R&D MANAGEMENT

Overseas institutional uncertainty and corporate innovation – evidence from an emerging economy

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Using the 2016 US presidential election as a source of plausibly exogenous variation in uncertainty, we examine the R&D effect of institutional uncertainty in Chinese listed firms. Our results show that innovation activities are adversely affected in firms exposed to external election shocks and that the effect is more pronounced in SOEs, older firms, and financially constrained firms. Our study contributes to the literature on uncertainty and R&D management by broadening the conceptual boundaries of institutional uncertainty and enriching the understanding of how overseas institutional uncertainty affects domestic firms' R&D activities. The findings have important implications for innovation strategy at firms and policymaking at governments.

1. Introduction

Innovation is the key to firms' long-term comparative advantage and the principal driver of economic growth (Querbach et al., 2020). Innovation generally involves a substantial amount of research and development (R&D) investments, and the management of corporations decides whether and how many resources to devote to innovative activities. However, R&D investments usually take a long time to yield fruitful results and are highly irreversible when external conditions change; hence, they are susceptible to uncertainty (Czarnitzki and Toole, 2011; Zhang et al., 2022). Therefore, R&D decision-making depends on corporate managers' judgments or estimates of future market conditions and expected payoffs that are 'unknown and unknowable' (Bylund, 2021). On the one hand, uncertainty may dampen business confidence and increase financing costs, thus decreasing investment in R&D when firms postpone or even abandon projects that are no longer attractive (Dixit and Pindyck, 1994; Xu, 2020). On the other hand, uncertainty might open windows of opportunity when R&D investments can create valuable growth opportunities (Caballero, 1991; Weeds, 2002).

Scholars have noted several types of unexpected shock events that can be incorporated into the innovation system framework. Different types of shocks might trigger disruptive uncertainties in various dimensions that are relevant to R&D management, including technological uncertainty coming from radical changes in technology (Folta, 1998), environmental uncertainty such as the pandemic or climate change (Soluk et al., 2021), market uncertainty such as changes in consumer demand or competition (Belderbos et al., 2019), and institutional uncertainty (Bylund and McCaffrey, 2017).

Referring to the lack of assuredness about the government's future actions and policies, institutional uncertainty represents a broad category of economic policy uncertainty (Gulen and Ion, 2016), trade policy uncertainty (Liu and Ma, 2020), and political uncertainty (Bhattacharya et al., 2017; Pertuze et al., 2019) and could be induced by policy changes (Clougherty and Zhang, 2021), political leader turnover (Zhong et al., 2019), techno-nationalism (Luo, 2022), and terrorism (Li et al., 2022). Institutional uncertainty may alter the environment in which innovative firms operate, causing changes in companies' judgmental decision-making regarding risk premia or expectations about project payoffs; this could affect corporate managers' strategic decisions on the diversion of the export market, changes in the product mix, or reductions in R&D investment to overcome obstacles (Kelly et al., 2016).

However, the existing uncertainty–innovation literature mainly analyzes domestic institutional uncertainty and largely overlooks institutional uncertainty stemming from a global perspective. In modern times, changes in the political stance of one country versus others may have implications for a range of actions or attitudes toward the focal country's business activities, especially for companies involved in international trade or overseas investment (Luiz et al., 2021). For example, the direction of US economic policy has significant repercussions for the performance of foreign economies, firm outcomes, and equity markets (Aizenman et al., 2016), affecting the R&D strategies of companies in global value chains (Petricevic and Teece, 2019). Despite its potentially large effect, few studies have considered overseas institutional change as a source of institutional uncertainty and its implications for domestic companies' decision-making. This study aimed to fill this void by investigating the R&D effect of overseas institutional uncertainty.

The empirical evidence on the R&D effect of institutional uncertainty is inconclusive, with a focus on advanced economies. Bhattacharya et al. (2017) find that industry-level innovation activities drop significantly during times of policy uncertainty based on a sample of 43 economies. Focusing on US economic policy uncertainty (EPU), Xu (2020) reports that EPU increases firms' cost of capital, which translates into lower innovation. Li et al. (2022) argue that terrorism reduces firms' R&D investment by increasing the value of the deferral option in R&D. In contrast, Atanassov et al. (2015) document that firms located in the affected states spend more on R&D during gubernatorial election years in the United States. However, scant evidence exists on emerging markets and developing countries.

Understanding the uncertainty–innovation nexus is crucial for emerging economies. The role of innovation for developing countries is particularly important in fostering economic growth and catching up with developed nations. Indeed, emerging economies are playing an increasingly important role as global innovators and contributors in technology rather than as laggards. Multinational enterprises generate successful innovation in emerging markets and then export the new knowledge to the rest of the world, including developed countries, a phenomenon called 'reserve innovation' (Govindarajan and Ramamurti, 2011; Yip and McKern, 2016). China, as the largest emerging economy, has led in all four categories of intellectual property rights filed to and granted by the WIPO in recent years (Luo, 2022). Moreover, emerging economies have increasingly participated in the global market and become more exposed to foreign uncertainty (Bai et al., 2021). These findings call for more in-depth studies on R&D management in emerging markets under global uncertainty.

In gauging institutional uncertainty, the use of a broad uncertainty index may suffer the compounding effects of political cycles and economic conditions (Jens, 2017). As an alternative, events such as an election can serve as a possible source of institutional uncertainty, as election outcomes are usually relevant to all aspects of policies (Bhattacharya et al., 2017). Political events such as presidential elections in the United States have the potential to affect business and investor behavior on a global scale, given their size and importance for international trade and finance (Julio and Yook, 2012). As truly exogenous regulatory and political shocks are difficult to come by, the unanticipated outcome of the 2016 U.S. presidential election combined with the sizable policy difference between the two candidates provides an opportunity to evaluate the effect of a shock on corporate innovation. As such, this paper leverages our empirical strategy on the surprise result of the 2016 election as a source of plausibly exogenous variation in institutional uncertainty.

2. Background and hypothesis development

2.1. *Foreign election as a source of institutional uncertainty*

Institutional economics perceives institutions as humanly devised constraints that shape the environment. These institutions, whether formal (such as laws) or informal (such as culture), aim to minimize transaction and information costs, foster reliable interactions, and encourage rational decision-making. According to Williamson's hierarchical model, institutions can be classified into four levels: informal institutions (L1), formal institutions (L2), organizations and governance (L3), and everyday market exchange (L4). The institutional environment is rife with uncertainty, and misalignments among different levels of institutions can give rise to institutional uncertainty.

While previous research on institutional uncertainty has predominantly focused on the domestic institutional environment, the global nature of business operations necessitates considering changes in foreign countries' institutions. Geographically dispersed institutions with distinct rules and norms can trigger institutional change and generate uncertainty. State tensions can impact international relations, business environments, and resource allocation, leading to conflicts in corporate policies. The perceived uncertainty poses challenges for corporate decision-makers, influencing their judgment and shaping corporate actions. Hence, a comprehensive understanding of institutional uncertainty should encompass changes in foreign countries' institutions.

Election activities reflect governmental instability and policy unpredictability, as changes in the government can bring about institutional changes for society as a whole. Governmental changes correspond to institutional change at the L2 level, resulting in misalignment with other levels of institutions, disrupting the original institutional equilibrium, and introducing uncertainty to the overall institutional system. The unexpected outcome of the 2016 US presidential election, which saw the election of Donald Trump, had significant ramifications for the business climate. Trump's economic and trade policies, characterized by his 'America First' doctrine and skepticism toward free trade agreements, introduced unpredictability and the potential for policy changes. This had implications for businesses, both domestically and internationally. For instance, Chinese firms anticipated the impact of Trump's proposed tariffs on imported goods.

2.2. *Hypothesis development*

Our hypothesis draws primarily from the theoretical lens of neo-institutional theory, which suggests that external institutional factors impact organizational behavior (Meyer and Rowan, 1977; DiMaggio and Powell, 1983). In understanding the determinants of corporate innovation, two schools of thought have emerged in the literature: the resource-based view (RBV) and the market-based view (MBV). The RBV emphasizes the significance of a firm's tangible and intangible resources in driving innovation (Barney, 1991; Carroll, 1993). Within this framework, the real options mechanism and the cost-of-capital mechanism predict reduced R&D investment in the face of heightened uncertainty. In contrast, the MBV views external market conditions as stimuli that regulate the type, direction, and degree of a firm's innovative activities (Tidd, 2001). From this perspective, innovative firms enjoy competitive advantages primarily due to barriers to competition arising from the market structure (Porter, 1980). Consistent with this line of thinking, strategic growth options and game theory suggest that innovation can be strategically motivated as a response to an uncertain business environment. Moreover, dynamic capabilities theory highlights the ability of firms to integrate, develop, and adapt internal and external competences to navigate rapidly changing contexts (Teece et al., 1997). This theory forms the basis for understanding the moderating role of firm characteristics in the relationship between uncertainty and innovation.

Specifically, the R&D implications of institutional uncertainty can be understood through various mechanisms. One such mechanism is the real options theory (Bernanke, 1983; McDonald and Siegel, 1986), which recognizes that innovation projects often entail significant upfront costs and uncertain future payoffs. Firms can view these projects as options, providing them with the flexibility to invest in or abandon them based on changing market conditions and new information. This mechanism highlights the importance of timing in innovation decisions, suggesting that firms can delay their investment in innovation projects to gather more information about market demand, technological advancements, or regulatory changes. By waiting, firms can reduce project uncertainty and make more informed investment decisions. Consequently, when facing heightened instability and uncertainty stemming from external institutional factors, firms tend to reduce their R&D investments to mitigate risks and defer potential losses. Collaborative evidence is found in empirical studies showing firms postpone fixed asset investment during politically uncertain gubernatorial elections (Julio and Yook, 2012; Jens, 2017).

Another mechanism predicting that institutional uncertainty leads firms to depress investment is the cost-of-capital analysis (Xu, 2020). Institutional uncertainty gives rise to an equity risk premium due to undiversifiable political risks, thereby influencing the firm-level cost of equity capital (Pástor and Veronesi, 2013). Uncertainty can also impact the cost of debt by affecting firms' default risk (Greenwald and Stiglitz, 1990). In line with the predictions of the RBV, the availability of financial resources can enhance a firm's capacity to support its innovative activities (Del Canto and Gonzalez, 1999). Given the importance of external finance for funding innovation, changes in financing costs are particularly critical for the development, implementation, and commercialization of new technologies and investment in innovation (Kerr and Nanda, 2015). Financing R&D investment tends to become costlier as financial intermediaries restrict credit growth and raise the cost of debt for businesses when political uncertainty exacerbates information asymmetries between firms and lending institutions (Chi and Li, 2017; Cuculiza et al., 2021).

In contrast to the aforementioned mechanisms, strategic growth option suggests a positive association by recognizing that corporations can leverage institutional uncertainty to their advantage for future growth opportunities (Kulatilaka and Perotti, 1998; Mair et al., 2012). An environment characterized by uncertainty provides firms with an opportunity to respond with innovative solutions to market changes (Hechavarría et al., 2023). Similarly, game theory suggests that greater economic and political uncertainties can incentivize firms to introduce innovations as a means to mitigate risks associated with uncertainty. Innovation has the potential to expand the market, create valuable growth opportunities, and optimize resource utilization (Caballero, 1991; Weeds, 2002; Goel and Nelson, 2021). Firms may find it beneficial to pursue immediate innovation to secure market share, especially when delaying innovation becomes excessively costly (Van Vo and Le, 2017; Tajaddini and Gholipour, 2020). In this context, innovation can be strategically motivated as a response to uncertain business environment.

In summary, the impact of institutional uncertainty on firm innovation is an empirical question, as it can either improve or hinder innovation depending on the specific context. Considering the significance of the US–China trade relationship, the sudden changes in policy and negative outlook on bilateral trade during the Trump presidency posed significant threats to Chinese firms, particularly exporters (Witt, 2019; Luo and Witt, 2022; Luo and Van Assche, 2023). In this context, the negative effects predicted by the real options theory (Bernanke, 1983; McDonald and Siegel, 1986) and the cost-of-capital model (Xu, 2020) are likely to outweigh the positive effects suggested by the strategic growth option (Kulatilaka and Perotti, 1998; Mair et al., 2012) and game theory perspective (Caballero, 1991; Weeds, 2002; Goel and Nelson, 2021) in the short term. Based on this analysis, we propose the following hypothesis:

> H1 Institutional uncertainty stemming from Trump's election will impede corporate innovation among Chinese public firms.

Dynamic capabilities theory is a theoretical framework that focuses on understanding how organizations can adapt and respond to rapidly changing environments in order to sustain competitive advantage and achieve superior performance. It suggests that firms' ability to integrate, build, and reconfigure internal and external competences in response to rapidly changing environments, known as dynamic capabilities, enables them to gain competitive advantages and withstand uncertainty. Therefore, the specific impact of institutional uncertainty on firms' R&D activities may vary across different enterprises due to variations in their dynamic capabilities.

The effectiveness of dynamic capabilities relies on firms' information acquisition processes (Eisenhardt and Martin, 2000). When it comes to uncertainty resulting from political changes, governments possess unique political information. Considering that information dissemination occurs through social interactions and interpersonal relationships (Granovetter, 1973; Bai et al., 2021), establishing connections with the government can enrich firms' information environment and enhance their dynamic capabilities. In emerging markets, where policymaking is not always transparent and verifiable, building strong political relationships becomes crucial for accessing political information (Bai et al., 2021). By developing robust political connections, firms can gain privileged political information, anticipate potential institutional changes, and effectively prepare for them (Li and Zhang, 2007; Zhang et al., 2019; Lin et al., 2021). Therefore, political relationship building may assist enterprises in better navigating the disruptive effects of institutional uncertainty when making decisions related to innovation.

Meanwhile, the emergence of dynamic capabilities is influenced by the path dependence of firms, relying heavily on their existing resource base (Eisenhardt and Martin, 2000; Helfat et al., 2007). Drawing from RBV, which asserts that firms' internal resources are valuable, rare, not easily imitated, and organized, these resources serve as inputs that, when combined and transformed by capabilities, generate innovative forms of competitive advantage (Barney, 1991; Kostopoulos et al., 2002). The various types of resources possessed by firms can influence their dynamic capabilities.

For instance, younger and smaller firms are more susceptible to environmental changes and exhibit higher exit rates. As firms accumulate resources over time, their exit rates decrease. Older and larger firms, with greater resources such as experience, managerial abilities, technologies, and organizational advantages, are better positioned to manage uncertainty and engage in innovative activities (Esteve-Pérez and Mañez-Castillejo, 2008).

Furthermore, growth opportunities, as a significant component of firm value, impact factors such as capital structure decisions, stock market reactions to financial decisions, and R&D investments according to Miller and Modigliani (1961). Growth opportunities often require firms to develop and leverage their dynamic capabilities to pursue and capitalize on those opportunities. As such, the level of growth opportunities can influence firms' sensitivity to uncertainty and their investment decisions.

Last, financial resources play a crucial role in supporting and enabling a firm's dynamic capabilities by providing the necessary funding and liquidity that allow firms to invest in developing and deploying dynamic capabilities effectively. These perspectives support the idea that organizations with a larger resource base are more likely to possess robust dynamic capabilities, thereby enhancing their resilience in the face of uncertainty. Considering the potential moderating effects of political relationship, age, size, growth, and financial resources, the following hypothesis is tested:

H2 The R&D effect of overseas institutional uncertainty is attenuated in firms that possess stronger political relationships, have a longer firm age, exhibit larger firm size, experience more rapid firm growth, and possess greater financial capability.

3. Methodology and data

In this study, we use a standard event study approach to investigate the R&D effect of institutional uncertainty using micro-level data on China's listed firms. Our sample starts with 3031 firms listed in stock exchanges in 2016. Excluding shares suspended for more than 3 months and those newly listed firms with fewer trading days than what is required for the event study, we are left with 2403 firms in 75 sectors according to the two-digit industry classification,[1] with the sample period spanning from 2010 to 2019. The wide spread of sectors in our sample firms allows us to investigate the heterogeneous impact and exposure of firms to Trump's election.

When markets are efficient, a firm's stock price will reflect all information about its future profits. External shocks that shift expectations about profit opportunities will cause the re-evaluation of the firm, so stock prices can gauge a firm's exposure to shocks. A firm's stock return is the percent change in its market value from time $t-1$ to t, and abnormal returns are the difference between the actual return during the event and an estimate of the 'normal' return that would have prevailed in the absence of any shocks. We calculated the abnormal return of firms' shares around the election on November 8, 2016. We choose the event day and the following 5 trading days for our baseline model and allow various lengths of intervals in the robustness check.[2]

To determine the 'normal' returns, we use the capital asset pricing model (CAPM) by Sharpe (1964) to associate a firm's expected return between trading days $t-1$ and t to the risk-free return across the interval and the firm's exposure to systematic risk.[3] Then, the abnormal return is calculated as follows:

$$AR_{it} = R_{it} - \left(\alpha_i + \beta_i R_{mt}\right), \quad 0 \le t \le 5 \qquad (1)$$

where R_{it} is the return of stock i on day t and R_{mt} is the market return, based on either the Shanghai Composite Index or the SZSE Composite Index, depending on the stock exchange on which the share is listed. To estimate α_i and β_i for individual shares, we use OLS based on the transaction data of 120 trading days, including 30 days prior to the event.[4] AR_{it} reflects the stock response of individual firms' net of market systematic risk.

For event windows longer than one day, we compute the cumulative abnormal return (CAR) as the variable of interest. CAR is the sum of the daily abnormal returns over the event window, capturing the accumulated impact of the event over the period of interest. We measure firms' exposure to the event by calculating cumulative abnormal returns as follows:

$$CAR_{i5} = \sum_{t=0}^{5} AR_{it}, \quad 0 \le t \le 5 \tag{2}$$

While the election surprise is the same for all assets, individual shares will respond to the election result differently, depending on whether the incoming administration's expected policies were viewed as favorable or unfavorable for a particular firm or industry. When $CAR > 0$, compared to the overall market, the focal firm was affected positively; when $CAR < 0$, firms were negatively affected by the shock.

Another variable central to this study is firms' innovation activities, for which we consider both input and output. For innovation input, we primarily look at the scale of investment in R&D, measured by Ln (R&D). Following Brav et al. (2018), after taking logarithms, we replace missing values with zero for firms with nonzero R&D from 2010 to 2019. We also consider personnel performing R&D activities in a firm by looking at the total number of R&D employees. These two measures can better manifest the investment and expenditure on firms' research and investment efforts and are less likely to be subject to accounting manipulation.[5] Regarding innovation output, we adhere to the existing literature and employ the logarithm of the total number of filed patent applications as a reliable measure of innovation performance. In addition to considering patent quantity, we also incorporate the total number of invention patents applied, which necessitate greater originality and novelty, as a more robust indicator of patent quality or success in innovation.

To explore the impact of institutional uncertainty stemming from the 2016 US presidential election on Chinese firms' innovation activities, we follow Greenland et al. (2020) and employ the generalized difference-in-difference (DID) model. DID is a nonexperimental statistical technique used to estimate treatment effects by comparing the change (difference) in the differences in observed outcomes between treatment and control groups across pretreatment and posttreatment periods. A more general DID regression allows the intercept term to vary for each cross-sectional unit and the common change in outcomes to vary across time. In the following generalized DID model, we can test the difference in innovation activities between firms exposed to external election shocks and firms not exposed in the before versus after election period:

$$innovation_{it} = \lambda_0 + \lambda_1 I(CAR[0,5] < 0)_i \times Post16_t + X_{it}\Gamma + \rho_i + \rho_t + \varepsilon_{it} \tag{3}$$

where $innovation_{it}$ measures firm i's innovation input or output in year t. To identify a firm's negative exposure and susceptibility to institutional uncertainty, we define $I(\text{CAR}[0, 5] < 0)$ to be one when the cumulative return is negative during the event window and zero otherwise. $Post16$ is a year dummy taking the value of one after 2016 and zero before. The coefficient estimate of the interaction item, λ_1, captures the relative change in innovation among firms with differential exposure to the election shock after versus before it occurs. When λ_1 is negative, H1 is supported. The firm fixed effect is included to account for any time-invariant firm characteristics, and a year fixed effect is also included to capture aggregate shocks that affect all firms. ρ_i and ρ_t represent the firm fixed and year fixed effects, respectively. X_{it} is a vector of control variables including firm size measured by total assets, firm age, book-to-market ratio, leverage, and return on assets. All standard errors are clustered at the firm level to alleviate concerns about residual serial correlation and adjusted for heteroscedasticity. Firm data are from the Wind database, and daily stock price and trading data are from the website of Rice Quant. The innovation input and output data and other financial data of the listed firms in China are from the CSMAR database.

Furthermore, to examine whether the relationship between foreign election-induced institutional uncertainty and corporate innovation varies with some firm characteristics (H2), we test the following model:

$$\begin{aligned} innovation_{it} = {} & \lambda_0 + \lambda_1 I(CAR[0,5] < 0)_i \times Post16_t + \lambda_2 TRAIT_{it} \\ & \times Post16_t + \lambda_3 TRAIT_{it} \times I(CAR[0,5] < 0)_i + \lambda_4 TRAIT_{it} \\ & \times I(CAR[0,5] < 0)_i \times Post16_t + X_{it}\Gamma + \rho_i + \rho_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where $TRAIT_{it}$ is one of the following: firm ownership, firm age, firm size, financial constraint, and growth. We introduce a dummy variable SOE to capture political relationships: SOE equals one if a company is state-owned and zero otherwise. Firm size is measured by logarithms of total assets, financial constraints are captured by leverage, and growth is captured by the growth rate of sales revenue. The coefficient of interest is λ_1, capturing the heterogeneous responses in innovation with respect to firm characteristics. The continuous variables in $TRAIT_{it}$ are demeaned for easier interpretation of the coefficients.

4. Empirical results

4.1. Main results

Table 1 reports the summary of CAR surrounding the event window. The average of CAR[0, 5] is −0.29%

with a standard deviation of 4.08%. The nonzero cumulative abnormal return of stock price during the election shows that firms on average are negatively affected by the surprise outcome of presidential election in the United States. The median of CAR[0, 5] is −0.57%, almost twice the value of sample mean, suggesting more than 50% of firms suffered a negative cumulative abnormal return in this event, with the hardest hit firm reporting a CAR of −10.95%. Figure 1a plots the right-skewed kernel density of CAR[0, 5], further confirming the overall negative impact on stock returns of Trump's election. This analysis provides intriguing evidence of how the market digests information on election outcomes.

Using CARs, we can evaluate firms' exposure across a wide range of industries and measure

Table 1. Summary statistics of CAR[0, 5]

	Obs	Mean	SD	Median	Min	Max
All firms	2,403	−0.0029	0.0408	−0.0057	−0.1095	0.1543
Panel A: by sector						
Nonmanufacturing	909	0.0015	0.0416	−0.0013	−0.1095	0.1543
Manufacturing	1,494	−0.0057	0.0401	−0.0078	−0.1095	0.1543
Panel B: by ownership						
Non-SOE	1,544	−0.0045	0.0413	−0.0063	−0.1095	0.1543
SOE	859	−0.0002	0.0398	−0.0042	−0.1095	0.1543

This table reports the summary of CAR surrounding the event window.

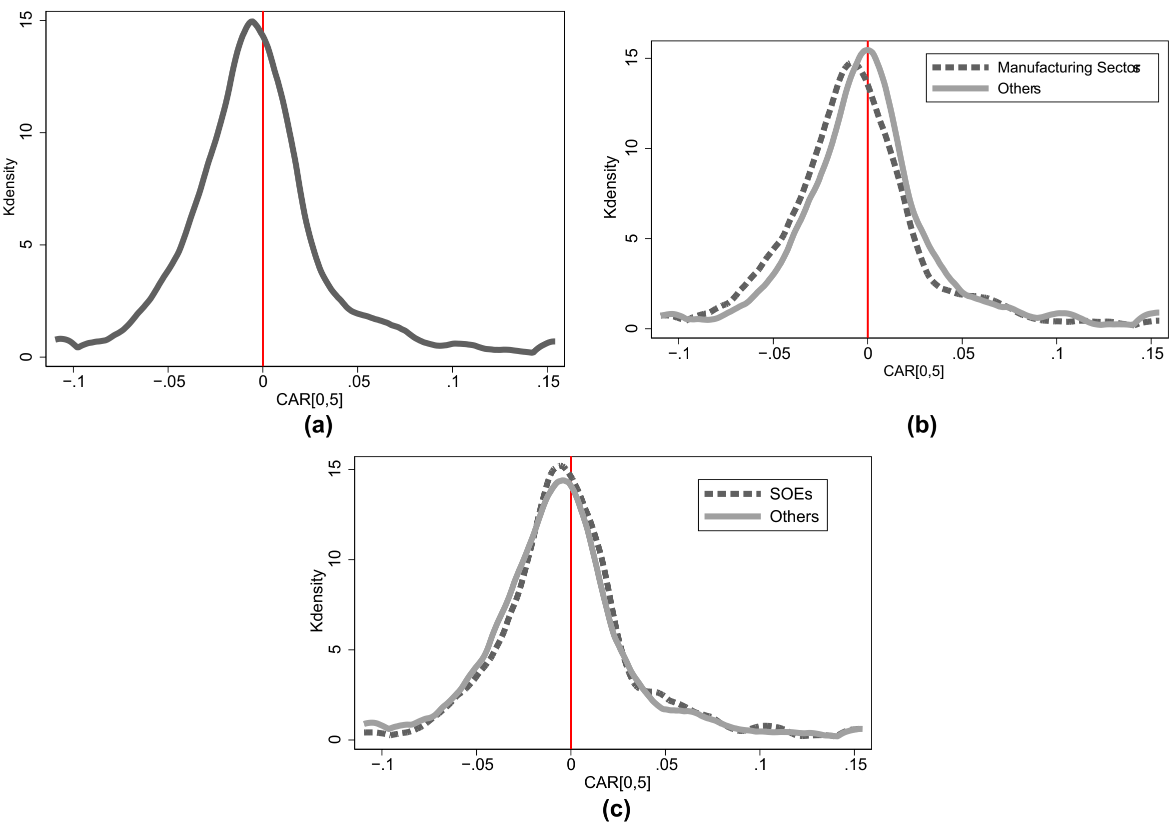

Figure 1. Distribution of CAR[0, 5]. Panel (a) displays the CAR distribution for the entire sample, while panel (b) illustrates the CAR distribution separately for the manufacturing and non-manufacturing industries, and panel (c) presents the CAR distribution for SOE and non-SOE firms.

heterogeneous exposure within those industries to determine whether Trump's policies were expected to have sector- versus firm-specific effects. We then divide our sample firms into manufacturing and nonmanufacturing firms. The former consists of 1494 firms, while the latter covers 909 firms in the agriculture, mining, and service sectors. Panel A of Table 1 shows that the mean values of CAR[0, 5] for manufacturing and nonmanufacturing firms are −0.57% and 0.15%, respectively, while the medians are −0.78% and −0.13%, respectively. This suggests that firms in the manufacturing industry suffered a larger negative impact of the event, whereas nonmanufacturing firms are less exposed.[6] Further tests confirm that the differences across the two groups are statistically significant at the 1% level.[7] Figure 1b shows the kernel density of CAR[0, 5] with manufacturing firms plotted as dotted lines and nonmanufacturing firms plotted as solid lines. The Kolmogorov–Smirnov test was conducted to confirm the significant difference between the two groups. This evidence points to deeper exposures of manufacturing firms to Trump's election.

Next, we compare firms with various ownership structures. Our sample includes 859 state-owned enterprises (owned by either the central government or the local government). Panel B of Table 1 shows that the mean and median of CAR for SOEs are −0.02% and 0.42%, respectively, with a standard deviation of 4%. Those values for non-SOEs are −0.45%, 0.63%, and 4.13%. This suggests a larger blow to the non-SOE of the election, and such a difference is statistically significant at the 5% level (p value 0.0136). Figure 1c depicts that non-SOE has a kernel distribution further to the left compared to SOE counterparts, and this difference is significant according to the K–S test result (p value 0.024). The difference may be because many SOEs focus mainly on the domestic market, or SOEs build stronger relationships with the government, have more political information and resources, and government backing could help counter the negative impact of foreign events. This is also consistent with the RBV projections, as discussed in Section 2.2.

Table 2 reports the summary statistics of firm innovation measures and their time trend. Judging by innovation input, we can see that both R&D investment and the amount of R&D staff show steady increases over the years. Compared to 2012, R&D investment in 2019 was 24 times as high ($e^{17.52-14.3}-1$). R&D employees increased by 77.43%. On innovation output, however, sharp increases in patents and inventions were recorded in 2015, but both indicators have since declined.[8]

Table 2. Corporate innovation indicators

Year	ln(R&D) (1)	ln(R&D staffs) (2)	ln(1 + #patents applied) (3)	ln(1 + #invention patents) (4)
2010	5.6279		0.9737	0.4993
2011	6.4447		1.1486	0.6321
2012	14.2986		1.0311	0.5372
2013	14.6800		1.1195	0.5809
2014	15.2189		1.1172	0.6477
2015	15.6066	4.6400	1.5583	1.0156
2016	16.0417	4.8370	1.2212	0.6746
2017	16.3563	4.9498	1.1652	0.6682
2018	17.1775	5.1261	0.9564	0.5867
2019	17.5189	5.2134	1.1340	0.6520

This table reports the average values of firm innovation measures in each year of the sample period.

Table 3 focuses on the period before the 2016 shock and separates our sample into two groups: those that experienced negative CARs in the five-day postelection period (CAR[0, 5] < 0) and those that experienced a positive return (CAR[0, 5] > 0). For each subsample, the number of observations, mean, standard deviation, and median are reported. The mean difference test results are reported in columns (13) to (15). By looking at the firm-level characteristics of the two subsamples over the period before the election from 2010 to 2016, we find that on average, firms with a weaker input to innovation and a weaker output of innovation had a positive CAR over the election period, whereas firms that had stronger innovation capability indicators suffered a negative CAR in the postelection period. In addition, Table 3 also shows that firms with fewer assets, smaller B/M ratios, and lower leverage experienced a negative CAR in the postelection period.

Furthermore, in Figure 2, we plot the trend of innovation measures for firms with positive and negative CARs surrounding the election date. Firms with CAR[0, 5] < 0 are plotted as solid lines, while firms with CAR[0, 5] > 0 are plotted as dashed lines. Panels a–d depict R&D investment, R&D staff number, patent application filed, and invention patent applied. Figure 2 shows that for the years before the shock, the solid lines for all four innovation measures lie on top of the dashed line, indicating that firms that were hard hit were mostly those with more innovation input and innovation output before the event. More importantly, in the period prior to the shock, we see that the two groups show basically parallel patterns, laying the foundation of our subsequent DID analysis.

Table 3. Sample statistics before the shock

Variable	N	Mean	SD	Median	N	Mean	SD	Median	N	Mean	SD	Median	Difference	SD	p value
	All samples				Sample (CAR[0, 5] < 0)				Sample (CAR[0, 5] > 0)				T-test		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ln(R&D)	13,008	12.9795	7.8270	16.9976	7609	13.3721	7.6368	17.1331	5399	12.4261	8.0556	16.8015	0.9460	0.1390	0.0000
ln(R&D staff)	4,259	4.7392	2.1708	5.2417	2500	4.9562	2.0120	5.3706	1759	4.4308	2.3445	5.0562	0.5255	0.0671	0.0000
ln(1 + #patents applied)	8,088	1.1805	1.7345	0.0000	4884	1.2196	1.7508	0.0000	3204	1.1208	1.7079	0.0000	0.0987	0.0394	0.0123
ln(1 + #invention patents)	7,266	0.6672	1.2270	0.0000	4448	0.7031	1.2607	0.0000	2818	0.6106	1.1698	0.0000	0.0925	0.0295	0.0017
ln(Asset)	14,746	22.0919	1.4339	21.8643	8542	22.0605	1.3344	21.8779	6204	22.1351	1.5595	21.8437	−0.0746	0.0239	0.0018
B/M	14,378	0.5883	0.2435	0.5898	8362	0.5746	0.2369	0.5745	6016	0.6073	0.2511	0.6141	−0.0327	0.0041	0.0000
Leverage	14,746	44.0316	22.6796	43.2760	8542	43.3294	21.9905	41.8728	6204	44.9984	23.5632	45.0753	−1.6690	0.3781	0.0000
ln(Age)	14,747	2.7285	0.3964	2.7726	8543	2.7279	0.3974	2.7726	6204	2.7293	0.3950	2.7726	−0.0014	0.0066	0.8339
ROA	14,746	4.1211	6.3666	3.8780	8542	4.5555	6.3136	4.2357	6204	3.5231	6.3914	3.4203	1.0324	0.1059	0.0000

The sample used in this table is the one before the election shock, that is., 2010 to 2016. *N* is the number of observations. Values in Column (13) are obtained by subtracting Column (10) from Column (6).

In Figure 2a,b, both innovation input indicators follow an upward trend before the event. After the election date, both measures of innovation input continue to grow, albeit at slower rates, and firms with negative CARs are more affected with sharper declines, narrowing the gap between the two groups. Regarding innovation output indicators, Figure 2c,d show that the group with negative CARs saw a decline in patents after the election, whereas firms with positive CARs recorded increases in their overall patents and invention patents; this suggests that firms with negative exposure to the election shock suffer lower innovation efficiency. These results provide some preliminary evidence on the relation between firms' exposure to the external shock and their innovation activities, which will be further tested in regression analysis.

In Table 4, we report the estimation of our baseline model using generalized DID regression as specified in Equation (3). We control for firm and time fixed effects in all regressions.[9] Columns (1), (3), (5), and (7) show the regression without firm-level control variables, and the remaining columns report the results including controls.[10] We can see that the interaction of the indicator variable $I(\text{CAR}[0, 5] < 0)$ and the year dummy $Post16$ loads negatively and significantly on all measures of innovation activities. That is, firms negatively exposed to the election shock have reduced their R&D investment and research staff employment; their patent applications and invention patents filed experienced similar trends. This confirms what we observed in Figure 2, indicating a negative link between exposure to the external shock and a firm's postelection innovation, supporting our H1 that institutional uncertainty stemming from Trump's election impedes Chinese firms' innovation activities. Our results are in line with those of He et al. (2020), who found that higher economic policy uncertainty decreases corporate innovation in China in the post-2008 period. Our findings also echo those of Benguria et al. (2022), who found that Chinese firms hit by higher trade policy uncertainty during the trade war reduced firm-level R&D expenditures.

4.2. Robustness tests

4.2.1. Continuous DID

We submit the results to a series of robustness checks. First, we use a continuous DID model to replace the indicator variable in Equation (3) to better account for the magnitude of cumulative return. We test the following model:

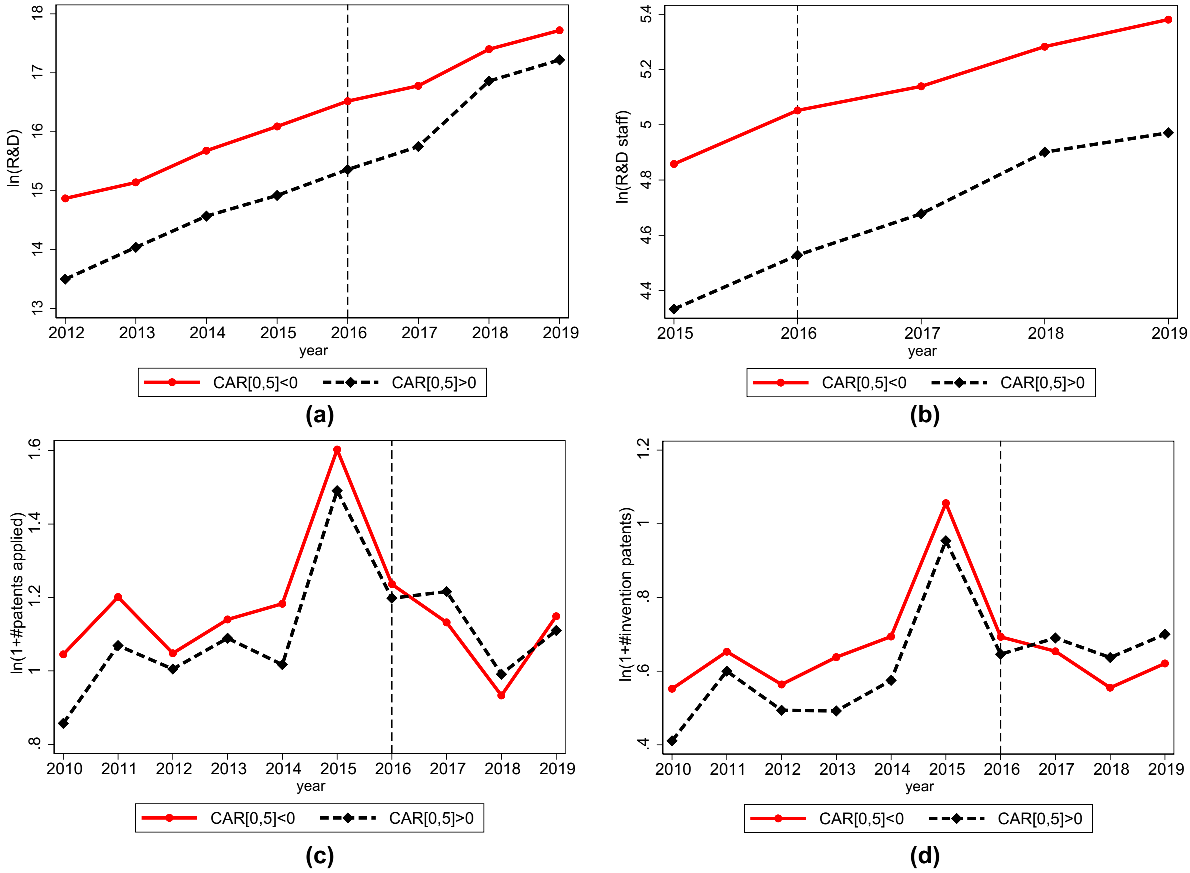

Figure 2. Political shock and innovation. Panel (a) illustrates the trend of R&D investment for firms based on their positive and negative CARs around the election date, while panels (b) to (d) display the corresponding trends for R&D staff numbers, filed patent applications, and applied invention patents, respectively.

$$innovation_{it} = \delta_0 + \delta_1(-CAR[0,5])_i \times Post16_t + X_{it}\Gamma + \rho_i + \rho_t + \varepsilon_{it} \quad (5)$$

The negative value of CAR measures the extent to which a firm was exposed to the shock. The coefficient δ_1 captures the average impact on firms' postelection innovation among all firms with various degrees of exposure. Table 5 reports the results. The estimated coefficient of the interaction term is significantly negative for R&D investment, R&D staff numbers, patent applications, and invention patents filed. Economically, a one standard deviation increase in the magnitude of CAR (approximately 4%) is associated with an 18% decrease in R&D investment, a 4.8% decline in R&D staff, and an 8% contraction in terms of inventions. The results are consistent with the baseline results.

4.2.2. Alternative CAR measures

The choice of an event window may influence the estimation results.[11] In addition to the window of 5 trading days in the baseline model, we now use CAR[0, 7] to re-estimate the relationship between firm exposure and postelection innovation activities. Panel A of Table 6 reports the results. The sign of the estimated coefficients is the same as those in Table 4, indicating that extending the event window does not alter our main findings.[12]

We further tried different methods of estimation for α and β in calculating CAR. We use the market model and the Fama–French three-factor model to predict the abnormal return for individual stocks for a 5-day event window and rerun the DID regression. Panel B and Panel C of Table 6 report the results. The coefficient estimates carry the same sign as Table 4, showing that our results are robust to alternative ways of estimating CARs.

4.2.3. Additional control variables

We next add more control variables to better account for other potential determinants of innovation performance. First, Aw et al. (2011) pointed out that exports and R&D investment can reinforce each other. Shortly after the election win of Trump, Chinese exporting firms, especially those relying

Table 4. Institutional uncertainty and corporate innovation (baseline)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(R&D)	ln(R&D)	ln(R&D staff)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #patents applied)	ln(1 + #invention patents)	ln(1 + #invention patents)
I(CAR[0, 5] < 0) xPost16	−0.4160**	−0.5243***	−0.0990**	−0.1383***	−0.1387*	−0.1357*	−0.1592**	−0.1638**
	(0.1860)	(0.1818)	(0.0503)	(0.0491)	(0.0815)	(0.0823)	(0.0646)	(0.0655)
ln(Asset)		1.4511***		0.7778***		−0.0173		−0.0302
		(0.1830)		(0.0654)		(0.0562)		(0.0422)
B/M		0.6246*		−0.3115***		0.0854		0.0327
		(0.3285)		(0.1069)		(0.1601)		(0.1217)
Leverage		−0.0317***		−0.0061***		0.0010		−0.0005
		(0.0056)		(0.0017)		(0.0018)		(0.0015)
ln(Age)		−3.5762***		−1.5241***		−0.6310**		−0.4027**
		(0.9800)		(0.4797)		(0.2639)		(0.1993)
ROA		−0.0041		−0.0013		0.0117***		0.0043*
		(0.0084)		(0.0023)		(0.0032)		(0.0023)
Constant	16.0205***	−5.1067	4.9888***	−7.5395***	1.1767***	3.1629**	0.6798***	2.4401**
	(0.0433)	(4.3142)	(0.0178)	(1.7929)	(0.0159)	(1.3364)	(0.0127)	(0.9979)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.610	0.622	0.811	0.822	0.277	0.278	0.303	0.304
Observations	16,245	15,877	10,669	10,448	11,972	11,728	10,632	10,419

R&D investment data are from 2012 to 2019, and R&D staff data are from 2015 to 2019. Patent data are from 2010 to 2019. Standard errors are clustered at firm level. All the regression control for firm and time fixed effects.
*$p<0.10$;
**$p<0.05$;
***$p<0.01$.

Table 5. Institutional uncertainty and corporate innovation (continuous DID)

	(1)	(2)	(3)	(4)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
(-CAR[0, 5])xPost16	−4.9408**	−1.2649**	−1.9296*	−2.1365**
	(2.1670)	(0.5573)	(1.1154)	(0.9236)
ln(Asset)	1.4443***	0.7768***	−0.0157	−0.0285
	(0.1829)	(0.0657)	(0.0558)	(0.0417)
B/M	0.6476**	−0.3085***	0.0900	0.0387
	(0.3286)	(0.1069)	(0.1601)	(0.1217)
Leverage	−0.0318***	−0.0061***	0.0010	−0.0005
	(0.0056)	(0.0017)	(0.0018)	(0.0015)
ln(Age)	−3.6131***	−1.5422***	−0.6401**	−0.4107**
	(0.9835)	(0.4808)	(0.2643)	(0.2003)
ROA	−0.0037	−0.0012	0.0118***	0.0045*
	(0.0084)	(0.0023)	(0.0032)	(0.0023)
Constant	−4.9794	−7.5120***	3.1261**	2.3921**
	(4.3163)	(1.7959)	(1.3285)	(0.9900)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
r2_a	0.622	0.822	0.278	0.304
Observations	15,877	10,448	11,728	10,419

R&D investment data are from 2012 to 2019, and R&D staff data are from 2015 to 2019. Patent data are from 2010 to 2019. Standard errors are clustered at firm level. All the regression control for firm and time fixed effects.
*$p < 0.10$;
**$p < 0.05$;
***$p < 0.01$.

on the US market, experienced significantly negative stock returns (Xie et al., 2020), revealing the market expectation of a potential trade war launched by Trump. In such a scenario, firms would reap less profit from their exports, leading to negative cumulative abnormal returns in shares and less innovation.

Another possible explanation is investment. Firms facing heightened trade barriers may step up their foreign direct investment as a substitution and, as a result, incur higher fixed costs (Helpman et al., 2004). Firms may also strengthen investment overseas to diversify the risk from their core business in the domestic market. With capital constraints, the substitution effect and risk diversification would both mean less R&D input.

Third, the high-tech sector is likely to lose the most following Trump's hostile policy against tech firms in China. The tough sanctions come in the form of cutting US supply chains for core products such as chips, batteries, rare earths, and medical supplies and banning US agencies and vendors from using certain Chinese-made telecommunications products and services. Without access to US technology supplies, China's high-tech firms would inevitably be affected, especially on the innovation front.

To single out the influences on firm innovation from the above three aspects, we test the following DID model:

$$\begin{aligned} innovation_{it} = {} & \lambda_0 + \lambda_1 I(CAR[0,5] < 0)_i \\ & \times Post16_t + \lambda_2 EIT \times Post16_t + X_{it}\Gamma \\ & + \rho_i + \rho_t + \varepsilon_{it} \end{aligned} \tag{6}$$

where $EIT \in \{Export, Investment, Technology\}$ and λ_2 capture the effect of trade dependence, investment, and technology on postelection innovation.

To test the trade effect, we match the firm profile with the database of the General Administration of Customs in 2015. Among our sample firms, we identify more than 900 firms with exports amounting to 69 billion USD in total. Approximately 500 firms sell their products to the US market with a total amount of 15.1 billion USD, which is 21.8% of the overall exports. We construct a dummy variable $I(Export > 0)$ to indicate exporting firms and another dummy variable $I(ExportUS > 0)$ to indicate those selling to the US market, and we consider the share of the United States in a firm's total exports. Panel A of Table 7 reports the result. After inserting the interaction of export dummy and year dummy $Post16$, the key coefficient of λ_1 remains negative in columns (1), (4), and (7),

Table 6. Institutional uncertainty and corporate innovation (alternative CAR measures)

	(1)	(2)	(3)	(4)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
Panel A: CAR[0, 7]				
I(CAR[0, 7] < 0)xPost16	−0.5028***	−0.1354***	−0.0629	−0.1243*
	(0.1799)	(0.0488)	(0.0810)	(0.0656)
ln(Asset)	1.4501***	0.7793***	−0.0186	−0.0301
	(0.1835)	(0.0659)	(0.0562)	(0.0421)
B/M	0.6209*	−0.3186***	0.0856	0.0315
	(0.3289)	(0.1069)	(0.1602)	(0.1219)
Leverage	−0.0318***	−0.0061***	0.0010	−0.0005
	(0.0056)	(0.0017)	(0.0018)	(0.0015)
ln(Age)	−3.6375***	−1.5618***	−0.6361**	−0.4126**
	(0.9833)	(0.4814)	(0.2648)	(0.2007)
ROA	−0.0040	−0.0013	0.0117***	0.0043*
	(0.0084)	(0.0023)	(0.0032)	(0.0023)
Constant	−4.9160	−7.4614***	3.1910**	2.4584**
	(4.3169)	(1.7913)	(1.3359)	(0.9966)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
r2_a	0.622	0.822	0.278	0.304
Observations	15,877	10,448	11,728	10,419
Panel B: CAR[0, 5] based on market model				
I(CAR^{m}[0, 5] < 0)xPost16	−0.2504	−0.1038**	−0.1217	−0.1371**
	(0.1740)	(0.0461)	(0.0815)	(0.0636)
ln(Asset)	1.4393***	0.7764***	−0.0152	−0.0282
	(0.1831)	(0.0653)	(0.0563)	(0.0420)
B/M	0.6416*	−0.3142***	0.0777	0.0247
	(0.3288)	(0.1070)	(0.1600)	(0.1218)
Leverage	−0.0318***	−0.0062***	0.0009	−0.0006
	(0.0056)	(0.0017)	(0.0018)	(0.0015)
ln(Age)	−3.5768***	−1.5378***	−0.6337**	−0.4078**
	(0.9832)	(0.4809)	(0.2639)	(0.2000)
ROA	−0.0039	−0.0013	0.0116***	0.0043*
	(0.0084)	(0.0023)	(0.0032)	(0.0023)
Constant	−4.9297	−7.4859***	3.1239**	2.4073**
	(4.3206)	(1.7922)	(1.3381)	(0.9965)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
r2_a	0.622	0.822	0.278	0.304
Observations	15,877	10,448	11,728	10,419
Panel C: CAR calculated based on the Fama–French three-factor model				
I(CAR[0, 5] < 0)xPost16	−0.3339*	−0.0701	−0.2543***	−0.1550**
	(0.1797)	(0.0458)	(0.0872)	(0.0688)
ln(Asset)	1.4350***	0.7725***	−0.0162	−0.0333
	(0.1821)	(0.0653)	(0.0562)	(0.0421)
B/M	0.6675**	−0.3007***	0.0911	0.0429
	(0.3282)	(0.1068)	(0.1600)	(0.1216)

(Continues)

Table 6. (Continued)

	(1)	(2)	(3)	(4)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
Leverage	−0.0317***	−0.0061***	0.0009	−0.0005
	(0.0056)	(0.0017)	(0.0018)	(0.0015)
ln(Age)	−3.5022***	−1.5010***	−0.5967**	−0.3775*
	(0.9802)	(0.4792)	(0.2643)	(0.2003)
ROA	−0.0035	−0.0011	0.0120***	0.0046*
	(0.0084)	(0.0023)	(0.0032)	(0.0024)
Constant	−5.0767	−7.5345***	3.0408**	2.4175**
	(4.3075)	(1.7906)	(1.3358)	(0.9996)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
r2_a	0.622	0.822	0.279	0.304
Observations	15,877	10,448	11,728	10,419

R&D investment data are from 2012 to 2019, and R&D staff data are from 2015 to 2019. Patent data are from 2010 to 2019. Standard errors are clustered at firm level. All the regression control for firm and time fixed effects.
*$p<0.10$;
**$p<0.05$;
***$p<0.01$.

with the magnitude slightly reduced to 0.45, 0.12, and 0.16 compared to the baseline model; this suggests that after accounting for the trade effect, the exposure to the political shock of the Trump election and the implied institutional uncertainty continue to matter for firms' innovation activities in R&D investment, research staff, and patent applications. The use of the dummy variable of exports to the United States and the ratio of US exports largely produce the same findings.

To capture Chinese companies acquiring foreign companies abroad, we focus on outbound M&A data from the CSMAR database. A total of 803 overseas cases of mergers and acquisitions were registered during the sample period, with 120 cases in the United States. The value of outward M&As peaked in 2015 at 185 billion USD and decreased to 54 billion USD in 2019. We introduce two dummy variables $I(MA>0)$ and $I(MAus>0)$ to indicate whether or not the firm engages in outward M&A and whether the M&A takes place in the United States. Panel B of Table 7 reports that the main coefficient of interest λ_1 continues to be negative and statistically significant after considering the potential influence of overseas M&As on innovation. The magnitude of the effect of political shock remained largely unchanged. The use of $I(MAus>0)$ supports this finding.

To unravel the effect in the high-tech sector, we divide our sample firms into high-tech firms and others according to the Patent-Intensive Industry Catalog (2016) issued by the China National Intellectual Property Administration. Firms are considered high tech if their patent intensity is above the national mean and they have great growth potential. Dummy variable $I(Tech=1)$ is constructed accordingly. Panel C of Table 7 shows that after accounting for the high-tech sector factor, the coefficient estimates of firm exposure to election shock are still negative and significant but with a much smaller effect. Columns (1) and (2) show that compared to the baseline model, λ_1 was lowered by 24% and 18% for R&D and research staff, respectively, but remains significant, implying that the effect of firm exposure can be partially explained by the influence of the trade war on the high-tech sector in particular.

To rule out the potential effect of other factors influencing firm's innovation activities, we have augmented our baseline regression model with more firm-level control variables, especially corporate governance factor. The results are reported in Panel D of Table 7. Specifically, when adding the ownership ratio of the largest holder and the ratio of independent directors, the estimated coefficients of interest remain negative and significant. Alternative measures such as the ownership of the top ten largest holders and the ratio of women directors produce similar results. The results from the above tests show that even after accounting for the possible influence of exports, foreign investment, the technology sector, and other corporate governance factors, the effect of political shocks on innovation remains negative and significant, rendering further support for H1.

Table 7. Institutional uncertainty and corporate innovation (additional control variables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D staff)	ln(R&D staff)	ln(R&D staff)	ln(1 + #invention patents)	ln(1 + #invention patents)	ln(1 + #invention patents)
Panel A: Trade dependence									
I(CAR[0, 5] < 0) xPost16	−0.4494**	−0.4718***	−0.5197***	−0.1198**	−0.1280***	−0.1369***	−0.1627**	−0.1630**	−0.1644**
	(0.1800)	(0.1804)	(0.1813)	(0.0485)	(0.0490)	(0.0490)	(0.0654)	(0.0654)	(0.0655)
I(Export>0)xPost16	−1.0036***			−0.2399***			−0.0272		
	(0.1494)			(0.0415)			(0.0642)		
I(Export US>0) xPost16		−0.9205***			−0.1775***			−0.0183	
		(0.1432)			(0.0443)			(0.0703)	
US ratioxPost16			−1.6285***			−0.3802***			−0.3127*
			(0.3310)			(0.0833)			(0.1713)
ln(Asset)	1.4280***	1.4466***	1.4425***	0.7762***	0.7788***	0.7737***	−0.0311	−0.0305	−0.0335
	(0.1824)	(0.1826)	(0.1828)	(0.0654)	(0.0655)	(0.0654)	(0.0423)	(0.0422)	(0.0422)
B/M	0.5610*	0.5609*	0.6295*	−0.3055***	−0.3085***	−0.2983***	0.0314	0.0316	0.0355
	(0.3258)	(0.3264)	(0.3282)	(0.1062)	(0.1065)	(0.1067)	(0.1219)	(0.1222)	(0.1215)
Leverage	−0.0311***	−0.0310***	−0.0314***	−0.0060***	−0.0060***	−0.0060***	−0.0005	−0.0005	−0.0004
	(0.0056)	(0.0056)	(0.0056)	(0.0017)	(0.0017)	(0.0017)	(0.0015)	(0.0015)	(0.0015)
ln(Age)	−3.2522***	−3.3360***	−3.4732***	−1.3922***	−1.4405***	−1.4788***	−0.3979**	−0.3995**	−0.3886*
	(0.9646)	(0.9722)	(0.9768)	(0.4751)	(0.4780)	(0.4784)	(0.1997)	(0.2000)	(0.1987)
ROA	−0.0022	−0.0027	−0.0039	−0.0008	−0.0010	−0.0012	0.0044*	0.0044*	0.0044*
	(0.0084)	(0.0084)	(0.0084)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Constant	−5.3918	−5.6191	−5.1984	−7.8581***	−7.7954***	−7.5814***	2.4502**	2.4397**	2.4768**
	(4.3096)	(4.3094)	(4.3128)	(1.7852)	(1.7915)	(1.7906)	(0.9989)	(0.9984)	(0.9986)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.624	0.623	0.623	0.823	0.823	0.823	0.304	0.304	0.304
Observations	15,877	15,877	15,877	10,448	10,448	10,448	10,419	10,419	10,419

(Continues)

Table 7. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(R&D)	ln(R&D)	ln(R&D staff)	ln(R&D staff)	ln(1 + #invention patents)	ln(1 + #invention patents)
Panel B: Outward M&A						
I(CAR[0, 5] < 0)xPost16	−0.5233***	−0.5223***	−0.1379***	−0.1379***	−0.1651**	−0.1637**
	(0.1817)	(0.1818)	(0.0490)	(0.0491)	(0.0656)	(0.0655)
I(MA > 0)xPost16	−0.1032		−0.0447		0.1094	
	(0.1727)		(0.0401)		(0.0984)	
I(MAus>0)xPost16		−0.6694***		−0.1232**		−0.0176
		(0.2165)		(0.0505)		(0.2378)
ln(Asset)	1.4532***	1.4534***	0.7791***	0.7786***	−0.0321	−0.0301
	(0.1833)	(0.1831)	(0.0656)	(0.0655)	(0.0422)	(0.0422)
B/M	0.6228*	0.6217*	−0.3127***	−0.3123***	0.0348	0.0326
	(0.3284)	(0.3285)	(0.1069)	(0.1070)	(0.1217)	(0.1217)
Leverage	−0.0317***	−0.0317***	−0.0061***	−0.0061***	−0.0005	−0.0005
	(0.0056)	(0.0056)	(0.0017)	(0.0017)	(0.0015)	(0.0015)
ln(Age)	−3.5686***	−3.5735***	−1.5180***	−1.5237***	−0.4063**	−0.4026**
	(0.9799)	(0.9799)	(0.4793)	(0.4797)	(0.1992)	(0.1993)
ROA	−0.0042	−0.0041	−0.0013	−0.0013	0.0044*	0.0043*
	(0.0084)	(0.0084)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Constant	−5.1734	−5.1642	−7.5846***	−7.5580***	2.4912**	2.4392**
	(4.3248)	(4.3163)	(1.7943)	(1.7933)	(0.9993)	(0.9978)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.622	0.622	0.822	0.822	0.304	0.304
Observations	15,877	15,877	10,448	10,448	10,419	10,419

	(4)	(5)	(6)
	ln(R&D)	ln(R&D staff)	ln(1 + #invention patents)
Panel C: High-tech sector			
I(CAR[0, 5] < 0)xPost16	−0.3533**	−0.1014**	−0.1657**
	(0.1781)	(0.0480)	(0.0659)

Table 7. (Continued)

	(4)	(5)	(6)
	ln(R&D)	ln(R&D staff)	ln(1 + #invention patents)
I(Export>0)xPost16	−0.8121***	−0.2006***	−0.0285
	(0.1409)	(0.0400)	(0.0645)
I(MAus>0)xPost16	−0.4002	−0.0838	−0.1274
	(0.4169)	(0.1088)	(0.2061)
I(Tech = 1)xPost16	−1.0531***	−0.2120***	0.0196
	(0.1693)	(0.0455)	(0.0613)
ln(Asset)	1.4330***	0.7707***	−0.0301
	(0.1826)	(0.0651)	(0.0423)
B/M	0.5171	−0.2870***	0.0308
	(0.3221)	(0.1052)	(0.1218)
Leverage	−0.0300***	−0.0057***	−0.0005
	(0.0056)	(0.0017)	(0.0015)
ln(Age)	−2.9554***	−1.2487***	−0.4045**
	(0.9539)	(0.4704)	(0.2002)
ROA	−0.0033	−0.0009	0.0044*
	(0.0084)	(0.0023)	(0.0023)
Constant	−6.1837	−8.1222***	2.4470**
	(4.3192)	(1.7771)	(0.9999)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
r2_a	0.626	0.824	0.304
Observations	15,877	10,448	10,419

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
Panel D: Corporate governance factors								
I(CAR[0, 5] < 0) xPost16	−0.5257***	−0.1346***	−0.1370*	−0.1650**	−0.5247***	−0.1368***	−0.1380*	−0.1649**
	(0.1820)	(0.0487)	(0.0822)	(0.0654)	(0.1815)	(0.0489)	(0.0823)	(0.0655)

(Continues)

Table 7. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
ln(Asset)	1.4481***	0.7754***	−0.0196	−0.0309	1.3598***	0.7457***	−0.0062	−0.0214
	(0.1829)	(0.0640)	(0.0562)	(0.0421)	(0.1801)	(0.0616)	(0.0570)	(0.0427)
B/M	0.6013*	−0.3256***	0.0952	0.0470	0.5070	−0.3141***	0.1029	0.0472
	(0.3326)	(0.1070)	(0.1619)	(0.1217)	(0.3317)	(0.1067)	(0.1605)	(0.1213)
Leverage	−0.0318***	−0.0064***	0.0011	−0.0004	−0.0287***	−0.0054***	0.0005	−0.0008
	(0.0056)	(0.0017)	(0.0018)	(0.0015)	(0.0057)	(0.0018)	(0.0018)	(0.0015)
ln(Age)	−3.5401***	−1.3913***	−0.6569**	−0.4261**	−2.7974***	−1.2844***	−0.7097***	−0.4613**
	(0.9940)	(0.4826)	(0.2631)	(0.1991)	(0.9989)	(0.4840)	(0.2669)	(0.2031)
ROA	−0.0045	−0.0018	0.0120***	0.0047**	−0.0067	−0.0015	0.0121***	0.0047**
	(0.0083)	(0.0023)	(0.0032)	(0.0024)	(0.0083)	(0.0023)	(0.0032)	(0.0023)
Independent director ratio	−0.7588	0.0185	−0.2388	0.1222				
	(1.1523)	(0.3733)	(0.5081)	(0.3628)				
Largest holder	0.0033	0.0081*	−0.0030	−0.0031				
	(0.0118)	(0.0048)	(0.0038)	(0.0029)				
Female director ratio					0.3371	−0.1445	−0.0050	0.0391
					(0.5535)	(0.1647)	(0.2207)	(0.1631)
Top 10 holders					0.0254***	0.0081**	−0.0036	−0.0027
					(0.0083)	(0.0035)	(0.0027)	(0.0021)
Constant	−4.9538	−8.1281***	3.4650**	2.5653**	−6.8604	−7.9960***	3.3481**	2.5622**
	(4.4722)	(1.8778)	(1.3537)	(1.0154)	(4.4129)	(1.8441)	(1.3349)	(1.0005)
r2_a	0.622	0.823	0.278	0.304	0.623	0.823	0.278	0.304
Observations	15,875	10,446	11,726	10,417	15,875	10,446	11,726	10,417

R&D investment data are from 2012 to 2019, and R&D staff data are from 2015 to 2019. Patent data are from 2010 to 2019. Standard errors are clustered at firm level. All the regression control for firm and time fixed effects.
*$p<0.10$;
**$p<0.05$;
***$p<0.01$.

Table 8. Moderating effects of firm characteristics

	(1)	(2)	(3)	(4)
	ln(R&D)	ln(R&D staff)	ln(1 + #patents applied)	ln(1 + #invention patents)
I(CAR[0, 5] < 0)xPost16				
xSOE	−1.0123**	−0.2951**	−0.1468	−0.1899
	(0.4212)	(0.1174)	(0.1796)	(0.1464)
xAge	−1.5568**	−0.3137*	−0.3138	−0.2546
	(0.6412)	(0.1648)	(0.3017)	(0.2451)
xSize	−0.2686	−0.0691	−0.0709	−0.0955
	(0.1636)	(0.0478)	(0.0805)	(0.0581)
xLeverage	−0.0191**	−0.0046*	−0.0052	−0.0017
	(0.0093)	(0.0026)	(0.0040)	(0.0030)
xGrowth	0.5856	−0.0562	−0.0088	0.1809
	(0.5330)	(0.1589)	(0.1940)	(0.1574)
Control	Yes	Yes	Yes	Yes
Firm/year fixed effect	Yes	Yes	Yes	Yes

Only the coefficient estimates of the three-item interaction are reported in the table. Except for SOE dummy, all the other firm characteristic variables are demeaned.
*$p < 0.10$;
**$p < 0.05$;

4.3. *Cross-sectional heterogeneity*

In Table 8, we report the coefficient estimates of the three-item interaction. The coefficients of the SOE-related three-item interaction are negative and significant in columns (1) and (2), indicating that the innovation impact of election shock is more pronounced in SOEs. One possible explanation is that despite the information advantage, SOEs are often tasked with many social functions, such as employment, and hence show a larger cut in their R&D input when facing heightened uncertainty after the election shock. The coefficients involving firm age are mostly negative and significant for innovation input, suggesting that stronger innovation implications of election shocks are found for older firms. Regarding firm size and sales growth, the coefficients are insignificant, implying that scale and growth opportunity do not exert moderating effects on the uncertainty–innovation relationship. Last, the R&D effect of exposure to shocks is more pronounced in firms with high leverage, highlighting the role of financial constraints in limiting a firm's innovation effort. In sum, these findings help us identify companies that fare better and provide important references for government relief measures.

5. Conclusion

In this paper, we examine the implications of overseas institutional uncertainty on corporate innovation in the largest emerging economy. We leverage our empirical strategy on an exogenous political shock in a quasi-natural experimental setting and focus on Trump's unexpected victory in the 2016 US presidential race. Employing the CARs to gauge firms' exposure to institutional uncertainty, we find that firms' innovation activities are adversely affected by the surprise election outcome, and the results continue to hold in a battery of robustness tests. Additional analysis further shows that the detrimental effect of this shock on Chinese firms' innovation is more pronounced in SOEs, older firms, and financially constrained firms. Our findings largely support the real options theory and cost-of-capital perspective regarding the R&D implications of institutional uncertainty stemming from external political shock.

Our contributions are twofold. First, from a theoretical standpoint, the majority of existing research has primarily concentrated on domestic institutional uncertainty, with limited attention given to the uncertainty arising from foreign institutional changes. In this regard, our study extends the scope of the institutional uncertainty literature by considering foreign election shock as a source of institutional disruption that generates uncertainty, thus broadening the conceptual boundaries and enriching the understanding of institutional uncertainty theory. This expansion allows for a more comprehensive examination of the factors influencing organizational behavior in the face of institutional uncertainty. Moreover, we add to the literature on the R&D management under disruptive uncertainty (Zhong et al., 2019; Clougherty and Zhang, 2021) by highlighting the relevance between uncertainty and innovation. Additionally, we contribute to the political economics of international trade and finance by examining the impact of the 2016 US election on R&D management, revealing a reduction in innovation input and output due to anticipated trade barriers, and expanding the literature on the effects of the US–China trade war.

Empirically, our study complements the existing literature, which primarily focuses on advanced countries, by providing some of the first evidence on the impact of institutional uncertainty regarding bilateral trade and investment relations on domestic corporate innovation in an emerging country. This enhances our understanding of how disruptive uncertainty interacts with R&D management in a global context. Additionally, our study stands out as the first to utilize an unexpected US presidential election outcome as a quasi-experiment to examine the effect of institutional uncertainty on the corporate innovation of its major trading partner. Compared to a news-based uncertainty index, our event study approach combined with a difference-in-difference framework allows for better control of compounding effects and provides a cleaner identification of the R&D effect resulting from institutional uncertainty (Jens, 2017; Caldara and Iacoviello, 2022).

The findings of this study have important managerial implications regarding R&D management. Shedding new light on the corporate finance implications of external political uncertainty, we offer valuable insights for firms in developing their innovation strategies. Given the current strained trade relationship and technology race between China and the United States, the results emphasize the need for Chinese firms to adopt proactive innovation strategies. At the micro-level, enterprises are encouraged to enhance their dynamic capabilities in order to effectively respond to institutional uncertainty resulting from foreign election shock. Specifically, the SOEs should proactively leverage their informational advantage to swiftly adjust investment strategies and increase investments in R&D, without being excessively cautious in response to external shocks. Companies having a longer history and larger scale should strategically capitalize on their resource advantages to cultivate dynamic capabilities, avoiding falling into organizational obsolescence (Winter, 2003), in order to better cope with uncertainty. Moreover, in environments characterized by high levels of uncertainty, businesses should exercise prudence regarding high leverage levels and strive to enhance their resilience against shocks.

Additionally, there is a call for innovation policymakers in governments to consider the impact of US actions and address rising unilateralism and protectionism on a global scale. At the macro-level, when examining or designing a country's innovation framework or ecosystem, it is crucial to consider the country's political and economic relations with other nations, as well as the institutional stability of those countries. Understanding these factors can help shape effective innovation policies that foster a conducive environment for innovation while accounting for external uncertainties.

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Conflict of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The data that support the findings of this study are openly available in CSMAR, WIND, and database of the General Administration of Customs (https://www.wind.com.cn/portal/en/EDB/index.html, https://www.gtadata.com/, http://english.customs.gov.cn/).

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Notes

1 The industry classification is based on the Guidelines for the Industry Classification of Listed Companies (2012 Revision), issued by the China Securities Regulatory Commission.

2 Following common practice in the event study literature, we estimate abnormal returns for varying lengths of the event window and try to strike the right balance between an event interval that is too narrow, risking potentially missing information that takes time to appear, and a window too wide, which may incorporate price change driven by confounding events.

3 We also used other models such as the Fama–French three-factor model to recalculate the expected return, and our main results remain unchanged.

4 In unreported robustness test, we also chose [−210, −10] as the estimation window period and obtained similar results.

5 One drawback of the R&D employee data is that they are reported only after 2015, a period rather short to reflect the trend before the event in 2016.

6 Naturally, manufacturing firms dependent on the international market are bound to be more susceptible to uncertainty and hit harder than firms in the service sector, whose market is mainly domestic.

7 The difference between the two means is −0.72% with the corresponding standard error being 0.17%, giving a t-statistic 4.2.

8 In unreported table, we show that information, software and communication, and scientific research and technology services are among the sectors with the highest R&D intensity. In terms of the number of patents filed and granted, mining industry and construction industry rank the highest.

9 To account for some potential effects of industry-wide innovation policy change, we also consider year fixed effect and industry fixed effect, and the results remain the same.

10 The inclusion of firm-level control variables enhances the explaining power of independent variables, with lower standard error for the estimated coefficients.

11 Too short a window may not allow enough time for the market to digest the influence of Trump's election, hence undermining the information embedded in CAR to reflect the impact of the shock. If the event window is too long, the market may pick up a response to other shocks.

12 We also used CAR[0, 3] to focus on a shorter event window and obtained basically the same results.

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APPENDIX

Variable definitions

Asset	Natural logarithm of total assets
ROA	Pretax income scaled by total assets
Leverage	Long-term debt scaled by total assets
Patents	The number of patents applied by each firm in a particular year
Invention patents	The number of invention patents applied by each firm in a particular year
Growth	Sales growth between year t and year $t-1$
R&D staff	The number of staff employed directly in the field of research and development (R&D)
R&D	Research and development expenditure scaled by total assets
B/M	Book-to-market ratio
Age	The age of firm in year *t*
CaAs	Operating cash flow
CashInv	Cash flow from financing
NetInv	Investment in fixed assets
Profit	Profit margin, calculated as the ratio of profit to sales