James Brugler, Seil Kim, Huu Nhan Duong, Kaitlin D. Wowak, Mostafa Monzur Hasan, Eric Tan, Kelvin Tan, Jacquelyn Humphrey, Xin Yu, Muhammad Al Mamun, Lin Mi, Khoa Hoang, Zoe Zhao (discussant), Hussain Ahmed Enamul Huda (discussant), Md Nazmul Hasan Bhuyan (discussant), the participants of FIRN Corporate Finance Meeting 2025, UQ Finance PhD Workshop 2025, UQ BEL PhD Research Colloquium 2024, and the seminar participants at University of Dhaka, Bangladesh Institute of Capital Market (BICM) for their insightful comments and suggestions.

1. Introduction

A product quality failure arises from flaws in design, manufacturing, or packaging that result in a product failing to meet regulatory safety standards, potentially causing consumer injury, sickness or death. US federal regulations mandate that firms initiate a 'product recall' for severe product quality failures, requiring the retrieval of the defective products from the market for repair, replacement or refund.[1] In 2022, US firms recalled a record-high 1.5 billion product units, more than double the amount in 2015 (Sedgwick, 2025). Product quality failures are a severe concern for firm management and shareholders due to their adverse effects on firm value, reputation, sales, brand equity, product liability lawsuits and regulatory sanctions (Kini et al., 2017; Lee et al., 2015; Dawar and Pilluda, 2000; and Jarrell and Peltzman, 1985). Furthermore, anecdotal evidence suggests that product quality failures may result in firms losing billions of dollars (e.g., Merck's stock price dropped by 40% resulting in a $50 billion loss due to Vioxx drug quality failure in 2004 (Berenson et al., 2004)), bankruptcy (e.g., Topps Meat filed for bankruptcy after 21.7 million pounds of hamburger beef quality failure in 2007 (Belson and Fahim, 2007)), or CEO career damage (e.g., Volkswagen CEO resigned over car emission scandal in 2015 (Ruddick, 2015)). Hence, it is important for firms to identify potential determinants of product quality failures to avoid such adverse consequences.

Although research on product quality failures has traditionally been dominated by the business and management scholars, it has recently garnered increasing attention in finance. For instance, Kini et al. (2017) show that financial leverage is a significant determinant of product quality failures. Similarly, Li et al. (2024) and Thirumalai and Sinha (2011) respectively show that financial analysts and R&D investments are additional determinants of product quality failures. In this study, we propose a novel determinant of product quality failures – regulatory fragmentation, defined as the oversight of a single issue of a firm by multiple regulatory agencies. The main aim of this study is to examine whether and how regulatory fragmentation affects product quality failures among US firms.

Regulatory fragmentation has become a foremost concern for the businesses, regulators and policy makers across the globe. The estimated global costs of regulatory fragmentation are about 5%-10% of the annual turnover of financial institutions, totalling approximately $780 billion per year (IFAC, 2018). This issue appears to be particularly pressing for the US economy

[1] Since 'product recall' is an objective and consistent measure of product quality failures across years and industries (Kini et al., 2017, 2022), we use 'product quality failure' and 'product recall' interchangeably throughout this paper.

where the complex and fragmented regulatory framework results in multiple federal agencies having jurisdictions over the same institutions for the same or related issues (GAO, 2016). The US policymakers have increasingly recognized the importance of reducing regulatory fragmentation, as it leads to inefficiencies and inconsistencies in regulatory processes, creates substantial challenges for businesses, and may inhibit economic activities across the US economy (GAO, 2016; Business Roundtable, 2019).[2]

Our paper draws motivation from the GAO (2014) report, which documents that consumer product safety regulation is fragmented across eight federal agencies, each responsible for consumer product safety including making rules, setting standards, assessing risks, enforcements and product recalls.[3] This fragmentation results in regulatory overlaps or unclear jurisdictions for certain products, with multiple agencies sometimes overseeing different components of a product or performing separate regulatory actions on the same product, creating a complex and potentially inefficient regulatory landscape.[4] Furthermore, Business Roundtable (2019) expresses concern that fragmented regulation regarding food safety imposes higher costs to food manufacturers due to repetitive inspections and data collection efforts, and inconsistent standards. Our study aims to examine whether these anecdotal claims of GAO (2014) and Business Roundtable (2019) are supported by empirical evidence showing the impacts of regulatory fragmentation on product quality failures.

Given the complexity and fragmentation of the U.S. regulatory system, there is a dearth of systematic research examining how regulatory fragmentation affects corporate policies and outcomes. Surprisingly, existing studies on regulatory fragmentation have predominantly focused on financial institutions.[5] Recently, this literature has been advanced by Kalmenovitz,

[2] In 2010, the US Congress tasked the US Government Accountability Office (GAO) to identify fragmentations, overlap and duplications across various federal agencies and to provide recommendations to mitigate these issues. As of December 2023, GAO has released 13 yearly reports on these issues and many of its recommendations have been addressed by Congress and federal agencies that led to approximately $600 billion in financial benefits to the US government. GAO estimates that addressing the remaining recommendations could lead to over $100 billion in future savings and greater efficiency in federal activities (GAO, 2023).

[3] These eight federal agencies are- Consumer Product Safety Commission (CPSC), Food and Drug Administration (FDA), National Highway Traffic Safety Administration (NHTSA), Environmental Protection Agency (EPA), Pipeline and Hazardous Materials Safety Administration, Department of Housing and Urban Development, Nuclear Regulatory Commission, and U.S. Coast Guard (within the Department of Homeland Security). Furthermore, there are at least twelve other agencies that are indirectly involved in the activities related to consumer product safety (GAO, 2014).

[4] Jurisdictions also vary depending on the product's usage. For instance, the jurisdiction of FDA overlaps with that of CPSC in case of toy laser products, because FDA oversees laser safety regulations whereas CPSC oversees the safety standards of children's products including toys. In another case, NHTSA (CPSC) oversees the hand-held infant carriers while used inside of cars (outside of cars) (GAO, 2014).

[5] See Kim and Kim (2023), Bischof et al. (2022), Charoenwong et al. (2019), Agarwal et al. (2014), among others.

Lowry and Volkova (2025) who develop a novel and comprehensive firm-specific measure of regulatory fragmentation for all listed U.S. financial and nonfinancial firms. This measure applies machine learning methods to data from the Federal Register (FR), the U.S. government's official daily publication. The FR reports comprehensive activities of federal agencies, including final rules, drafts of proposed rules, enforcements etc. Kalmenovitz et al. (2025) provide the first systematic evidence showing that regulatory fragmentation increases firms' costs while reducing their productivity, growth and profitability. In our study, we build on their novel measure to investigate whether and how regulatory fragmentation contributes to product quality failures in the U.S.

How regulatory fragmentation may affect product quality failures is unclear ex ante and therefore, remains an empirical question. On the one hand, as per the *public interest theory* of regulation, which advocates regulation as a welfare increasing mechanism (Pigou, 1938; and Joskow and Rose, 1989), the presence of multiple federal regulatory agencies should not hinder oversight and effectiveness, as they share the goal of maximizing stakeholders' welfare. Their combined expertise could facilitate more comprehensive oversight, addressing concerns like product safety (GAO, 2014), and potentially reducing product quality failures. Furthermore, regulatory competition and a "race-to-the-bottom" among multiple regulators may allow firms to seek out less restrictive regulators (Kim and Kim, 2024), reducing compliance costs and freeing resources for quality investments, which could ultimately lower product quality failures.

On the other hand, from the perspective of the *private interest theory* of regulation that postulates regulation as a rent-seeking process (Krueger, 1974; Posner, 1974; Becker, 1983; Benmelech and Moskowitz, 2010), different federal agencies may oversee a similar topic to capture internal promotions (Kalmenovitz et al., 2025), or to build empires and attract more budgets and resources from the government (Niskanen, 1971). Fragmented regulations impose higher compliance costs on manufacturers (Kalmenovitz et al., 2025) due to regulatory inefficiencies, duplicative inspections and data collection efforts (GAO, 2014 and Business Roundtable, 2019). When facing performance or cost pressures, firms often compromise their quality culture by curtailing innovation and favoring cost-cutting strategies that undermine product quality (Li et al., 2021b; 2021c). Regulatory fragmentation induced-cost pressures may similarly weaken firms' quality culture and increase the likelihood of quality failures. In addition, firms may offset higher compliance costs by sourcing cheaper inputs from developing countries, which often entails lower input quality and greater product quality failures (Steven et al., 2014; Steven and Britto, 2016). Finally, regulatory fragmentation creates uncertainty through inconsistent and unpredictable oversights (Kalmenovitz et al., 2025), which may discourage innovation (Bhattacharya et al., 2017) and potentially increase product quality failures (Kini et al., 2017).

To empirically test these two competing hypotheses on regulatory fragmentation and product quality failures, we manually collect product recall data of all US firms from the websites of three federal agencies (*i.e.*, NHTSA, FDA and CPSC) covering the period from 1996 to 2023. We also collect regulatory fragmentation data from Kalmenovitz et al. (2025), and company fundamentals from Compustat. Our final sample consists of 56,348 firm-year observations from 7,619 unique firms. The baseline results from probit regression models reveal a significant and positive association between regulatory fragmentation and recall propensity. This relationship is also economically meaningful: a one standard deviation increase in regulatory fragmentation increases a firm's recall propensity by approximately 0.92%, which corresponds to 15.4% of the unconditional probability of undertaking a product recall event, resulting in about 516 additional recalls. An alternative, though simplistic, interpretation shows that a 1% increase in regulatory fragmentation results in about 172 additional recalls.

The interpretation of the estimates regarding the effects of regulatory fragmentation on product recalls may be challenging due to potential endogeneity concerns, such as omitted variable bias, latent factors correlated with both regulatory fragmentation and product quality failures, or reverse causality. To mitigate these endogeneity concerns and establish causality, we exploit Donald Trump's surprise 2016 election win as an exogenous shock to regulatory fragmentation, following an emerging body of literature (Wagner et al., 2018; Child et al., 2021; Dagostino et al, 2023; Kundu, 2024; and Armstrong et al., 2025). Trump's election campaign emphasized deregulation, and after taking office he signed Executive Orders 13771 and 13781 to reduce regulatory burdens, duplication and redundancy of federal agencies. These policies led to at least 18 federal agencies coordinating to streamline oversight (Business Roundtable, 2019), contributing to a sharp decline in regulatory fragmentation between 2017 and 2020. This setting provides a unique opportunity to examine whether reduced regulatory fragmentation lowers product quality failures.

We implement a difference-in-difference (DiD) design with a six-year event window (2014-2019). Firms more exposed to overlapping regulations pre-election (treatment group) are expected to be disproportionately affected by Trump's deregulatory policies post-election relative to less-exposed firms (control group). Using a propensity score matched sample of treatment and control firms, our DiD estimates show that reduced fragmentation is associated with significantly fewer product quality failures. These results reinforce our baseline evidence that greater regulatory fragmentation increases the likelihood of product quality failures. We also conduct the parallel trend analysis and falsification tests that validate our DiD results.

To shed light on the mechanisms, we examine whether regulatory fragmentation affects product quality failures through quality culture, innovation, and input sourcing. We find strong evidence that regulatory fragmentation weakens firms' quality culture—consistent with cost pressures that shift priorities away from safety and toward cost-cutting—and dampens innovation by reducing R&D investment and patent quality. In contrast, while theory suggests that cost pressures may encourage firms to substitute toward lower-quality inputs from developing countries, we find little empirical support for this channel. Overall, our results indicate that regulatory fragmentation primarily undermines product quality through internal organizational mechanisms (quality culture and innovation), rather than through external supply-chain sourcing.

Our baseline results remain robust to alternative measures of regulatory fragmentation and product quality failures. We also confirm that our recall measure captures true product quality failures rather than regulatory effectiveness (i.e., more recalls reflect stringent oversights by multiple regulators): greater regulatory fragmentation increases customer complaints, most severe recalls, and firm-initiated voluntary recalls, collectively reinforcing that recalls reflect deteriorating product quality. Our main results are also not explained by alternative factors such as firm structure, financial flexibility, external monitoring, political activity, supply chain complexity, or executive incentives. Finally, our cross-sectional tests further show that the adverse effects of regulatory fragmentation on product quality failures are stronger among firms in highly competitive markets, with broader scope, or facing greater policy uncertainty.

This study makes significant contributions to two strands of literature. First, it contributes to the literature on product quality failures. While prior research identifies several important determinants of product quality failures, such as financial leverage (Kini et al., 2017; Phillips and Sertsios, 2013), labor unionization (Kini et al., 2022), financial analysts (Li et al., 2024), lobbying (Singh and Grewal, 2023), R&D (Thirumalai and Sinha, 2011), stock repurchases (Bendig et al., 2018), and top management characteristics (Wowak et al., 2015), little is known about the impact of regulatory burdens on product quality failures. We fill this void in literature by showing novel empirical evidence that regulatory fragmentation is a determinant of product quality failures, which is consistent with the anecdotal claims made in GAO (2014) and Business Roundtable (2019) reports.

Second, this study advances the nascent body of literature on regulatory fragmentation. While prior studies on regulatory fragmentation are clustered around the financial institutions, exploring issues such as opportunistic insider trading (Kim and Kim, 2024), increased risk disclosures and reporting transparency (Bischof et al., 2022; and Costello et al., 2019), and stricter bank supervisions (Granja and Leuz, 2024), little work has examined the broader implications of regulatory fragmentation. Recently, Kalmenovitz et al. (2025), using a novel firm-specific measure of regulatory fragmentation for all US financial and non-financial firms, show that regulatory fragmentation leads to higher costs and lower productivity, growth and profitability. We advance this literature by demonstrating that regulatory fragmentation also undermines non-financial outcomes, specifically by increasing firms' product quality failures.

The remainder of this study is structured as follows. Section 2 develops the hypotheses, and Section 3 describes the data and sample construction. Section 4 presents the empirical analyses and results. Finally, Section 5 concludes the paper along with several key policy implications.

2. Hypothesis Development

Ex ante, the relationship between regulatory fragmentation and product quality failures is theoretically ambiguous. Two fundamental theories of regulation – the *public interest theory* and the *private interest theory* – can help explain this relationship.

On the one hand, the *public interest theory* of regulation considers regulation as a welfare increasing mechanism (Joskow and Rose 1989; and Pigou, 1938). In line with this theory, the presence of more than one federal regulator should increase the efficacy of their oversight, as they share similar objectives *i.e.*, to maximize the welfare of all stakeholders of the regulated firms. The engagement of multiple federal agencies endowed with diversified expertise and resources could facilitate more wide-ranging and coordinated oversight. Their coordinated oversight can address a variety of regulatory concerns, including product safety (GAO, 2014), which may reduce product quality failures.

Furthermore, regulatory competition and a race-to-the-bottom among the regulators could enable firms to shop around the least restrictive regulators (Kim and Kim, 2024). This behaviour could result in potential savings of regulatory compliance costs. Firms could allocate these cost savings to investments in product quality, which may ultimately result in lower product quality failures. Therefore, we hypothesize that

H_{1a}: Regulatory fragmentation is *negatively* associated with product quality failures.

On the other hand, the *private interest theory* of regulation suggests that regulation is a rent-seeking process (Krueger, 1974; Posner, 1974; Becker, 1983; Benmelech and Moskowitz, 2010). In line with this theory, several federal agencies may oversee a single topic, sometimes even going beyond their core expertise areas, for their own benefits such as capturing internal promotions (Kalmenovitz et al., 2025) or building empires to attract more budgets and resources from the government (Niskanen, 1971). Firms facing fragmented regulations experience higher operating costs (Kalmenovitz et al., 2025) due to regulatory inefficiencies, duplicative inspections and data collection efforts by multiple regulators (GAO, 2014 and Business Roundtable, 2019). To meet these higher regulatory compliance costs, firms may need to divert resources (e.g., labor and capital) from discretionary investments (Kalmenovitz, 2023), including investments in product quality.

Firms facing cost pressures or short-term performance pressures often compromise their corporate quality culture. For instance, pressures from financial analysts weaken firms' commitment to quality (Li et al., 2021c), while the 2014 GM massive recall was attributed to a cost-focused culture that neglected safety in response to heightened cost constraints (Fielkow, 2014). Furthermore, firms with weak quality culture respond to challenging environments by curtailing innovation and favouring cost-cutting strategies (Li et al., 2021b), thereby exacerbating quality failures. Therefore, we argue that regulatory fragmentation induced-cost pressures may similarly weaken firms' quality culture, thereby impair product quality and increase the likelihood of product quality failures.

Furthermore, in response to these regulatory fragmentation-induced cost pressures, firms may trade-off the quality of input materials by shifting the sourcing of inputs from developed to developing countries to obtain cheaper materials, which may lower input quality and increase the likelihood of product quality failures (Steven and Britto, 2016; Steven et al., 2014).

Finally, firms facing regulatory fragmentation experience greater uncertainties arising from inconsistent regulations and the difficulty of predicting future regulatory decisions from multiple agencies (Kalmenovitz et al., 2025). Firms operating in uncertainties reduce innovative activities (Bhattacharya et al., 2017), which, in turn, may negatively affect product quality (Kini et al., 2017). Therefore, we argue that regulatory fragmentation-induced uncertainties may discourage firms' long-term investment in quality and weaken innovative activities, thereby contributing to higher product quality failures.

Overall, the *private interest theory* suggests that regulatory fragmentation-induced heightened cost pressures and uncertainties may weaken quality culture, reduce innovative activities, and undermine input quality, and thereby increase product quality failures. Thus, we propose the following competing hypothesis:

H_{1b}: Regulatory fragmentation is *positively* associated with product quality failures.

3. Data and Sample Construction

We manually collect product recall data for US firms from three regulatory agencies that oversee product quality and safety issues in the US, covering the period from 1996 to 2023.[6] Specifically, we collect recall data on vehicles, equipment, car tires or seats from the National Highway Traffic Safety Administration (NHTSA); on drugs, foods, and medical devices from the Food and Drug Administration (FDA); and on various consumer products such as children's products, home furnishings, household appliances, hardware and tools, heating and cooling equipment etc. from the US Consumer Product Safety Commission (CPSC). We only include publicly listed firms from the recalling universe sample, as their financial information is necessary for the analysis. The detailed procedures for recall data collection and the matching procedures between recalling firms and Compustat identifier 'GVKEY' are discussed in Appendix A.

In addition, we collect data on our key independent variable '*Regulatory Fragmentation*' from Kalmenovitz et al. (2025).[7] We also collect the data on company fundamentals from Compustat. Following standard recall literature (Kini et al., 2017, 2022; Li et al., 2024), we use one-year lag for the independent and control variables to address reverse causality concern. To construct our final sample, we begin with the universe of firm-specific regulatory fragmentation data (where the company identifier is Central Index Key- CIK) for all listed US companies available since 1995 (210,912 firm-year observations). Using the CIK-GVKEY linking table, we match 131,281 firm-year observations with Compustat GVKEY. We then

---

[6] Our recall sample begins in 1996 because the data on our key independent variable *Regulatory Fragmentation*, which is used as a one-year lag in the baseline regression, is available since 1995.

[7] We sincerely thank Kalmenovitz et al. (2025) for making these data available at https://sites.google.com/view/jkalmenovitz/home.

merge one-year lagged regulatory fragmentation data with the product recall data (using the common identifier- GVKEY), resulting in 126,771 firm-year observations.

We then apply several screening criteria following standard literature (Kini et al., 2017, 2022; Li et al., 2024). First, firms under financial and utility industries are excluded. Second, firms in three-digit SIC industries that have no recall events during the sample period are excluded. This is because product recalls are not an appropriate measure of product quality failures in these industries (e.g., finance, insurance, electricity, gas, hotel and restaurant services, newspaper industries etc.). After dropping observations with missing controls, our final sample consists of 56,348 firm-year observations from 7,619 unique firms. In this sample, there are 12,474 (43,874) firm-year observations for recalling (non-recalling) firms from 885 (6,734) unique recalling (non-recalling) firms.[8]

As illustrated in Panel- A of Table 1, our final sample encompasses 12,172 recall events during 1996-2023, including 3,132, 8,020 and 1,020 recall events under the NHTSA, FDA and CPSC subsamples, respectively.[9] Our year-wise recall sample distribution is comparable to prior recall literature (Kini et al., 2017, 2022; and Li et al., 2024),[10] with the number of recall events evenly distributed across the years. Our sample covers recall events from a broad range of industries: 51 (171) two (three)-digit SIC industries. In Panel- B of Table 1, we present two-digit SIC industry-wise number of recall events for the top 20 industries ranked from the highest to lowest number of recalls. The Measuring, Analyzing and Controlling Instruments industry has the highest number of recalls (4,388), followed by Transportation Equipment (2,845), and Chemicals and Allied Products (1,670). These top three industries cover about 73% of total recall events. This is comparable with prior recall literature (Kini et al., 2017; and Li et al., 2024).[11]

< Insert Table 1 here >

[8] Recalling firms are those that have at least one recall event during our sample period, while non-recalling firms, belonging to the same three-digit SIC industries, have no recall events and serve as our 'control sample'.
[9] As many firms have multiple product recall events in a year, these 12,172 recall events result in 3,261 firm-year observations of the recalling firms where the *Recall Dummy* variable takes the value of one.
[10] However, there are some discrepancies in the FDA recall data for years prior to 2012 between our sample and that of Kini et al. (2017, 2022) due to changes in the data structure. Following Li et al. (2024), we address this concern by two additional robustness tests: (1) excluding all FDA recalling firms and their industries and (2) starting the sample from 2012, both of which support our baseline results (see Section 4.4.3).
[11] Our baseline results persist if we exclude these top three two-digit SIC industries from the sample. (see Section 4.4.3).

4. Data Analyses and Results

4.1 Summary Statistics

Table 2 provides summary statistics of the key variables. The mean value of *Recall Dummy* indicates that on an average, 6% of firms in our sample recall their products during the sample period. The average number of recall events (*Recall Frequency1*) firms experience in year 1 is 0.12.[12] In contrast, the mean of *Regulatory Fragmentation* is 0.80, indicating that firms, on average, experience greater fragmentated regulations from multiple federal agencies. Additionally, firms are also exposed to greater topic dispersion within the firms, indicated by the mean (0.94) of *Topic Dispersion within Firm*. Our sample firms also have an average size of $4,635 million, R&D of 6%, leverage of 16%, Book-to-Market ratio of 0.57, and Profitability of -2%. The mean values of industry-adjusted Herfindahl Index and Total Factor Productivity are 1% and 17%, respectively. Overall, these statistics are consistent with prior literature (Kalmenovitz et al., 2025; Li et al., 2024).

< Insert Table 2 here >

Furthermore, Table OA1 in Online Appendix, which presents Correlation Matrix and Variance Inflation Factor (VIF), shows that there are no multicollinearity issues among the independent variables (all VIF values are less than 10). Furthermore, the Correlation matrix shows that *Regulatory Fragmentation* and *Recall Dummy* are positively correlated and statistically significant at 5% level, which provides preliminary support to our second hypothesis (H_{1b}).

4.2 Baseline Regressions: Regulatory Fragmentation and Recall Likelihood

To estimate the association between regulatory fragmentation and recall likelihood, we run the following baseline regression model shown in Equation (1):

$$Recall\ Dummy_{i,t} = \alpha + \beta_1 Regulatory\ Fragmentation_{i,t-1} + X_{i,t-1} + \lambda_t + \theta_j + \varepsilon_{i,t} \ldots\ldots\ldots\ldots(1)$$

where, *Recall Dummy*$_{i,t}$ takes the value of one if a firm *i* recalls a product in year *t* and zero otherwise (Kini et al, 2017).[13] *Regulatory Fragmentation*$_{i,t-1}$ is the weighted average of 100 regulatory topic's fragmentation across federal agencies where weights are each topic's

[12] If we consider only the recalling firms that have at least one recall event during the sample period, the mean of *Recall Dummy* (*Recall Frequency1*) is 26% (0.52).

[13] For robustness, we use several alternative measures of product quality failures such as *Recall Frequency* (i.e., *Recall Frequency1, Recall Frequency2* and *Recall Frequency3* taking the cumulative number of recall events of a firm in year *t;* year *t* and *t+1*; and year *t, t+1* and *t+2*, respectively) (Kini et al., 2022) and *Recall Quantity* (i.e., natural logarithm of the annual quantity of recalled product items) (see Section 4.5.2).

relevance for each firm-year based on the percentage of words in a firm's 10-K report dedicated to the topic (Kalmenovitz et al., 2025) (see Appendix B for a brief discussion on the construction of this measure). $X_{i,t-1}$ is the vector of controls. All independent variables are one-year lagged to alleviate reverse causality concern (Kini et al., 2017). The definitions of all variables are included in Appendix C. We also incorporate year fixed effects (λ_t) and industry fixed effects (θ_j) to capture any variations in product recalls across time-series and industries. $\varepsilon_{i,t}$ is the error term.

Following standard literature, we control for several variables that may influence product quality failures. First, we control for *R&D,* as firms with higher R&D expenditure tend to experience fewer quality failures (Kini et al., 2017, 2022). We also control for *Leverage,* as highly levered firms are more likely to experience product quality failures (Kini et al., 2017, 2022). Furthermore, we control for *Firm Size* since larger firms have higher likelihood of experiencing quality failures compared to smaller firms (Kini et al., 2017, 2022). We also control for *Profitability,* as lower profitability is correlated with higher product quality failures (Rose, 1990). Following Li et al. (2024), we control for stock valuation using the *Book-to-Market* (B/M) ratio, as firms with a higher B/M ratio may have fewer growth and investment opportunities and, therefore, invest less. This lower investment may reduce production efficiency, resulting in lower product quality and an increase in product quality failures.

Furthermore, we control for *Total Factor Productivity (TFP)*, a measure of managerial ability, as firms with higher TFP tend to experience lower product quality failures (Kini et al., 2017). We estimate *TFP* following the approach of Kovenock and Phillips (1997) and Faleye et al. (2006). We also control for industry concentration by using the sales-based *Herfindahl Index* (*HHI)* of a firm's three-digit SIC industry, as firms in concentrated industries tend to have lower product quality (Matsa, 2011) and a higher likelihood of experiencing product quality failures. Finally, following Kalmenovitz et al. (2025), we also control for a firm's *Topic Dispersion within Firm* to disentangle the influence of a firm's regulatory fragmentation across multiple federal agencies from topic dispersion within the firm.

In Table 3, we present the marginal effects of the Probit regression models based on our baseline Equation (1) in first three columns.[14] Column (1) includes only regulatory fragmentation as a determinant of product recalls with both year and Fama-French 48 industry

[14] Our baseline results remain unchanged if we run Logistic regressions instead of Probit (untabulated).

FEs. Column (2) presents our main baseline model considering all relevant controls along with both year and Fama-French 48 industry FEs.[15] Column (3) presents a tighter specification where we control for Fama-French 48 Industry×Year FE.[16] We also present the coefficients of Linear Probability Models (LPM) based on our baseline Equation (1) in Columns (4) and (5) that correspond to Columns (2) and (3), respectively. Heteroscedasticity robust standard errors clustered at the firm level are shown in parentheses.

In all columns, we find a positive association between regulatory fragmentation and recall likelihood. Specifically, as a firm's regulatory topics become more fragmented across multiple agencies, its likelihood of recalling products increases. This relationship is statistically significant at the 1% level in all specifications and is also economically meaningful. For instance, in our main baseline regression in Column (2), a one standard deviation increase in regulatory fragmentation increases a firm's recall likelihood by approximately 0.92%, which corresponds to 15.4% of the unconditional probability of a product recall event, resulting in about 516 additional recalls.[17] The economic significance can also be interpreted in a simpler way. For example, a 1% increase in regulatory fragmentation leads to about 172 additional recalls in Column (2) (i.e., 0.3071×0.01×56,072; where 56,072 is the number of observations).[18] Consistent with the *private interest theory* of regulation, this finding corroborates our second competitive hypothesis (H_{1b}), which posits that regulatory fragmentation is positively associated with product quality failures.

The results of control variables are mostly consistent with prior literature. For instance, *R&D*, a proxy for long-term investment in product quality, has a significant negative association with recall propensity. This is consistent with the idea that firms investing in quality over the long term can produce better quality products and thus experience fewer product

[15] Our baseline results also hold if we control for three-digit SIC industry FE instead of Fama-French 48 industry FE in all specifications.
[16] We lose about one-fourth of the observations in Column (3) due to controlling for Fama-French 48 Industry×Year FE as there is no variation in the value of *Recall Dummy* variable in some Fama-French 48 Industry×Year groups in our sample.
[17] The marginal effect of *Regulatory Fragmentation* is 0.3071 in Column (2). Hence, increasing *Regulatory Fragmentation* by one standard deviation (0.03) increases the propensity to recall by 0.3071×0.03= 0.0092 or, 0.92%. This 0.92% increase in recall propensity corresponds to 15.4% of the unconditional probability of announcing a product recall event (6%). This is equivalent to about 516 additional recall events (0.92% of 56,072 observations in Column (2)).
[18] Based on this alternative interpretation approach, our baseline results can be compared with those of Kini et al. (2017). They find that a 10% increase in financial leverage leads to 191 additional recalls (see Column 8 of Table 3 in Kini et al. (2017)). We find in Column (2) that a 10% increase in regulatory fragmentation leads to 0.3071×0.10×56,072=1,722 additional recalls. Hence, it seems that in terms of economic significance, regulatory fragmentation is a stronger determinant of product recalls than financial leverage.

quality failures (Kini et al., 2017, 2022). We also find that firms with higher *Financial Leverage* have greater recall propensity, as distressed financial conditions can adversely affect product quality (Kini et al., 2017). In addition, we find that larger firms have greater propensity to recall their products due to their complexity, higher volumes of production and sales, and coordination problems, which increase the likelihood of product quality failures (Kini et al., 2017, 2022). We also find that firms with higher *Book-to-Market* ratio, and lower *Profitability* have a higher propensity to recall their products (Li et al., 2024). However, *Total Factor Productivity* do not significantly impact recalls. Additionally, we find that Herfindahl Index (*HHI*) is positively associated with product recalls, suggesting that firms in more concentrated industries may prioritise low-cost production over quality, leading to more product quality failures. Finally, we find that *Topic Dispersion within Firm* does not have a consistently significant association with recall propensity as the coefficients are not significantly different from zero in Columns (2) and (3). This is not inconsistent with our narrative as it implies that *Topic Dispersion within Firm* may not influence recall propensity, rather, it is regulatory fragmentation across multiple federal agencies that affects recall propensity.

Overall, our baseline regression analyses show that firms experiencing more regulatory fragmentation from multiple regulatory agencies are more likely to recall their products from markets due to product quality failures.

< Insert Table 3 here >

4.3 Difference-in-Difference Analysis Using a Quasi-Natural Exogenous Shock

There are several empirical challenges for investigating the impact of regulatory fragmentation on firms' product quality failures. First, there could be an omitted variable bias, or a latent factor that may be correlated with both regulatory fragmentation and product quality failures. Second, our baseline regression model may omit the differences between recalling firms and non-recalling firms. In other words, our results could be driven by our research design choices. Finally, there may be a concern for reverse causality as firms, because of higher product quality failures, may be exposed to greater regulatory fragmentation. Overall, these endogeneity concerns could make the interpretation of our results challenging.

To address these endogeneity concerns and establish causality, we exploit the US President Donald Trump's surprise election win in 2016 as a plausible quasi-natural exogenous shock to the expected regulatory fragmentation in the US. Recently, a nascent body of literature uses the largely unexpected win of Trump as an exogenous shock to the expectations about US regulatory policies (Wagner et al., 2018; Child et al., 2021; Dagostino et al, 2023; Kundu, 2024; and Armstrong et al., 2025).

Trump's election campaign was highly focused on deregulation through minimising government agencies' intervention in the economy and reducing federal regulatory burdens on businesses and to some extent he fulfilled those promises (Belton and Graham, 2020). After assuming his presidency office in January 2017, Trump signed the executive order 13771 to reduce regulation by repealing two existing regulations for one new regulation and to reduce regulatory costs by the federal agencies (Federal Register, 2017a).

Trump also signed the executive order 13781 in March 2017 to reorganize governmental functions by reducing duplication and redundancy of federal agencies (Federal Register, 2017b). Following this executive order, at least eighteen federal agencies signed Memorandum of Understanding (MoU) to reduce regulatory fragmentation across their regulatory activities (Business Roundtable, 2019). As a likely result of these policy actions, there has been a sharp decline in average regulatory fragmentation during the Trump presidency from 2017 to 2020 (see Figure 1). Therefore, Trump's surprise election win offers an appropriate setting to investigate the causal impact of reduced regulatory fragmentation on product quality failures.

< Insert Figure 1 here >

To do so, we employ a difference-in-difference (DiD) analysis using a 6-year event window including three years prior to the election (2014-2016) and three years after the election (2017-2019).[19] We create a dummy variable *Post* that takes the value of one for the years 2017 to 2019 and zero otherwise. We define our treatment (control) firms as the firms exposed to the number of related proposed active US federal regulations in the pipeline above (below) the sample median during pre-election period.[20] Generally, the higher number of proposed active US federal regulations in the pipeline are arguably more likely to involve multiple federal agencies to formulate and implement these regulations, which may eventually result in greater regulatory fragmentation.[21] However, in the post-election period, these treatment firms are expected to be more affected by Trump's deregulatory policies, as a part of

[19] Although the election was held in November 2016, President-elect Trump assumed his office in January 2017.
[20] We thank Chang et al. (2023) for providing the regulatory pipeline data.
[21] The correlation between the firms' exposure to proposed active US federal regulations in the pipeline and regulatory fragmentation is 0.51.

fulfilling his promises made in the pre-election deregulation campaign, compared to the control firms.

We create a dummy variable *Treatment* taking the value of one (zero) for the treatment (control) firms during the event window. Then we apply propensity score matching (PSM) technique to match treatment and control firms, where we run a logistic regression model with all baseline controls to estimate the propensity score. This procedure yields a total of 5,900 observations in our matched sample.[22] We create an interaction variable *Treatment*×*Post* and expect this coefficient to be negative. This is because the treatment firms are likely to be more affected by Trump's post-election deregulation policies that are likely to result in lower regulatory fragmentation and consequently, we expect lower product quality failures for these firms, compared to the control firms.

Now, we re-run our main baseline regression model including the above interaction variable on this propensity-matched sample. The results of main DiD regressions are shown in Panel B of Table 4. We run Probit regressions in Columns (3) and (4), and LPM in Columns (5) and (6). We control for year FE and Fama-French 48 industry FE in Columns (3) and (5), whereas Columns (4) and (6) show tighter specifications where we control for Fama-French 48 Industry×Year FE. In all these specifications, we find that as per our expectation, post-election deregulation policies that result in lower regulatory fragmentation are negatively and significantly related to product quality failures. These findings bolster our main baseline results that firms exposed to greater regulatory fragmentation are more likely to experience higher product quality failures.

4.3.1 Parallel Trend Tests

We also check the validity of the parallel trend assumption in our DiD analysis (e.g., there is no significant difference in product quality failures between treatment and control firms in the pre-election period 2014-2016) using two approaches. First, following Lennox (2016), we create an indicator variable *Trend* that takes the value of one for year 2016, two for year 2015, and three for year 2014. Then, we interact this variable with *Treatment* and expect the coefficient of this interaction variable *Treatment*×*Trend* not to be statistically significant, which will indicate that the two groups of firms exhibit similar trends for product quality failures in the pre-event period. The results presented in Column (1) show that as per our expectation,

[22] Table OA2 in Online Appendix shows that the covariates of treatment and control samples are mostly identical in post-PSM using two-tailed *t*-tests for mean difference.

Treatment×*Trend* is not significantly different from zero, indicating the parallel trend assumption holds.

Second, following Li et al (2024) and Lai et al. (2024), we create year dummies $Year_j$ taking the value of one for year *j* and zero otherwise (where *j* ranges from 2014 to 2019). Then, we interact these year dummies with *Treatment* and expect the coefficients of these interaction variables $Treatment \times Year_j$ not to be statistically significant for the pre-election period (2014-2016), implying that treatment and control firms exhibit similar trends for product quality failures in the pre-election period. The results shown in Column (2) show that the coefficients of $Treatment \times Year_{2015}$ and $Treatment \times Year_{2016}$ are not significantly different from zero, indicating the parallel trend assumption is valid in our setting.[23] Moreover, we find that the coefficients of some interaction variables in the post-election period (e.g., $Treatment \times Year_{2017}$ and $Treatment \times Year_{2018}$) are negative and statistically significant,. These findings are consistent with our main DiD regression results that the treatment firms experience significantly lower product quality failures than the control firms in the post-election period, whereas there is no significant difference in product quality failures between these two groups of firms in the pre-election period.

4.3.2 Falsification Tests

We also conduct two falsification tests using two Psuedo-election year events in Panel C of Table 4. First, we use the year 2013 as a Psuedo-election year which is three years prior to the actual Trump election year (see Column (7)). Second, we use the year 2019 as a Psuedo-election year which is three years after the actual Trump election year (see Column (8)). Then, for each of these Psuedo events, we re-run our baseline DiD regression model using a six-year event window of PSM matched sample. We find that the coefficients of the interaction term *Treatment*×*Post* are not significantly different from zero in both columns, which suggest that our DiD analysis findings are not mechanical, rather these are based on a valid exogenous shock to regulatory fragmentation. Overall, these findings bolster our baseline results that greater regulatory fragmentation leads to higher product quality failures.

< Insert Table 4 here >

4.4 Underlying Channels

After establishing the fact that regulatory fragmentation leads to product quality failures, now we identify several underlying channels (e.g., quality culture, innovation, and

[23] $Treatment \times Year_{2014}$ is omitted from the regression model to avoid perfect multicollinearity problem.

input quality) through which regulatory fragmentation may affect product quality failures. Table 5 depicts the results.

4.4.1 Quality Culture

Firms facing cost pressures or short-term performance imperatives often compromise their corporate quality culture. Li et al. (2021c) provide empirical evidence that pressures from financial analysts weaken firms' commitment to quality, while the 2014 General Motors (GM) massive recall of about 2.6 million cars with defective ignition switches illustrates the consequences of such weakening of quality in practice. In Congressional testimony, CEO Mary Barra acknowledged that GM's prior management, operating under intense cost constraints, undermined quality culture by prioritizing cost savings over safety, contributing to product failures (Fielkow, 2014). More broadly, firms with weak quality cultures respond to challenging environments by curtailing innovation and favouring cost-cutting strategies, both of which exacerbate risks of quality failures (Li et al., 2021b). Extending this logic, we argue that heightened regulatory burden and compliance costs associated with greater regulatory fragmentation may similarly weaken firms' quality culture, ultimately impairing product quality and increasing the likelihood of product quality failures.

To assess whether quality culture conditions the impact of regulatory fragmentation on product quality, we construct a *Quality Culture Dummy* to proxy for weak quality culture. The dummy equals one if a firm's quality culture score—a text-based measure of corporate quality culture developed by Li et al. (2021a)—falls below the sample median, and zero otherwise. We then interact this dummy with our key explanatory variable, *Regulatory Fragmentation*. If regulatory fragmentation disproportionately impairs firms with weaker quality cultures, we expect the coefficient on the interaction term, *Regulatory Fragmentation*×*Quality Culture Dummy*, to be positive. We re-estimate our baseline specification including this interaction term, and the results in Column (1) support this prediction: the coefficient is positive and statistically significant at 1% level. These results provide evidence consistent with the mechanism that regulatory fragmentation exacerbates product quality failures by weakening corporate quality culture.

4.4.2 Innovation

Product innovation is positively linked to product quality (Chan et al., 2023), yet firms reduce innovation when faced with uncertainty (Bhattacharya et al., 2017). Similarly, heightened regulatory compliance diminishes innovative activity, lowering both the number and quality of patents (McFarland, 2023). Reduced innovation, in turn, undermines product quality and increases product quality failures (Kini et al., 2017). We posit that regulatory fragmentation, by increasing uncertainty and compliance costs, discourages firms' long-term investments in quality (i.e., R&D) and weakens innovative activities (i.e., patent quality and quantity), thereby heightening product quality failures.

To test this innovation mechanism, we use three measures of innovation: R&D (innovation input) and patent quality and patent number (innovation outputs). We construct three dummies: an *R&D Dummy* equals one if a firm's R&D is below the sample median and zero otherwise; a *Patent Quality Dummy* (*Patent Number Dummy*) equals one if its patent citations (patent counts) are below the sample median and zero otherwise. We then interact each dummy with *Regulatory Fragmentation* and expect these interaction coefficients to be positive.

The results in Columns (2)–(4) show that all these interaction coefficients are positive as we expected, however, only *Regulatory Fragmentation*×*R&D Dummy* and *Regulatory Fragmentation*×*Patent Quality Dummy* are statistically significant. These findings indicate that regulatory fragmentation increases product quality failures by reducing R&D investment and impairing patent quality.

4.4.3 Input Quality

Input quality is a critical determinant of product quality (Kugler and Verhoogen, 2012). Since firms in less developed countries tend to produce lower-quality goods (Bloom et al., 2021), U.S. firms that source material inputs from these suppliers are more susceptible to product quality failures (Steven et al., 2014; Steven and Britto, 2016). Li et al. (2021c) further show that firms facing short-term performance pressures from financial analysts restructure their supply chains by shifting input imports from developed to developing countries, which subsequently increases product quality failures. Therefore, it is plausible that heightened cost pressures arising from regulatory fragmentation may similarly encourage firms to substitute higher-quality inputs from developed countries with lower-cost inputs from developing countries, thereby raising the likelihood of product quality failures.

To test this conjecture, we use the text-based 'offshore input' measure developed by Hoberg and Moon (2017), which identifies the countries from which U.S. firms source material inputs during 1997–2017. Following the World Bank's income-level classification, we categorize each country annually as developed or developing. To proxy for lower input quality, we construct an *Input Quality Dummy* equal to one if a firm sources its input materials exclusively from developing countries, and zero otherwise. We then interact this dummy with *Regulatory Fragmentation* and expect the interaction coefficient to be positive.

The results, reported in Column (5), show that the coefficient of *Regulatory Fragmentation*×*Input Quality Dummy* is positive as expected but not significantly different from zero. This suggests that while input quality is theoretically relevant, we find little evidence that it is the operative channel through which regulatory fragmentation drives product quality failures. One possible explanation is that certain developing-country suppliers have undergone quality upgrading in response to global competition, weakening the link between sourcing location and input quality. Furthermore, the binary nature of our input quality proxy may mask variation in supplier quality within developing countries.

Overall, we find strong evidence that fragmentation exacerbates product quality failures by weakening firms' quality culture and by discouraging innovative activities, particularly R&D investment and patent quality. Contrarily, while theory suggests that sourcing from developing-country suppliers could impair input quality, our empirical results provide little support for this channel. One possibility is that firms mitigate input risks through engaging with upgraded suppliers in developing economies. Overall, these findings suggest that regulatory fragmentation primarily undermines product quality through internal organizational factors—culture and innovation—rather than through external input sourcing.

< Insert Table 5 here >

4.5 Robustness Checks

Having explored the potential channels through which regulatory fragmentation affects product quality failures, we now turn to assessing the robustness of our baseline findings. Specifically, we conduct a battery of robustness tests including firm FE regressions, alternative measures of product quality failures and regulatory fragmentation and other robustness tests. Table 6 presents these results.

4.5.1 Firm FE Regressions

In our baseline regressions, the dependent variable *Recall Dummy* is an indicator variable (Table 3), and therefore, we include year and industry fixed effects following Kini et al. (2017). However, the results may still be influenced by omitted, time-invariant firm-level heterogeneity. To address this concern, we re-estimate Equation (1) controlling for firm and year FE, with results reported in Column (1) of Table 6. We further estimate a more stringent specification that includes firm FE along with Fama-French 48 industry × year FE, reported in

Column (2). Across both specifications, the Linear Probability Model estimates show that the coefficient on *Regulatory Fragmentation* remains positive and statistically significant, corroborating our baseline findings that higher regulatory fragmentation increases the likelihood of product quality failures.

4.5.2 Alternative Measures of Product Quality Failures

One might argue that the dependent variable in our baseline regression, *Recall Dummy,* (i.e., taking the value of one if a firm recalls its products in year *t* and 0 otherwise) may not capture the comprehensive picture of product quality failures. This is because some firms may experience multiple recall events in a year and some firms may recall their products in larger quantities than others. Besides, we use one-year lagged *Regulatory Fragmentation* variable in our baseline regression assuming that firms experiencing greater regulatory fragmentation in a year may experience product quality failures in the next year. However, it is also plausible that the impact of regulatory fragmentation on product quality failures may extend for more than one year.

To address these concerns, we use several alternative measures of product quality failures such as *Recall Frequency* and *Recall Quantity* (i.e., natural logarithm of the total annual quantity of recalled products). Following Kini et al. (2022), we construct three measures of *Recall Frequency* such as *Recall Frequency1, Recall Frequency*2 and *Recall Frequency3* that represent the cumulative number of recall events of a firm in year *t;* year *t* and *t+1*; and year *t, t+1* and *t+2*, respectively. In Panel B of Table 6, we run Poisson regression models where the dependent variables are *Recall Frequency1, Recall Frequency*2 and *Recall Frequency3*, respectively in Columns (3) to (5). We find that the estimated coefficients of *Regulatory Fragmentation* are positive and statistically significant in all specifications. These findings suggest that firms exposed to greater regulatory fragmentation experience more frequent recall events and the effect of regulatory fragmentation on experiencing frequent recall events may last up to three years.

Additionally, in Column (6), we run an OLS model of our baseline regression where the dependent variable is *Recall Quantity*- the natural logarithm of total quantity of recalled products of a firm in year *t*. We find that the coefficient of *Regulatory Fragmentation* is positive and statistically significant, implying that the firms experiencing greater regulatory fragmentation recall their defective products in larger quantities. Overall, all these alternative measures of product quality failures corroborate our baseline findings.

4.5.3 Alternative Measures of Regulatory Fragmentation

In Panel C of Table 6, we use two alternative measures of regulatory fragmentation: 5-year rolling average of regulatory fragmentation and regulatory fragmentation dummy variable. The 5-year rolling average of regulatory fragmentation variable captures the effects of past regulatory activities and regulatory fragmentation dummy variable captures the non-linear effects of regulatory fragmentation.

First, total regulatory burden that firms may face arises from both new and past regulatory activities such as one-time costs for compliance with new rules, continuing requirements related to existing rules, efforts associated with new potential regulations, etc. Each of these activities possibly contributes to the costs related to fragmentation (Kalmenovitz et al., 2025). While our existing flow-based fragmentation measure, *Regulatory Fragmentation,* weighs new regulatory activities the highest and includes a subset of past regulatory activities like notices (e.g., filing details, revised requirements, etc.), one might argue that this measure may not fully incorporate the effects of all past regulatory activities. To address this concern, we use an alternative stock-based fragmentation measure, *RegFrag 5Y Average*, which is the weighted average of regulatory activities based on the Federal Register over the past five years, where more recent years are given more weights (e.g., year *t-1*, *t-2*, *t-3*, *t-4*, and *t-5* have weights of 1, 1/2, 1/3, 1/4, and 1/5, respectively).[24] We re-run our baseline model with this alternative measure in Column (7) of Table 6 and the results are similar to our baseline findings.

Second, the relationship between regulatory fragmentation and product quality failures may vary between firms depending on the magnitude of exposure to regulatory fragmentation. For example, firms facing greater regulatory fragmentation may be more sensitive to product quality failures than the firms with smaller regulatory fragmentation. To capture this non-linear relationship, we create a dummy variable *RegFrag Dummy* taking the value of one (zero) if a firm belongs to above (below) the median of *Regulatory Fragmentation* measure in a year. We re-estimate our baseline regression replacing *Regulatory Fragmentation* with *RegFrag Dummy* in column (8) of Table 6. We find that firms exposed to greater fragmentation of regulatory topics are more likely to experience product quality failures than the firms with fewer regulatory fragmentation, which in consistent with our baseline findings.

[24] We thank Kalmenovitz et al. (2025) for providing this data. As this variable is available up until 2019, the number of observations in this specification is lower than our baseline specifications.

< Insert Table 6 here >

4.5.4 Other Robustness Tests

We also conduct several other robustness tests, and the results are presented in Table OA3 of online appendix.

4.5.4.1 Addressing Several Sampling Issues

We address some potential concerns about our sample. First, as product recall is a common phenomenon in automobile industry, we re-run our baseline regression by excluding the NHTSA (automobiles) observations from our final sample. As shown in column (1) of Table OA3, we find that our baseline findings still remain qualitatively unchanged.

Second, with the unavailability of comprehensive FDA recall data prior to 2012, there could be a bias which we address by conducting two additional tests. (1) We exclude the FDA subsample from our final sample and re-run the baseline regression. (2) We drop all observations prior to 2012 and start our final sample from 2012 to 2023. The results are reported in columns (2)-(3) of Table OA3. In both the tests, our baseline results still persist.

Third, we exclude top three two-digit SIC industries (e.g., Measuring, Analyzing and Controlling Instruments- 4,338 recalls; Transportation Equipment- 2,829 recalls; and Chemicals and Allied Products- 1,658 recalls) that experience the highest number of recall events (see Panel B of Table 1). Then, we re-estimate our baseline regression and find consistent results in Column (4) of Table OA3.

4.5.4.2 Controlling for Regulation Quantity and 10K Report Size

Kalmenovtiz et al. (2025) show that regulatory fragmentation measure is different from regulation quantity and 10K report size. To disentangle the effects of regulatory fragmentation from regulatory quantity and number of 10K report words, we control for *Regulation Quantity* and *Log(10K Words#)* in our baseline regression and present the results in Column (5) and (6) of Table OA3, respectively. Even after including these additional controls, our baseline findings remain qualitatively unchanged.[25]

4.6 Ruling Out Alternative Explanations

In this section, we rule out several plausible alternative explanations that could question our baseline findings.

[25] We thank Kalmenovitz et al. (2025) for sharing the data on *Log(10K Words#)* with us. As this variable is available up to 2019, we lose about one-fourth observations in Column (6).

4.6.1 Do Recalls Capture Product Quality Failures or Regulatory Effectiveness?

In this study, we argue that greater regulatory fragmentation undermines firms' product quality, and therefore, an increase in product recalls primarily reflects quality failures. However, an alternative explanation is that the presence of multiple regulators strengthens oversight by imposing more rigorous testing and reporting requirements, which could make defects more likely to be detected and addressed through recalls. To ensure that our dependent variable, *Recall Dummy*, captures product quality failures rather than regulatory effectiveness, we conduct three complementary tests as follows.

4.6.1.1 Customer Complaints

First, we employ customer complaints to regulators as an alternative proxy for product quality failures. Unlike recalls, customer complaints directly reflect consumer-identified defects and safety issues and are not influenced by the rigor of regulatory oversight. For example, automobile customers who detect defects or safety hazards in their vehicles can file complaints with NHTSA, prompting further investigation. If our argument is correct, greater regulatory fragmentation should be associated with more customer complaints, consistent with lower product quality rather than stronger regulatory effectiveness.

We collect the customer complaints data from NHTSA only as the other two regulators (i.e., FDA and CPSC) do not provide such data.[26] This data has customers' safety-related complaints about automobile manufacturers received by NHTSA since 1995 and contains full information on each complaint (e.g., manufacturer's name, vehicle make-model-year, dates of complaint and incident, number of incidences, crash or fire incidence, number of persons injured or dead, etc.). We follow the similar matching procedure described in Appendix A to manually match the manufacturing firm names from the complaints data with Compustat firm names. We could successfully assign GVKEYs for 201 unique firms from the complaint data. However, after merging with our final sample, we end up with 117 unique firms and 1,964 firm-year observations.

We compute *Total Complaints* for a firm as the sum of number of incidences, crashes, fire incidents, injuries and deaths reported in the customer complaints about the manufacturing firm in a year. We then standardize this variable by dividing it by the maximum number of total complaints about the manufacturing firm over the sample period to keep the range of this variable from 0 to 1. Finally, we re-estimate our baseline equation replacing *Recall Dummy*

[26] NHTSA Customer Complaints data is available at https://www.nhtsa.gov/nhtsa-datasets-and-apis.

with *Total Complaints* and controlling for year FE and firm FE in Column (1) of Table 7. We find that the coefficient of *Regulatory Fragmentation* is still positive and statistically significant, implying that firms with greater regulatory fragmentation receives more complaints from customers related to product safety issues. This finding reinforces our interpretation that product recalls in our baseline analysis capture underlying product quality failures rather than heightened regulatory effectiveness.

4.6.1.2 Recall Severity

Second, we examine whether regulatory fragmentation affects the severity of recalls, using the FDA subsample. Unlike NHTSA and CPSC, the FDA classifies each recall into severity categories: Class I (most severe, involving risk of death or serious health consequences), Class II (temporary or reversible adverse effects), and Class III (least severe). If multiple regulators enhance oversight effectiveness, we should observe fewer Class I recalls. Contrarily, if fragmentation undermines product quality, firms should be more likely to face Class I recalls. Following Kini et al. (2017), we construct a categorical variable *Recall Severity* that takes a value of three for Class I recalls, two for Class II recalls, one for Class III recalls, and zero for non-recalling firms. Ordered probit estimates (Column (2), Table 7) reveal that regulatory fragmentation is positively associated with the likelihood of Class I recalls, indicating that regulatory fragmentation worsens rather than mitigates the most severe product quality failures.

4.6.1.3 Voluntary vs. Mandatory Recalls

Finally, we distinguish between firm-initiated voluntary recalls and regulator-initiated mandatory recalls. If regulatory fragmentation merely reflects tougher oversight, the effect should concentrate in regulator-initiated recalls. Contrarily, if fragmentation reflects declining product quality, firms should be more likely to initiate voluntary recalls. To test this conjecture, we construct a categorical variable *Voluntary Dummy* taking the value of two for firm-initiated voluntary recalls, one for regulator-initiated mandatory recalls and zero for the non-recalling firms. Ordered probit results (Column (3), Table 7) show that greater regulatory fragmentation significantly increases the propensity of voluntary recalls. This finding again suggests that regulatory fragmentation leads to product quality failures, prompting firms themselves to act.

Taken together, these three tests provide consistent evidence that recalls capture product quality failures rather than enhanced regulatory effectiveness, thereby reinforcing the validity of our baseline interpretation.

< Insert Table 7 here >

4.6.2 Additional Alternative Explanations

We further examine the robustness of our findings by addressing several alternative explanations that may also influence product quality failures. The results are reported in Table OA4 of the Online Appendix.

First, we control for *Vertical Integration* as vertically integrated firms may bring some or all the layers in the production process under one umbrella to decrease coordination costs which may result in better quality products and consequently, leading to lower product quality failures (Kini et al., 2017). Using the text-based and industry-adjusted vertical integration score developed by Frésard et al. (2020)[27], we find that our baseline results remain robust (Column (1)). Second, firms with better cash flow are less financially constrained and more likely to invest in quality-enhancing initiatives, resulting in lower product quality failures (Kini et al., 2017). To capture this, we control for *Free Cash Flow (FCF) Shock* (i.e., changes in a firm's FCF compared to its average FCF over the last three years) in Column (2). Our baseline results remain robust to the inclusion of this variable.

Third, we control for *Business Segments* (i.e., the number of business segments of a firm in a year, calculated based on the Compustat Segments database) because the more segments a firm has, the lower profits it generates (Kalmenovitz et al., 2025). This may be due to greater coordination costs and not being able to efficiently manage those higher numbers of segments, which may result in lower product quality and therefore, higher product quality failures. We find that firms with more business segments indeed experience more quality failures, but our main results remain intact (Column (3)).

Fourth, we control for the coverage of *Financial Analysts* (i.e., the number of financial analysts following a firm) because firms followed by more financial analysts may prioritize short-term performance under market pressure, at the expense of product quality (Li et al., 2024). Our main results persist even after accounting for analyst coverage (Column (4)). Fifth, firms may experience fewer number of product recalls if they spend more on lobbying to reduce regulatory scrutiny (Singh and Grewal, 2023). Therefore, we control for *Lobbying* (i.e.,

[27] We thank Frésard et al. (2020) for making the data available at https://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite/index.html

lobbying expenditure in million dollars divided by total assets) in Column (5) and our baseline findings remain unchanged.[28]

Sixth, Kini et al. (2017, 2022) find that firms with higher labor unionization rate experience greater product quality failures. Hence, we control for *Labor Unionization* (i.e., unionization rate of a firm's primary industry in a year in Column (6).[29] Consistent with Kini et al. (2017, 2022), higher unionization is positively associated with quality failures, yet the effect of regulatory fragmentation remains unchanged. Seventh, we control for *Stock Repurchase*, as such payouts may divert resources away from quality-related investments and thereby increasing quality failures (Bendig et al., 2018). Our results are robust to the inclusion of this variable (Column (7)).

Eighth, firms with greater numbers of suppliers may experience higher product quality failures because it is more challenging and expensive for a firm to coordinate with many suppliers and monitor the quality of all inputs sourced from many suppliers, leading to low product quality (Kini et al., 2017). We control for *No. of Suppliers* (i.e., number of major suppliers of a firm based on Compustat Segment database) in Column (8) and find consistent results with Kini et al. (2017). Nevertheless, our baseline results remain robust.

Finally, product quality failures of a firm may also be influenced by its top management characteristics such as CEO stock options (Wowak et al., 2015). To this end, we control for CEOs' firm related wealth by using *CEO Stocks and Options* (i.e., Natural logarithm of the value of CEOs' stocks and options portfolio), CEOs' pay-performance sensitivity using *CEO Delta* (i.e., dollar changes in CEO wealth due to 1% change in a firm's stock price), and CEOs' risk taking incentives using *CEO Vega* (i.e., dollar changes in CEO wealth due to 1% change in the standard deviation of a firm's stock returns).[30] We find that CEO risk-taking incentives (i.e., *CEO Vega*) are positively and significantly associated with product quality failures, but our main results remain unchanged (Column (9)).

Taken together, these analyses rule out a wide range of alternative explanations—spanning firm structure, financial flexibility, external monitoring, political activity, supply

---

[28] We collect lobbying data from Kim's (2018) LobbyView database. Note that the number of observations in Column (5) is much lower because we could successfully match lobbying data with only about one-fifth of our final sample firm-year observations.

[29] We collect industry-level unionization rates from *Union Stats* website (http://www.unionstats.com).

[30] We thank Coles et al. (2006) for providing the data (extended up to 2022) online on these CEO compensation measures estimated based on Core and Guay (2002) methodology.

chain complexity, and executive incentives. Across all specifications, our central result holds: greater regulatory fragmentation robustly predicts higher product quality failures.

4.7 Cross-sectional Analyses

To gain deeper insights into the relationship between regulatory fragmentation and product quality failures, we explore how this effect varies across different firm and market environments. In particular, we examine heterogeneity along three key dimensions: product market competition, firm scope, and policy uncertainty. The results of these cross-sectional analyses are reported in Table 8.

4.7.1 Product Market Competition

Product quality is a key determinant of a firm's ability to maintain market share and competitive position, particularly in highly competitive markets. Since firms divert their resources (e.g., labor and capital) away from discretionary investments (e.g., investments in quality) to meet up increased regulatory compliance costs (Kalmenovitz, 2023) induced by greater regulatory fragmentation, such a reduction in investments in quality may result in lower product quality and consequently, higher product quality failures. This adverse effect on product quality is more likely to be pronounced for the firms operating in a higher competitive product market compared to the firms in a lower competitive product market. This is because the marginal costs of reducing investments in quality are higher for firms facing greater product market competitions as these firms experience significantly higher losses in market value during product quality failure events compared to the firms in a lower competitive product market (Kini et al., 2023).

To test our argument, we split our sample into high and low product market competition categories based on the *Product Market Fluidity* measure (i.e., the magnitude of competitive threat and product market change surrounding a firm) of Hoberg et al. (2014) where a firm belonging to above (below) the median value of product market fluidity measure is assigned to the high (low) category.[31] We re-estimate our baseline regression for both subsamples and the results are presented in Panel A of Table 8. We find that the coefficient of *Regulatory Fragmentation* is positive and significant for both high and low product market competition firms, but significantly higher for the firms operating in highly competitive product markets. This finding indicates that the detrimental impact of regulatory fragmentation on product

[31] We thank Hoberg et al. (2014) for providing this data online at http://hobergphillips.tuck.dartmouth.edu/tnic_competition.html

quality failures is amplified in environments characterized by greater product market competition.

4.7.2 Firm Scope

A firm's scope refers to the number of industry-level markets that the firm likely operates in a year (Hoberg and Phillips, 2024). Larger scope firms operating in greater numbers of industry-level markets produce and sell more products than smaller scope firms and, therefore, are more likely to experience product quality failures because of purely mechanical reasons or greater coordination costs for dealing interactions among many parties within the firm as well as with external stakeholders. Therefore, we conjecture that the effects of regulatory fragmentation on product quality failures are more likely to be pronounced for the larger scope firms than the smaller scope firms.

We test our conjecture by dividing our sample into two categories- large and small based on the measure of *Firm Scope* (i.e., the number of product markets a firm operates in) developed by Hoberg and Phillips (2024).[32] We categorize a firm belonging to above (below) the median value of firm scope measure as the large (small) category. We re-estimate our baseline regression for both subsamples and the results are presented in Panel B of Table 8. We find that the coefficient of *Regulatory Fragmentation* is positive and significant for large scope firms only, indicating that the influences of regulatory fragmentation on product quality failures are more pronounced for the larger scope firms operating in a greater number of product markets.

4.7.3 Policy Uncertainty

Firms often face substantial uncertainty regarding the timing, content, and likely consequences of policy decisions made by politicians and regulatory agencies. High levels of macroeconomic policy uncertainty lead firms to reduce investments (Gulen and Ion, 2016) and curtail innovation activities (Bhattacharya et al., 2017), which, in turn, may negatively affect product quality. Regulatory fragmentation further amplifies uncertainty by increasing the difficulty of predicting new regulatory decisions and creating inconsistencies across multiple federal agencies (Kalmenovitz et al., 2025). We therefore hypothesize that the effect of regulatory fragmentation on product quality failures is more pronounced for firms operating in environments with higher aggregate policy uncertainty.

[32] We thank Hoberg and Phillips (2024) for making the data available at https://faculty.marshall.usc.edu/Gerard-Hoberg/HobergPhillipsScope/index.html.

We test our argument by splitting our sample into two categories- high and low based on the *Policy Uncertainty Index* developed by Baker et al. (2016).[33] A firm is assigned to the high (low) subsample in a year if the news-based policy uncertainty factor is above (below) its median value. Then, we re-run our baseline regression for both subsamples and the results are presented in Panel C of Table 8. We find that the coefficient of *Regulatory Fragmentation* is positive and significant for both high and low subsamples, but substantially higher for the high policy uncertainty subsample. This finding suggests that the impacts of regulatory fragmentation on product quality failures are more pronounced for the firms operating in a higher aggregate policy uncertainty environment.

Overall, the cross-sectional analyses show that the adverse effect of regulatory fragmentation on product quality failures is more pronounced for firms in highly competitive markets, with larger scope, or facing greater policy uncertainty. These findings underscore that the effects of regulatory fragmentation on product quality failures are heterogeneous and context-dependent, highlighting the importance of firm- and market-specific factors in shaping the impact of regulatory fragmentation.

< Insert Table 8 here >

5. Conclusion and Policy Implications

We investigate whether and how regulatory fragmentation influences product quality failures based on a comprehensive hand-collected product recall dataset of all US firms from three US federal agencies (*i.e.*, NHTSA, FDA and CPSC) during 1996-2023. We also exploit a novel text-based firm-specific measure of regulatory fragmentation recently developed by Kalmenovitz et al. (2025).

The key finding of our baseline analysis is that firms with greater regulatory fragmentation have higher likelihood of product quality failures. This is also economically meaningful. For example, one standard deviation increase in regulatory fragmentation increases a firm's recall likelihood by approximately 0.92%, corresponding to 15.4% of the unconditional probability of undertaking a product recall event and resulting in about 516 additional recalls. An alternative but simplistic interpretation shows that a 1% increase in regulatory fragmentation leads to about 172 additional recalls. We establish a causal link

[33] We thank Baker et al. (2016) for providing this monthly data at https://www.policyuncertainty.com/us_monthly.html. To make it compatible with our all-other annual variables, we annualize this monthly data by taking the average of monthly indexes in each year.

between regulatory fragmentation and product quality failures by employing Donald Trump's 2016 surprise election win as an exogenous shock to regulatory fragmentation. Our baseline results also survive a battery of robustness checks, and several alternative explanations.

Furthermore, our cross-sectional analyses reveal that the impacts of regulatory fragmentation on product quality failures are more pronounced for the firms that have larger scope, operate in a greater competitive product market and in a higher policy uncertainty environment. We also find that regulatory fragmentation affects product quality failures through the channels of weakening quality culture, decreasing R&D investment and patent quality.

We acknowledge that the findings presented in this study should be interpreted with caution. A limitation of this study is that we do not assess the net social costs and benefits of regulatory fragmentation. While our analysis identifies product quality failures as an important potential cost, regulatory fragmentation may also generate benefits (e.g., positive externalities for firms or broader society). A comprehensive evaluation of both costs and benefits remains essential for informing policy debates, and future research may undertake such an assessment to provide a more balanced understanding of the welfare implications of regulatory fragmentation.

Despite this limitation, we believe this study makes significant contributions to both product quality failures and regulatory fragmentation literatures by showcasing the novel empirical evidence that regulatory fragmentation is a determinant of product quality failures. The findings of this study have important implications for various stakeholders of firms including policy makers, regulators, board of directors, managers and shareholders. For instance, policy makers and regulatory agencies should take necessary steps to optimally reduce regulatory fragmentation to avoid its unintended adverse consequences on the product quality of US firms. In addition, the board of directors and top management of firms should take regulatory fragmentation into account while formulating policies regarding their product qualities so that they can avoid the adverse consequences of product quality failures on the firm value, reputation and various stakeholders. Finally, while taking investment decisions, shareholders should consider a firm's exposure to regulatory fragmentation to avoid any wealth losses due to product quality failure events in future.

References

Agarwal, S., Lucca, D., Seru, A., and Trebbi, F. (2014). Inconsistent regulators: Evidence from banking. *The Quarterly Journal of Economics*, *129*(2), 889-938.

Armstrong, D. M., Glaeser, S., and Hoopes, J. L. (2025). Measuring firm exposure to government agencies. *Journal of Accounting and Economics*, *79*(1), 101703.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Becker, G. S. (1983). A theory of competition among pressure groups for political influence. *The Quarterly Journal of Economics*, *98*(3), 371-400.

Belson, K. and Fahim, K. (2007). After Extensive Beef Recall, Topps Goes Out of Business. *The New York Times* (October 6), https://www.nytimes.com/2007/10/06/us/06topps.html (Accessed on December 12, 2023)

Belton, K. B., and Graham, J. D. (2020). *Deregulation Under Trump*. Cato Institute.

Bendig, D., Willmann, D., Strese, S., and Brettel, M. (2018). Share repurchases and myopia: Implications on the stock and consumer markets. *Journal of Marketing*, *82*(2), 19-41.

Benmelech, E., and Moskowitz, T. J. (2010). The political economy of financial regulation: Evidence from US state usury laws in the 19th century. *Journal of Finance*, *65*(3), 1029-1073.

Berenson, A., Harris, G., and Meier, B. (2004). Despite Warnings, Drug Giant Took Long Path to Vioxx Recall. *The New York Times* (November 14), https://www.nytimes.com/2004/11/14/business/despite-warnings-drug-giant-took-long-path-to-vioxx-recall.html# (Accessed on December 12, 2023)

Bhattacharya, U., Hsu, P. H., Tian, X., and Xu, Y. (2017). What affects innovation more: policy or policy uncertainty?. *Journal of Financial and Quantitative Analysis*, *52*(5), 1869-1901.

Bischof, J., Daske, H., Elfers, F., and Hail, L. (2022). A tale of two supervisors: Compliance with risk disclosure regulation in the banking sector. *Contemporary Accounting Research*, *39*(1), 498-536.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, *81*(4), 1347-1393.

Business Roundtable (2019). Reducing Regulatory Overlap in the 21st Century. Available at https://s3.amazonaws.com/brt.org/BRT.ReducingRegulatoryOverlapinthe21stCentury.2019.05.31.pdf (Accessed on December 12, 2023)

Chan, M., Petrin, A., and Warzynski, F. (2023). The Effect of R&D on Quality, Productivity, and Welfare. *Working Paper*. National Bureau of Economic Research.

Chang, S., Kalmenovitz, J., and Lopez-Lira, A. (2023). Follow the pipeline: Anticipatory effects of proposed regulations. *Working Paper.*

Charoenwong, B., Kwan, A., and Umar, T. (2019). Does regulatory jurisdiction affect the quality of investment-adviser regulation?. *American Economic Review*, *109*(10), 3681-3712.

Child, T. B., Massoud, N., Schabus, M., and Zhou, Y. (2021). Surprise election for Trump connections. *Journal of Financial Economics*, *140*(2), 676-697.

Coles, J. L., Daniel, N. D., and Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, *79*(2), 431-468.

Core, J., and Guay, W. (2002). Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research*, *40*(3), 613-630.

Costello, A. M., Granja, J., and Weber, J. (2019). Do strict regulators increase the transparency of banks?. *Journal of Accounting Research*, *57*(3), 603-637.

Dagostino, R., Gao, J., and Ma, P. (2023). Partisanship in loan pricing. *Journal of Financial Economics*, *150*(3), 103717.

Dawar, N., and Pillutla, M. M. (2000). Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *Journal of Marketing Research*, *37*(2), 215-226.

Faleye, O., Mehrotra, V., and Morck, R. (2006). When labor has a voice in corporate governance. *Journal of Financial and Quantitative Analysis*, *41*(3), 489-510.

Federal Register (2017a). Reducing Regulation and Controlling Regulatory Costs. https://www.federalregister.gov/documents/2017/02/03/2017-02451/reducing-regulation-and-controlling-regulatory-costs (Accessed on February 15, 2025)

Federal Register (2017b). Comprehensive Plan for Reorganizing the Executive Branch. https://www.federalregister.gov/documents/2017/03/16/2017-05399/comprehensive-plan-for-reorganizing-the-executive-branch (Accessed on February 15, 2025)

Fielkow, B. (2014). With GM's Massive Recall, Is Corporate Culture to Blame?. *Entrepreneur* (April 22). https://www.entrepreneur.com/growing-a-business/with-gms-massive-recall-is-corporate-culture-to-blame/233279 (Accessed on February 15, 2025)

Frésard, L., Hoberg, G., and Phillips, G. M. (2020). Innovation activities and integration through vertical acquisitions. *Review of Financial Studies*, *33*(7), 2937-2976.

Government Accountability Office (GAO) (2014). Consumer Product Safety Oversight: Opportunities Exist to Strengthen Coordination and Increase Efficiencies and Effectiveness (GAO-15-52). Available at https://www.gao.gov/products/gao-15-52 (Accessed on December 12, 2023)

Government Accountability Office (GAO) (2016). Financial Regulation: Complex and Fragmented Structure Could Be Streamlined to Improve Effectiveness (GAO-16-175). Available at https://www.gao.gov/products/gao-16-175 (Accessed on December 12, 2023)

Government Accountability Office (GAO) (2023). Government Efficiency and Effectiveness: Opportunities to Reduce Fragmentation, Overlap, and Duplication and Achieve Billions of Dollars in Financial Benefits (GAO-23-106864). Available at https://www.gao.gov/products/gao-23-106864 (Accessed on December 12, 2023)

Granja, J., and Leuz, C. (2024). The death of a regulator: strict supervision, bank lending, and business activity. *Journal of Financial Economics*, *158*, 103871.

Gulen, H., and Ion, M. (2016). Policy uncertainty and corporate investment. *Review of Financial Studies*, *29*(3), 523-564.

Hoberg, G., and Moon, S. K. (2017). Offshore activities and financial vs operational hedging. *Journal of Financial Economics*, *125*(2), 217-244.

Hoberg, G., and Phillips, G. M. (2024). Scope, scale and competition: The 21st century firm. *Journal of Finance*, *forthcoming*.

Hoberg, G., Phillips, G., and Prabhala, N. (2014). Product market threats, payouts, and financial flexibility. *Journal of Finance*, *69*(1), 293-324.

International Federation of Accountants (IFAC) (2018). Fragmented Financial Regulation: A $780 Billion Tax on the Global Economy. https://www.ifac.org/knowledge-gateway/discussion/fragmented-financial-regulation-780-billion-tax-global-economy (Accessed on December 12, 2023)

Jarrell, G., and Peltzman, S. (1985). The impact of product recalls on the wealth of sellers. *Journal of Political Economy*, *93*(3), 512-536.

Joskow, P. L., and Rose, N. L. (1989). The effects of economic regulation. *Handbook of Industrial Organization*, *2*, 1449-1506.

Kalmenovitz, J. (2023). Regulatory intensity and firm-specific exposure. *Review of Financial Studies*, *36*(8), 3311-3347.
Kalmenovitz, J., Lowry, M., and Volkova, E. (2025). Regulatory fragmentation. *The Journal of Finance*, *80*(2), 1081-1126.
Kim, I. S. (2018). Lobbyview: Firm-level lobbying and congressional bills database. *Working paper.*
Kim, S., and Kim, S. (2024). Fragmented securities regulation, information-processing costs, and insider trading. *Management Science*, *70*(7), 4407-4428.
Kini, O., Shen, M., Shenoy, J., and Subramaniam, V. (2022). Labor unions and product quality failures. *Management Science*, *68*(7), 5403-5440.
Kini, O., Shenoy, J., and Subramaniam, V. (2017). Impact of financial leverage on the incidence and severity of product failures: Evidence from product recalls. *Review of Financial Studies*, *30*(5), 1790-1829.
Kini, O., Shenoy, J., and Subramaniam, V. (2023). Relative leverage and valuation consequences of product recalls along the supply chain. *European Financial Management Association 2023 Annual Meeting.*
Kovenock, D., and Phillips, G. M. (1997). Capital structure and product market behavior: An examination of plant exit and investment decisions. *Review of Financial Studies*, *10*(3), 767-803.
Krueger, A. O. (1974). The political economy of the rent-seeking society. *American Economic Review*, *64*(3), 291-303.
Kugler, M., and Verhoogen, E. (2012). Prices, plant size, and product quality. *Review of Economic Studies*, *79*(1), 307-339.
Kundu, S. (2024). Impact of regulations on firm value: Evidence from the 2016 US presidential election. *Journal of Financial and Quantitative Analysis*, *59*(4), 1659-1691.
Lai, S., Lin, C., and Ma, X. (2024). RegTech adoption and the cost of capital. *Management Science*, *70*(1), 309-331.
Lee, L. F., Hutton, A. P., and Shu, S. (2015). The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research*, *53*(2), 367-404.
Lennox, C. S. (2016). Did the PCAOB's restrictions on auditors' tax services improve audit quality?. *The Accounting Review*, *91*(5), 1493-1512.
Li, Y., Lin, Y., Wang, X., and Yang, S. (2021c). Financial analysts and product quality failures. *Working paper.*
Li, Y., Lin, Y., Wang, X., and Yang, S. (2024). Wall street and product quality: The duality of analysts. *The Accounting Review*, *99*(5), 387-420.
Li, K., Mai, F., Shen, R., and Yan, X. (2021a). Measuring corporate culture using machine learning. *Review of Financial Studies*, *34*(7), 3265-3315.
Li, K., Liu, X., Mai, F., and Zhang, T. (2021b). The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis*, *56*(7), 2545-2583.
Matsa, D. A. (2011). Competition and product quality in the supermarket industry. *The Quarterly Journal of Economics*, *126*(3), 1539-1591.
McFarland, T. (2023). Regulating Inventors. *Working Paper*.
Niskanen, J. (1971). *Bureaucracy and representative government*. Routledge.
Phillips, G., & Sertsios, G. (2013). How do firm financial conditions affect product quality and pricing?. *Management Science*, *59*(8), 1764-1782.
Pigou, A. (1938). *The economics of welfare*. Routledge.
Posner, R. A. (1974). *Theories of economic regulation* (No. w0041). National Bureau of Economic Research.

Rose, N. L. (1990). Profitability and product quality: Economic determinants of airline safety performance. *Journal of Political Economy*, *98*(5, Part 1), 944-964.

Ruddick, G. (2015). Volkswagen chief quits over emissions scandal as car industry faces crisis. *The Guardian* (September 24). https://www.theguardian.com/business/2015/sep/23/volkswagen-chief-martin-winterkorn-quits-emissions-scandal (Accessed on February 15, 2025)

Sedgwick (2025). U.S. product recalls reach second-highest level in six years during 2024. https://www.sedgwick.com/press-release/u-s-product-recalls-reach-second-highest-level-in-six-years-during-2024/ (Accessed on February 15, 2025)

Singh, K., and Grewal, R. (2023). Lobbying and Product Recalls: A Study of the US Automobile Industry. *Journal of Marketing Research*, *60(4)*, 728-749.

Steven, A. B., and Britto, R. A. (2016). Emerging market presence, inventory, and product recall linkages. *Journal of Operations Management*, *46*, 55-68.

Steven, A. B., Dong, Y., and Corsi, T. (2014). Global sourcing and quality recalls: An empirical study of outsourcing-supplier concentration-product recalls linkages. *Journal of Operations Management*, *32*(5), 241-253.

Thirumalai, S., and Sinha, K. K. (2011). Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences. *Management Science*, *57*(2), 376-392.

Wagner, A. F., Zeckhauser, R. J., and Ziegler, A. (2018). Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics*, *130*(2), 428-451.

Wowak, A. J., Mannor, M. J., and Wowak, K. D. (2015). Throwing caution to the wind: The effect of CEO stock option pay on the incidence of product safety problems. *Strategic Management Journal*, *36*(7), 1082-1092.

Appendix A: Recall Data Construction and Matching Procedures

Following standard recall literature (Kini et al., 2017, 2022; and Li et al., 2024), we construct the product recall database by manually collecting recall data of the US firms from the regulatory filings from three federal regulatory agencies as illustrated below.

First, we collect automobile recall data on vehicles, equipment, car tires or seats from the National Highway Traffic Safety Administration (NHTSA) available at https://www.nhtsa.gov/nhtsa-datasets-and-apis. This data includes the following information such as record number, recall campaign number, recalling firm, reason for recall, number of recalled units, vehicle make/model, report received date, record creation date, recall initiator, and recall remedy from 1980 to 2023. Second, we collect consumer product recall data on various consumer products such as children's products, home furnishings, household appliances, hardware and tools, heating and cooling equipment etc. from the US Consumer Product Safety Commission (CPSC) available at https://www.cpsc.gov/Recalls. This data includes the following information such as unique recall number, recall date, recall reason, number of recalled units, hazard description, incidents, recall remedy, recall initiator and the names of manufacturer, importer, and distributor from 1966 to 2023.

Finally, we collect recall data on drugs, foods and medical devices from the Food and Drug Administration (FDA) based on the weekly enforcement reports available at https://www.accessdata.fda.gov/scripts/ires/index.cfm from 2012 to 2023. In addition, we collect FDA recall data prior to 2012 from several archived webpages. For instance, we collect archived weekly enforcement reports from 2010 to 2011 available at https://wayback.archive-it.org/7993/20161021235226/http://www.fda.gov/Safety/Recalls/EnforcementReports/Archived/default.htm, from 2007 to 2009 available at https://www.fda.gov/safety/recalls-market-withdrawals-safety-alerts/archive-recalls-market-withdrawals-safety-alerts and from 1995 to 2006 available at https://web.archive.org/web/20070909062024/http:/www.fda.gov/opacom/Enforce.html.

Unfortunately, none of these recall datasets contain any unique firm identifiers (*e.g.*, GVKEY) to match with standard databases (e.g., Compustat). Hence, to find out which of these recalling firms are publicly listed in the US, we follow the following procedures to link each unique recalling firm name in the recall database to its unique GVKEY identifier in Compustat.

First, we create a linking file that includes each unique company name on Compustat and its GVKEY along with the beginning and ending year. Then, we manually search for the name of each recalling firm in that linking file. While searching, we only use firm names excluding any suffix items (e.g., Inc., Corp., Ltd. and so on) and took care of firm names having "1st" or "21st". Finally, when we find a name match, we check if the recall year is within the Compustat beginning and ending year. If both criteria are satisfied, we record the GVKEY of the Compustat firm as the GVKEY of the recalling firm in the recall database.

However, if a name match is not successful, it is likely that the firm is a private firm or a subsidiary of a publicly listed parent company. Then, we match the recalling firm name with the unique subsidiary firm names in the WRDS Company Subsidiary Database. When we find a name match, we check if the recalling firm has been acquired by the parent company before the recall year (but has not been divested before the recall). If these criteria are fulfilled, we record the GVKEY of the parent company as the GVKEY of the recalling firm. Sometimes we also rely on Google searches and the company's website information to make additional inferences on ownership.

Finally, regarding the recalling firms that are still unmatched because of not satisfying the above criteria, we keep the GVKEY field blank as the recalling firm is plausibly a private firm at the time of the recall. Consequently, these private recalling firms are excluded from our recall sample.

Appendix B: The Firm-specific Measure of Regulatory Fragmentation

Our key independent variable is *Regulatory Fragmentation*, a firm-specific continuous measure of regulatory fragmentation that varies across cross-section and time. Kalmenovitz et al. (2025) have recently constructed this novel and comprehensive measure by exploiting the novel data from Federal Register (FR)- the US federal government's official daily publication where every federal agency reports their comprehensive activities including final rules, drafts of proposed rules, and enforcements. Below is a brief discussion of the steps how they construct the regulatory fragmentation measure.[34]

First, they use machine learning methods (*i.e.*, Latent Dirichlet Analysis- LDA) to classify all federal activities into 100 regulatory topics through textual analysis of the FR.

Second, they identify which federal agencies regulate each topic and compute each topic's fragmentation across federal agencies.

Third, they compute each topic's relevance for each firm-year based on the percentage of words in a firm's 10-K report dedicated to the topic.

Finally, they calculate regulatory fragmentation measure by multiplying each topic's fragmentation with its relevance for every firm-year and aggregate the products across all 100 topics. This measure ranges from 0 to 1 where greater value means higher regulatory fragmentation.

[34] See Kalmenovitz et al. (2025) for the detailed construction procedures of this measure.

Appendix C: Definitions of Variables

Variables	Definition
Recall related variables	(Source: NHTSA, FDA and CPSC)
Recall Dummy	A dummy variable taking the value of one if a firm recalls its products in a year t and 0 otherwise.
Recall Frequency1	Cumulative number of recalls of a firm in year t.
Recall Frequency2	Cumulative number of recalls of a firm in year t and $t+1$.
Recall Frequency3	Cumulative number of recalls of a firm in year t, $t+1$ and $t+2$.
Recall Quantity	Natural logarithm of the annual quantity of recalled product items.
Complaints Ratio	Total number of all types of customer complaints submitted to NHTSA about a product of a firm in a year, standardized by dividing by the maximum number of customer complaints about the firm over the sample period.
Recall Severity	A categorical variable taking the value of three for FDA Class I (most severe) recalls, two for FDA Class II recalls, 1 for FDA Class III (least severe) recalls and 0 for the control firms without any recalls.
Voluntary Dummy	A categorical variable taking the value of 2 for firm-initiated recalls, 1 for regulator-initiated recalls and 0 for the control firms without any recalls.
Regulatory Fragmentation related variables	(Source: Kalmenovitz et al. (2025))
Regulatory Fragmentation	$= 1 - \Sigma_{Topic}\Sigma_{Agency}P_{Firm,Topic,Year}\omega^2_{Topic,Agency,Year}$ A text-based measure that calculates the weighted average of each of the 100 regulatory topic's fragmentation across federal agencies each year ($\omega_{Topic,Agency,Year}$) where the weights are each topic's relevance for each firm-year based on the percentage of words in a firm's 10-K report dedicated to the topic ($P_{Firm,Topic,Year}$).
Topic Dispersion within Firm	$= 1 - \Sigma_{Topic}P^2_{Firm,Topic,Year}$, where $P_{Firm,Topic,Year}$ is the percentage of words in a firm's 10-K report every year dedicated to a given regulatory topic.
Regulation Quantity	$= \Sigma_{Topic}P_{Firm,Topic,Year}$. *log(Topic Words in FR)*, where $P_{Firm,Topic,Year}$ is the percentage of words in a firm's 10-K report every year dedicated to each of 100 regulatory topics and *log(Topic Words in FR)* is the natural logarithm of the number of words in each topic in the Federal Register.
Regulatory Fragmentation 5Y Average	The weighted average of regulatory activities based on the Federal Register over the past five years, where the weights for year $t-1$, $t-2$, $t-3$, $t-4$, and $t-5$ are 1, 1/2, 1/3, 1/4, and 1/5, respectively.
Regulatory Fragmentation Dummy	A dummy variable taking the value of one (zero) if a firm belongs to above (below) the median value of *Regulatory Fragmentation* each year.
Log(10K Words#)	Natural logarithm of the number of words in a firm's 10K report.
Firm-specific variables	(Source: Compustat, except mentioned otherwise)
R&D	Research and development expenditure divided by total assets.
R&D Dummy	A dummy taking the value of one if the firm's R&D is below the sample median in a year and zero otherwise.
Financial Leverage	Long-term debt divided by total assets.
Profitability	Income before extraordinary items divided by total assets.

Book-to-Market	Book value of common equity divided by the market value of common equity of a firm.
Size	Natural logarithm of a firm's market value of equity.
Herfindahl Index (HHI)	Sales-based Herfindahl index for the three-digit SIC industry of a firm.
Total factor productivity (TFP)	Following Kovenock and Phillips (1997) and Faleye et al. (2006) and assuming a Cobb-Douglas production function, we regress the logarithm of sales revenue on the logarithm of number of employees and the logarithm of net property, plant, and equipment for each two-digit SIC industry group. The residual of this regression is the Total factor productivity for the firms of two-digit SIC industry group of the firm.
Post	A dummy variable taking the value of one for the years 2017 to 2019 and zero otherwise.
Treatment	A dummy variable taking the value of one for the treatment firms during the event window (2014-2019) and zero otherwise.
Trend	A categorical variable that equals one in the year 2016, two in 2015 and three in 2014.
Quality Culture Dummy	A dummy taking the value of one if the firm's corporate quality culture score (i.e., a text-based firm-level measure of corporate quality culture developed by Li et al. (2021a)) is below the sample median score in a year and zero otherwise.
Patent Citation Dummy	A dummy taking the value of one if the firm's citation per patent is below the sample median in a year and zero otherwise (Source: WRDS US Patents).
Patent Number Dummy	A dummy by taking the value of one if the firm's number of patent is below the sample median in a year and zero otherwise (Source: WRDS US Patents).
Input Quality Dummy	A dummy taking the value of one if a firm sources its input materials from developed countries only and zero otherwise. (Source: Hoberg and Moon (2017)).
Vertical Integration	The text-based industry-adjusted vertical integration score of a firm. (Source: Frésard et al. (2020)).
Free Cash Flow (FCF) Shock	FCF of a year minus prior 3-year average FCF, where FCF= (income before extraordinary items+ depreciation- change in net working capital-capital expenditures) / market value of assets).
Business Segments	Number of business segments of a firm in a year (Source: Compustat Segments).
Financial Analysts	Number of financial analysts following a firm in a year (Source: I/B/E/S).
Lobbying	A firm's lobbying expenditure in mln$ divided by total assets (Source: Kim (2018)).
Labor Unionization	Unionization rate of a firm's primary industry in a year (Source: Union Stats). We assign industry unionization rates to our sample firms by manually matching the 4-digit Census Industry Classification (CIC) industries of Union Stats database with the corresponding 4-digit SIC industries (if not possible, then corresponding 3-digit SIC industries) of Compustat database.
Stock Repurchase	A dummy taking the value of one if a firm repurchases stocks in a year and zero otherwise.
No. of Suppliers	Number of major suppliers of a firm based on Compustat Segment database. As per FASB requirement, firms report the names of their

	customers comprising at least 10% of their sales. We utilize this Compustat Segment data to detect the suppliers for all Compustat firms and then estimate the number of suppliers for our sample firms for each year. Though it is not possible to capture all the suppliers for a firm based on these databases, we believe that this is a reasonable proxy as our proxy for the number of suppliers is more likely to have a monotonic relationship with the actual number of suppliers (Kini et al., 2017).
CEO Stocks and Options	Natural logarithm of the value of CEOs' stocks and options portfolio. (Source: Coles et al. (2006)
CEO Delta	Dollar changes in CEOs' wealth due to 1% change in the firm's stock price. (Source: Coles et al. (2006)
CEO Vega	Dollar changes in CEOs' wealth due to 1% change in the standard deviation of the firm's stock returns. (Source: Coles et al. (2006)
Product Market Fluidity	A text-based measure of product market competition indicating the magnitude of competitive threat and product market changes surrounding a firm, developed by Hoberg et al. (2014).
Firm Scope	The number of product markets a firm operates in. (Source: Hoberg and Phillips, 2024).
Policy Uncertainty Index	An index indicating the aggregate level of news-based policy uncertainty each year, developed by Baker et al. (2016).

Table 1: Recall Sample Distribution

In this table, Panel A exhibits year-wise number of recall events by recalling firms during 1996-2023. These recall events are governed by three US regulatory agencies including the National Highway Traffic Safety Administration (NHTSA), the Food and Drug Administration (FDA), and the Consumer Product Safety Commission (CPSC). Panel-B shows two-digit SIC industry-wise number of recall events of top 20 industries in descending order over the sample period.

Panel- A: Year-wise number of recall events

Recall Year	No. of recall events			
	NHTSA	FDA	CPSC	Total
1996	67	67	12	146
1997	11	56	6	73
1998	35	100	10	145
1999	29	116	18	163
2000	99	169	26	294
2001	76	113	27	216
2002	80	214	28	322
2003	117	208	26	351
2004	178	269	45	492
2005	119	341	66	526
2006	95	286	56	437
2007	122	153	80	355
2008	99	64	46	209
2009	78	133	56	267
2010	100	371	52	523
2011	103	428	50	581
2012	96	451	41	588
2013	74	508	36	618
2014	178	549	38	765
2015	152	452	38	642
2016	127	540	32	699
2017	117	420	44	581
2018	124	477	32	633
2019	134	430	21	585
2020	148	274	36	458
2021	198	341	33	572
2022	203	285	27	515
2023	173	205	38	416
Total	**3,132**	**8,020**	**1,020**	**12,172**

Panel- B: Two-digit SIC industry-wise number of recall events (Top 20 industries in descending order)

Two-digit SIC	Description of Industry	No. of Recalls
38	Measuring, Analyzing and Controlling Instruments	4,388
37	Transportation Equipment	2,845
28	Chemicals and Allied Products	1,670
20	Food and Kindred Products	542
99	Nonclassifiable Establishments	503
35	Industrial and Commercial Machinery and Computer Equipment	387
54	Food Stores	266
53	General Merchandise Stores	209
51	Wholesale Trade - Nondurable Goods	190
59	Miscellaneous Retail	154
36	Electronic and Other Electrical Equipment and Components	137
80	Health Services	115
73	Business Services	82
50	Wholesale Trade - Durable Goods	65
25	Furniture and Fixtures	64
30	Rubber and Miscellaneous Plastic Products	61
39	Miscellaneous Manufacturing Industries	61
24	Lumber and Wood Products, Except Furniture	60
56	Apparel and Accessory Stores	59
57	Home Furniture, Furnishings and Equipment Stores	32
	Other Industries	282
	Total	**12,172**

Table 2: Summary Statistics

This table presents the summary statistics of the key variables used in this study covering product recalls under three US federal agencies such as NHTSA, FDA and CPSC during 1996-2023. All continuous variables are winsorized at 1% and 99% levels. All variables are defined in Appendix C.

Variables	Mean	Standard Deviation	p25	Median	p75	N
Recall Dummy	.06	.23	0.00	0	0	56348
Recall Frequency1	.12	.56	0.00	0	0	56348
Regulatory Fragmentation	.80	.03	0.78	.80	.82	56348
Topic Dispersion within Firm	.94	.01	0.93	.94	.95	56348
R&D	.06	.11	0.00	.01	.08	56348
Financial Leverage	.16	.17	0.00	.12	.28	56348
Book-to-Market	.57	.50	0.24	.43	.73	56348
Profitability	-.02	.21	-0.03	.03	.08	56348
Herfindahl Index (HHI)	.01	.01	0.00	0	.01	56348
Total Factor Productivity (TFP)	.17	.70	-0.17	.14	.55	56348
Size (Log)	6.30	2.10	4.76	6.25	7.72	56348
Size (Million$)	4635.93	14542.48	116.67	516.10	2263.81	56348

Table 3: Baseline Regressions: Regulatory Fragmentation and Recall likelihood

This table presents the baseline results of the association between regulatory fragmentation and recall likelihood of US public firms during 1996-2023. *Recall Dummy* is the dependent variable that takes the value of one if a firm recalls its products in year *t* and 0 otherwise. *Regulatory Fragmentation* is the key independent variable measured by the weighted average across all 100 regulatory topics of each topic's fragmentation across federal agencies where weights are each topic's relevance for each firm-year based on the percentage of words in a firm's 10-K report dedicated to the topic. All independent variables are one-year lagged to address the reverse causality concern. The marginal effects of Probit regression model (*Probit*) are presented in first three columns and the coefficients of Linear Probability Model (*LPM*) are in last two columns. In Columns (1), (2) and (4), we control for both year fixed effects (FE) and Fama-French 48 Industry FE, whereas Columns (3) and (5) show a tighter specification where we control for Fama-French 48 Industry×Year FE. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. The coefficients of constant are suppressed for brevity. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

	Dependent Variable: *Recall Dummy*				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Probit	***Probit***	***Probit***	***LPM***	***LPM***
Regulatory Fragmentation	**0.8007*** **	**0.3071*** **	**0.4358*** **	**0.4712*** **	**0.4468*** **
	(0.1084)	(0.0862)	(0.1221)	(0.0948)	(0.1022)
Topic Dispersion within Firm		-0.2408	-0.3242	-0.5295**	-0.4935**
		(0.1557)	(0.2081)	(0.2105)	(0.2173)
R&D		-0.2107***	-0.2712***	-0.1257***	-0.1244***
		(0.0297)	(0.0409)	(0.0208)	(0.0209)
Financial Leverage		0.0440***	0.0593***	0.0480***	0.0515***
		(0.0096)	(0.0128)	(0.0110)	(0.0112)
Book-to-Market		0.0176***	0.0217***	0.0193***	0.0194***
		(0.0035)	(0.0047)	(0.0032)	(0.0033)
Profitability		-0.0194*	-0.0283**	-0.0080	-0.0066
		(0.0109)	(0.0140)	(0.0085)	(0.0088)
Size		0.0235***	0.0308***	0.0260***	0.0260***
		(0.0012)	(0.0024)	(0.0018)	(0.0019)
Herfindahl Index (HHI)		0.8730***	1.1266***	1.4315***	1.3779***
		(0.3151)	(0.4163)	(0.4858)	(0.4923)
Total Factor Productivity (TFP)		0.0024	0.0037	0.0019	0.0016
		(0.0025)	(0.0033)	(0.0024)	(0.0024)
Pseudo/Adjusted R^2	0.196	0.324	0.317	0.160	0.167
Observations	56072	56072	42363	56348	56348
Year FE	Yes	Yes	No	Yes	No
Industry FE	Yes	Yes	No	Yes	No
Industry×Year FE	No	No	Yes	No	Yes
Standard Errors Clustered	Firm-level	Firm-level	Firm-level	Firm-level	Firm-level

Figure 1: Average Regulatory Fragmentation during the Sample Period

This figure illustrates average regulatory fragmentation over the sample period (1996-2023) and shows the declining trend in average regulatory fragmentation since 2017 when the US President Donald Trump took his office.

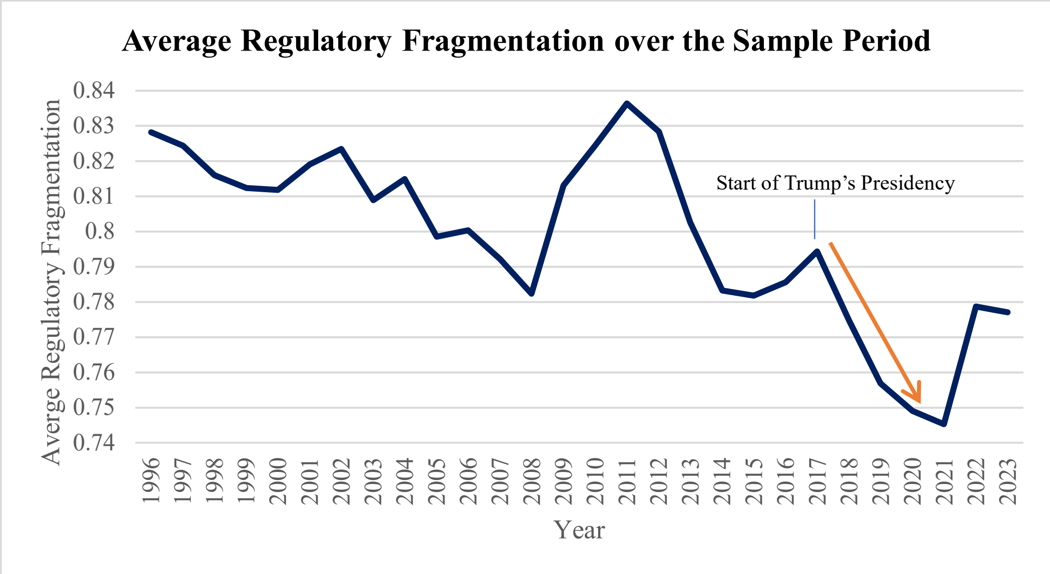

Table 4: Difference-in-Difference Analysis Using a Quasi-Natural Experiment

This table presents the results of Difference-in-Difference (DiD) analyses exploiting the US President Trump's surprise election win in November 2016 as an exogenous shock to regulatory fragmentation. We use a 6-year event window including three years before election (2014-2016) and three years after election (2017-2019). *Post* is a dummy variable taking the value of one for the years 2017 to 2019 and zero otherwise. We apply Propensity Score Matching to match treatment and control firms. Firms with the number of proposed US federal active regulations in the pipeline above (below) the sample median during pre-election period are categorized as treatment (control) firms. *Treatment* is a dummy variable taking the value of one for the treatment firms during the event window and zero otherwise. *Recall Dummy* is the dependent variable that takes the value of one if a firm recalls its products in year *t* and 0 otherwise. Panel A shows the results of the validity of parallel trend assumption. In Column (1), *Trend* is a categorical variable that equals one in the year 2016, two in 2015 and three in 2014. In Column (2), $Year_j$ is a dummy variable taking the value of one for year *j* and zero otherwise (where *j* ranges from 2014 to 2019). Panel B shows the results of main DiD regressions. In Panel C, we conduct two falsification tests using two Psuedo-election year events: year 2013 and 2019 in Columns (7) and (8), respectively. In all specifications, we present the marginal effects of Probit regression models except Columns (5) and (6) showing the coefficients of Linear Probability Models (LPM). We include all baseline controls (suppressed for brevity) in all specifications. We control for year FE and Fama-French 48 industry FE in all specifications except Columns (4) and (6) where we control for Fama-French 48 Industry×Year FE as tighter specifications. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

Dependent Variable:	**Panel-A: Parallel Trend Tests**		**Panel-B: Main DiD Regressions**				**Panel-C: Falsification Tests**	
Recall Dummy	***Probit***	***Probit***	***Probit***	***Probit***	***LPM***	***LPM***	***Probit***	***Probit***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treatment×Trend	-0.0036							
	(0.0127)							
Treatment×$Year_{2015}$		-0.0207						
		(0.0249)						
Treatment×$Year_{2016}$		-0.0079						
		(0.0255)						
Treatment×$Year_{2017}$		-0.0414*						
		(0.0246)						
Treatment×$Year_{2018}$		-0.0436*						
		(0.0265)						
Treatment×$Year_{2019}$		-0.0409						
		(0.0273)						
Treatment×Post			**-0.0322****	**-0.0426****	**-0.0327****	**-0.0310***	-0.0207	0.0190
			(0.0142)	(0.0179)	(0.0153)	(0.0167)	(0.0154)	(0.0171)
Treatment	0.0048	0.0072	-0.0027	-0.0041	0.0034	0.0014	-0.0047	-0.0052
	(0.0281)	(0.0192)	(0.0118)	(0.0148)	(0.0125)	(0.0131)	(0.0112)	(0.0121)
Post			-0.0155	-0.0350	0.0000	0.0000	-0.0506***	-0.0472**
			(0.0152)	(0.0759)	(.)	(.)	(0.0191)	(0.0224)

Table 4 (*continued*)

Dependent Variable: *Recall Dummy*	**Panel-A: Parallel Trend Tests**		**Panel-B: Main DiD Regressions**				**Panel-C: Falsification Tests**	
	Probit	***Probit***	***Probit***	***Probit***	***LPM***	***LPM***	***Probit***	***Probit***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Trend	-0.0066							
	(0.0111)							
$Year_{2015}$		-0.0024						
		(0.0205)						
$Year_{2016}$		-0.0131						
		(0.0223)						
$Year_{2017}$		0.0191						
		(0.0209)						
$Year_{2018}$		-0.0026						
		(0.0223)						
$Year_{2019}$		-0.0087						
		(0.0230)						
Pseudo/Adjusted R^2	0.337	0.343	0.343	0.327	0.241	0.232	0.368	0.358
Observations	2863	5279	5279	4262	5900	5883	3851	3999
Baseline Controls included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Industry FE	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Year×Industry FE	No	No	No	Yes	No	Yes	No	No
Standard Error Clustered	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level

Table 5: Underlying Channels

This table demonstrates the results of underlying channels through which regulatory fragmentation affects product quality failures. We consider several potential channels such as corporate quality culture, innovation input (i.e., R&D investment), innovation outputs (i.e., patent numbers and citations) and input quality. *Recall Dummy* is the dependent variable that takes the value of one if a firm recalls its products in year *t* and 0 otherwise. *Regulatory Fragmentation* is the weighted average across all 100 regulatory topics of each topic's fragmentation across federal agencies where weights are each topic's relevance for each firm-year based on the percentage of words in a firm's 10-K report dedicated to the topic. *Quality Culture Dummy* indicates the poor corporate quality culture of a firm by taking the value of one if the firm's corporate quality culture score (i.e., a text-based firm-level measure of corporate quality culture developed by Li et al. (2021a)) is below the sample median score in a year and zero otherwise. *R&D Dummy* indicates the lower R&D investment of a firm by taking the value of one if the firm's R&D is below the sample median in a year and zero otherwise. *Patent Citation Dummy* indicates the poor patent quality of a firm by taking the value of one if the firm's citation per patent is below the sample median in a year and zero otherwise. *Patent Number Dummy* indicates the lower patent numbers of a firm by taking the value of one if the firm's number of patent is below the sample median in a year and zero otherwise. *Input Quality Dummy* indicates the lower quality of input materials of a firm by taking the value of one if a firm sources its input materials from only developing countries in a year and zero otherwise. In all specifications, we include all baseline controls (suppressed for brevity) and we control for year FE and Fama-French 48 industry FE. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

Variables	**Dependent Variable: *Recall Dummy***				
	Quality Culture	**Innovation**	**Patent Citations**	**Patent Numbers**	**Input Quality**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Regulatory Fragmentation × Quality Culture Dummy	**0.3322*****				
	(0.1106)				
Regulatory Fragmentation × R&D Dummy		**0.1416***			
		(0.0848)			
Regulatory Fragmentation × Patent Citation Dummy			**0.4442***		
			(0.2499)		
Regulatory Fragmentation × Patent Number Dummy				0.0390	
				(0.2448)	
Regulatory Fragmentation × Input Quality Dummy					0.1202
					(0.3209)
Regulatory Fragmentation	0.1447	0.2212**	0.0999	0.3135	0.3557***
	(0.1540)	(0.0983)	(0.2770)	(0.2967)	(0.1101)
Quality Culture Dummy	-0.2530***				
	(0.0880)				
R&D Dummy		-0.1272*			
		(0.0686)			
Patent Citations Dummy			-0.3906*		
			(0.2012)		
Patent Number Dummy				-0.0140	
				(0.1970)	
Input Quality Dummy					-0.0976
					(0.2615)
Pseudo R^2	0.341	0.320	0.351	0.345	0.321
Observations	28420	56072	11034	11217	36439
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Standard Errors Clustered	Firm level	Firm level	Firm level	Firm level	Firm level

Table 6: Robustness Tests

This table presents the results of several robustness tests of our baseline findings. In Panel A, we run firm fixed effect regressions where we control for firm FE and year FE in Column (1) and for firm FE and Fama-French 48 industry × year FE in Column (2). In Panels A and C, *Recall Dummy* is the dependent variable, a key measure of product quality failures, taking the value of one if a firm recalls its products in year *t* and 0 otherwise. In Panel B, we use several alternative measures of product quality failures as dependent variables such as Recall Frequency (e.g., *Recall Frequency1, Recall Frequency2, Recall Frequency3* are the cumulative number of recalls of a firm in year *t;* year *t* and *t+1*; and year *t, t+1* and *t+2*, respectively) and Recall Quantity (e.g., *Recall Quantity)* is the natural logarithm of total units of products recalled in year *t*) in Col. (3) to (6), respectively. In Panel C, we use two alternative measures of Regulatory Fragmentation such as *Regulatory Fragmentation 5Y Average* (i.e., the weighted average of regulatory activity based on the Federal Register over the past five years, where the weights for year *t-1*, *t-2*, *t-3*, *t-4*, and *t-5* are 1, 1/2, 1/3, 1/4, and 1/5, respectively) and *Regulatory Fragmentation Dummy* (i.e., taking the value of one (zero) if a firm belongs to above (below) the median value of Regulatory Fragmentation each year) in Col. (7) and (8), respectively. In all specifications, all independent variables are one-year lagged to address the reverse causality concern. Columns (1), (2) and (6) shows OLS regressions, Columns (3) to (5) show Poisson regressions, and Columns (7) to (8) show the marginal effects of Probit regressions. In all specifications, we include all baseline controls (suppressed for brevity). We control for year FE and Fama-French 48 industry FE in Columns (3) to (8). Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

	Panel A: Firm FE Regressions		**Panel B: Alternative measures of Product Quality Failures**				**Panel C: Alternative measures of Regulatory Fragmentation**	
Variables	**Recall Likelihood**		**Recall Frequency**			**Recall Quantity**	**Regulatory Fragmentation 5Y Average**	**Regulatory Fragmentation Dummy**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Regulatory Fragmentation	**0.288***** (0.100)	**0.255**** (0.104)	**4.997***** (1.889)	**4.413**** (2.075)	**4.465**** (2.201)	**4.462***** (0.889)	**0.368***** (0.139)	**0.005*** (0.003)
Adjusted / Pseudo R^2	0.007	0.028	0.335	0.387	0.41	0.159	0.316	0.323
Observations	56348	56348	56072	47034	39950	56348	34703	56072
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No	No	No	No
Industry × Year FE	No	Yes	No	No	No	No	No	No
Standard Errors Clustered	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Table 7: Do Recalls Capture Product Quality Failures or Regulatory Effectiveness?

This table presents the results of several tests to rule out the plausibility of regulators' effectiveness where higher recalls may indicate the effectiveness of multiple regulators who may detect more defective products. To rule out this alternative explanation, we conduct three tests. First, based on the customer complaints to the automobile regulator NHTSA regarding defective automobiles, we run OLS regressions in Column (1) where the dependent variable is *Complaints Ratio* (i.e., total no. of all types of customer complaints about a product of a firm in a year, standardized by dividing by the maximum no. of customer complaints about the firm over the sample period). Second, we conduct recall severity test in Column (2) using Ordered probit regression model where the dependent variable is *Recall Severity Dummy*- a categorical variable taking the value of three for FDA Class I (i.e., most severe) recalls, two for FDA Class II recalls, 1 for FDA Class III (least severe) recalls and 0 for the control firms without any recalls. The coefficient of Regulatory Fragmentation in Column (2) is the average marginal effects for the outcome of most severe Class I recalls. Finally, we conduct voluntary versus mandatory recall test in Column (3) using Ordered probit regression model where the dependent variable is *Voluntary Dummy*- a categorical variable taking the value of 2 for firm-initiated voluntary recalls, 1 for regulator-initiated mandatory recalls and 0 for the control firms without any recalls. The coefficient of Regulatory Fragmentation in Column (3) is the average marginal effects for the outcome of voluntary recalls. In all specifications, all independent variables are one-year lagged to address the reverse causality concern, and we include all baseline controls, year FE and Fama-French 48 industry FE (except firm FE in Column (1)). Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level (except FF48 industry level in Column (1)). Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

Variables	**Customer Complaints (NHTSA)**	**Recall Severity**	**Voluntary vs. Mandatory Recalls**
	(1)	**(2)**	**(3)**
Regulatory Fragmentation	**0.971***	**0.0321****	**0.3947*****
	(0.503)	(0.0128)	(0.1049)
Adjusted / Pseudo R^2	0.072	0.327	0.431
Observations	1867	56348	47135
Baseline Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Firm FE	Yes	No	No
Standard Error Clustered	Industry level	Firm level	Firm level

Table 8: Cross-sectional Analyses

This table states the results of cross-sectional heterogeneity tests to see whether our baseline findings differ between sub-samples based on different characteristics of firms. Panel A deals with product market competition where a firm belonging to the above (below) median of *Product Market Fluidity,* a text-based measure developed by Hoberg et al. (2014) regarding a firm's competitive threat and product market change surrounding the firm, in a year is grouped into High (Low) subsample. Panel B deals with firm scope where a firm belonging to the above (below) median of *Firm Scope,* a text-based measure developed by Hoberg et al. (2024) regarding a firm's number of product markets it operates in, in a year is grouped into Large (Small) subsample. Panel D deals with news-based policy uncertainty where a firm belonging to the above (below) median of news-based *Policy Uncertainty* index (Baker et al., 2016) in a year is grouped into High (Low) subsample. In all specifications, *Recall Dummy* is the dependent variable taking the value of one if a firm recalls its products in year *t* and 0 otherwise. All independent variables are one-year lagged to address the reverse causality concern, and we include all baseline controls (suppressed for brevity), year FE and Fama-French 48 industry FE. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

Variables	**Panel A: Product Market Competition**		**Panel B: Firm Scope**		**Panel C: Policy Uncertainty**	
	High	**Low**	**Large**	**Small**	**High**	**Low**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Regulatory Fragmentation	**0.3679*** **	**0.1957** **	**0.4111*** **	0.1199	**0.4465*** **	**0.2144*** **
	(0.0725)	(0.0921)	(0.0822)	(0.0843)	(0.0886)	(0.0720)
Pseudo R^2	0.401	0.280	0.371	0.287	0.341	0.316
Observations	25504	27596	25714	25374	25729	29981
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err. Clustered	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level
Chi^2 test statistic:						
High=Low	3.41*				3.34*	
Large=Small			3.58*			

Online Appendix

Table OA1: Multicollinearity Tests

This table presents two types of multicollinearity tests namely Correlation Matrix and Variance Inflation Factor (VIF) in Panel- A and B, respectively. All variables are defined in Appendix C. Here, * refers to statistical significance at 5% level.

Panel- A: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Recall Dummy	1.00									
(2) Regulatory Fragmentation	0.02*	1.00								
(3) Topic Dispersion within Firm	-0.01	-0.02*	1.00							
(4) R&D	-0.05*	-0.04*	0.31*	1.00						
(5) Financial Leverage	0.06*	-0.14*	-0.20*	-0.26*	1.00					
(6) Book-to-Market	-0.07*	0.04*	-0.07*	-0.20*	0.00	1.00				
(7) Profitability	0.07*	0.13*	-0.22*	-0.63*	0.09*	0.00	1.00			
(8) Size	0.21*	-0.08*	-0.16*	-0.14*	0.23*	-0.42*	0.28*	1.00		
(9) HHI	0.03*	0.02*	-0.05*	-0.24*	0.05*	0.08*	0.14*	0.00	1.00	
(10) TFP	0.01*	-0.07*	-0.01*	-0.07*	-0.05*	-0.06*	0.23*	0.07*	0.04*	1.00

Panel- B: Variance Inflation Factor (VIF)

Variables	VIF
R&D	2.06
Profitability	1.97
Size	1.46
Book-to-Market	1.34
Financial Leverage	1.19
Topic Dispersion within Firm	1.15
Total Factor Productivity	1.08
Regulatory Fragmentation	1.07
HHI	1.06

Table OA2: Comparisons of Treatment and Control Samples in Propensity Score Matching (PSM)

This table shows the *t*-statistics of the mean differences of covariates between the treatment sample (*i.e.*, recalling firms having at least one recall during the sample period) and the control sample (*i.e.*, non-recalling firms that belong to the same three-digit SIC industry as the recalling firms but do not have any single recall event during the sample period) under Propensity Score Matching (PSM) method. ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

Variables	**Pre-PSM**			**Post PSM**		
	Treatment	**Control**	**Difference**	**Treatment**	**Control**	**Difference**
Topic Dispersion within Firm	0.936	0.937	-0.001**	0.937	0.937	0.000
R&D	0.023	0.062	-0.039***	0.055	0.055	-0.001
Financial Leverage	0.245	0.188	0.057***	0.191	0.191	-0.001
Profitability	0.022	0.000	0.023***	0.003	-0.002	0.004
HHI	0.008	0.006	0.002***	0.007	0.007	0.000
Book-to-Market	0.529	0.447	0.082***	0.450	0.426	0.024***
TFP	0.293	0.361	-0.067***	0.339	0.301	0.037***
Size	7.593	7.297	0.296***	7.375	7.490	-0.115***

Table OA3: Additional Robustness Tests

This table presents the marginal effects of Probit regressions for several additional robustness test results of our baseline findings. We exclude the NHTSA automobile sample in Column (1), exclude the FDA sample in Column (2), consider the commencement of sample period from 2012 (as FDA adopted new data format methodology since 2012) in Column (3), exclude top three recalling two-digit SIC industries in Column (4), and controlling for *Regulation Quantity* and *Log(10K Words#)* in Columns (5) and (6), respectively. *Recall Dummy* is the dependent variable taking the value of one if a firm recalls its products in year *t* and 0 otherwise. All independent variables are one-year lagged to address the reverse causality concern. In all specifications, we include all baseline controls (suppressed for brevity), year FE and Fama-French 48 industry FE. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

	Excluding NHTSA sample	**Excluding FDA sample**	**2012-23 Sample**	**Excluding top 3 industries**	**Regulation Quantity**	**10K Words**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Regulatory Fragmentation	**0.339*****	**0.248****	**0.551*****	**0.311*****	**0.287*****	**0.271****
	(0.092)	(0.098)	(0.139)	(0.074)	(0.089)	(0.108)
Regulation Quantity					-0.026	
					(0.030)	
Log(10K Words#)						-0.008*
						(0.005)
Adjust. / Pseudo R^2	0.322	0.325	0.364	0.265	0.324	0.315
Observations	52581	47939	23657	41965	56072	39671
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err. Clustered	Firm	Firm	Firm	Firm	Firm	Firm

Table OA4: Ruling out Additional Alternative Explanations

This table presents the marginal effects of Probit regressions to rule out several additional alternative explanations of our baseline findings. We control for several additional variables that may explain product recall likelihood of firms such as *Vertical Integration* (i.e., a text-based industry-adjusted vertical integration score of a firm (Frésard et al., 2020), *Free Cash Flow (FCF) Shock* (i.e., FCF of a year minus prior 3-year average FCF, where FCF= (income before extraordinary items+ depreciation- change in net working capital- capital expenditures)/market value of assets), *Business Segments* (i.e., no. of business segments of a firm), *Financial Analysts* (i.e., no. of financial analysts following a firm), and *Lobbying* (i.e., a firm's lobbying expenditure in mln$ divided by total assets), *Labor Unionization* (i.e., labor unionization rate of a firm's primary industry), *Stock Repurchase* (i.e., a dummy taking the value of one if a firm repurchases stocks in a year and zero otherwise), *No. of Suppliers* (i.e., no. of suppliers of a firm), and CEO traits including *CEO Stocks and Options* (i.e., CEO stocks and options portfolio value), *CEO Delta* (i.e., dollar changes in CEO wealth due to 1% change in a firm's stock price), and *CEO Vega* (i.e., dollar changes in CEO wealth due to 1% change in the standard deviation of a firm's stock returns) in Columns (1) to (9), respectively. In all specifications, *Recall Dummy* is the dependent variable taking the value of one if a firm recalls in year *t* and 0 otherwise. All independent variables are one-year lagged to address the reverse causality concern, and we include all baseline controls (suppressed for brevity), year FE and Fama-French 48 industry FE. Heteroscedasticity robust standard errors are shown in parentheses and clustered at firm level. Here, ***, ** and * refer to statistical significance at 1%, 5% and 10% level, respectively. All variables are defined in Appendix C.

	Vertical Integration	**FCF Shock**	**Business Segments**	**Financial Analysts**	**Lobbying**	**Labor Unionization**	**Stock Repurchase**	**No. of Suppliers**	**CEO Traits**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Regulatory Fragmentation	**0.298*** **	**0.318*** **	**0.296*** **	**0.341*** **	**0.728*** **	**0.329*** **	**0.304*** **	**0.302*** **	**0.360** **
	(0.089)	(0.110)	(0.087)	(0.115)	(0.265)	(0.108)	(0.086)	(0.086)	(0.172)
Vertical Integration	-0.262								
	(0.189)								
FCF Shock		-0.011							
		(0.012)							
Business Segments			0.001*						
			(0.001)						
Financial Analysts				0.000					
				(0.000)					
Lobbying					2.557				
					(3.135)				
Labor Unionization						0.036*			
						(0.021)			
Stock Repurchase							0.002		
							(0.003)		
No. of Suppliers								0.011***	
								(0.002)	

Table OA4 (*continued*)

	Vertical Integration	FCF Shock	Business Segments	Financial Analysts	Lobbying	Labor Unionization	Stock Repurchase	No. of Suppliers	CEO Traits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEO Stocks and Options									0.002
									(0.003)
CEO Delta									-0.000
									(0.000)
CEO Vega									.0001***
									(.00003)
Adjusted / Pseudo R^2	0.322	0.308	0.326	0.324	0.378	0.341	0.324	0.327	0.316
Observations	52310	41047	55003	37960	8188	36998	56072	56072	26004
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err. Clustered	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level	Firm level