Safety Uncertainty, Government Intervention, and Corporate Innovation—Evidence from Terrorist Attacks

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Abstract

Numerous studies investigate how economic policy uncertainty affects corporate investment but empirical research on the impact of safety uncertainty is scarce. This study empirically examines the impact of safety uncertainty on corporate innovation and the mitigating and exacerbating government intervention effects, by employing a difference-in-differences approach to establish causality, considering terrorist attacks as an exogenous shock to safety uncertainty. It finds that firms located near terrorist attack sites generate poor innovation outcomes, as measured via patents and citations. The impact of safety uncertainty is attenuated in state-owned enterprises and firms in favored industries, while the impact is more significant for firm in regions with stricter internet censorship and that are subject to a high tax burden. Furthermore, R&D investment and inventor mobility are two plausible channels underlying the finding that safety uncertainty drives firms to cut R&D investment and lose valuable inventors. Hence, safety uncertainty arguably impedes corporate innovation, while government intervention has a mitigating effect through state ownership and industry policy and an exacerbating effect through a high tax burden and strict censorship.

Keywords: safety uncertainty, terrorist attack, corporate innovation, government intervention, mitigating-exacerbating effects

1. Introduction

While numerous studies examine how economic policy uncertainty affects corporate investment (e.g., Dixit 1989; Dixit and Pindyck 1994; Bloom et al. 2007; Jeong 2002; Julio and Yook 2012; Li et al. 2016; Gulen and Ion 2016), recent studies have documented that safety uncertainty impedes corporate innovation and exert associated economic impacts such as increased cost of business, human capital outflow, and drastic fluctuations in financial markets (Abadie and Gardeazabal 2003; Chen and Siems 2004; Llussá and Tavares 2011; Enders et al. 2006; Cuculiza et al. 2020). However, empirical studies on the impact of safety uncertainty are scarce, despite exceptions such as Dai et al. (2020) who study the impact of terrorism on CEO compensation in the United States. The greatest challenge is identifying a causal effect free of endogeneity concerns because safety uncertainty and corporate innovation are likely to be correlated with unobserved economic, financial, and political characteristics.

Thus, to address potential endogeneity concerns, this study exploits a natural experiment (i.e., terrorist attacks) to empirically investigate how safety uncertainty affects risky corporate investment such as investment in innovation. There are two reasons for choosing terrorist attack. First, a terrorist attack creates an unexpected unambiguous negative change in an environment, allowing for a causal inference between safety uncertainty and firm decisions (Cuculiza et al. 2020; Dai et al. 2020). Thus, terrorist attacks are largely exogenous to all firms and are not driven by firms' patenting activities. Second, the impact of safety uncertainty from terrorist attacks is normally significant. In recent years, terrorist attacks, accompanied by mass destruction and damaging effects,[5] have drawn extensive attention.

Further, this study examines how government intervention moderates the relationship between safety uncertainty and corporate innovation. We propose that government intervention either mitigates or exacerbates the effects of safety uncertainty on corporate innovation in a transition economy (i.e., China) where government interventions exist.

[5] These effects include disturbing political stability (Meierrieks and Gries 2013), destabilizing capital markets (Abadie and Gardeazabal 2003; Chen and Siems 2004), and reducing investment and consumption (Llussá and Tavares 2011; Enders et al. 2006). According to *PR Newswire*, losses from terrorism worldwide amounted to $33 billion in 2018. For details, please see https://www.prnasia.com/story/265348-1.shtml.

According to the Global Terrorism Database (GTD),[6] since the late 1980s, China has seen more than 250 terrorist incidents employing illegal force and violence. Given the considerable variation in terrorist attack locations, China provides an ideal setting for studying the impact of safety uncertainty on corporate decisions due to the minimal confounding effects of local factors, such as different political and legal systems in international studies. Using a panel of 2,361 publicly listed firms from 2003 to 2014, we adopt a difference-in-differences (DID) approach to investigate the innovation output of firms near terrorist attack sites relative to that of firms far removed from such sites. Specifically, this study collected the time, coordinates, and targets of each terrorist attack from the GTD. It then employed the distance calculated by the latitude and longitude of each terrorist attack site to identify affected companies (situated within 50 km of terrorist attacks). Our baseline results show that affected firms innovate less significantly. Specifically, the threat of terrorism leads to 9.5% and 7.4% fewer patents and citations, respectively.

Hence, to test whether the parallel trend assumption of the DID approach holds, we follow Bertrand and Mullainathan (2003) and examine the dynamics of innovation output in the case of terrorist attacks. Accordingly, there is no pretreatment trend in innovation output. Further, we implement two placebo tests to investigate whether our results are purely driven by chance and find that the DID estimates differ insignificantly from zero. Thus, to address the concern that the findings might be subject to the firm self-selection issue, the study adopts a propensity score matching technique to mitigate the observable difference in the pre-shock characteristics between the treatment and control groups. We find quantitative results similar to those of the full panel sample.

Subsequently, we identify the economic mechanism underlying our findings. First, according to the theory of the real option of waiting, uncertainty increases the waiting option value, causing firms to postpone their investment until the uncertainty is resolved (Julio and Yook 2012; Gulen and Ion 2016). Consistently, we find that the threat of terrorism to safety uncertainty forces firms to withhold investment in R&D, which directly lowers the innovation output in affected firms. Second, consistent with prior findings that safety uncertainty stimulates a negative psychological impact on human capital

6 The National Consortium for the Study of Terrorism and Response to Terrorism (START) constructs the GTD. For details, please see https://www.start.umd.edu/data-tools/global-terrorism-database-gtd

and hurts creativity (Becker and Rubinstein 2011; Ahern 2018), we find that safety uncertainty from terrorism is positively associated with the outflow of inventors.

Further, to test our proposition that government intervention could either positively or negatively moderate the relationship between safety uncertainty and corporate innovation, we conduct several cross-sectional analyses to examine the heterogeneous impact on firm innovation. On the one hand, the impact of safety uncertainty is less significant in state-owned enterprises (SOEs) and the favored industry because these firms obtain favorable treatment from the government, lowering the impact of uncertainty on corporate innovation. On the other hand, government intervention exerts externalities over corporate innovation by imposing a high tax burden and strict internet censorship. Thus, firm innovation is more negatively sensitive to terrorist attacks. Firm innovation activities are less sensitive to terrorism in regions with a higher degree of marketization and good social stability, thus supporting our baseline argument that the external environment stability is conducive to innovation development.

Finally, this study conducts a series of robustness tests. First, it introduces alternative measures for firms near terrorist attacks (within 25 km or 10 km of terrorist attacks). Second, it excludes firms located in provinces with an extremely high frequency of terrorist attacks to minimize the confounding effect of outliers. Third, it restricts control firms to those adjacent to affected firms to minimize the confounding effect of local factors. All ensuing results remained valid.

This study contributes to the literature in three ways. First, while previous studies emphasize economic growth, inflation, and government fiscal spending (Gupta et al. 2004; Tavares 2004; Öcal and Yildirim 2010; Meierrieks and Gries 2013; Shahbaz 2013), this study assesses the economic consequences of safety uncertainty at the firm level. In particular, it finds that safety uncertainty affects corporate investment decisions. Moreover, it shows that the outflow of inventors indicates a brain drain effect of safety uncertainty.

Second, this study contributes to the literature on the determinants of firm innovation. Few studies have examined the impact of safety uncertainty on corporate innovation. Thus, this study bridges the research gap by providing novel evidence on whether and how safety uncertainty affects firm innovation in an emerging market. The findings offer a clear implication that external environment stability is conducive to innovation development.

Third, this study contributes to the literature on the economic consequences of government intervention. Existing studies document that the government can either assist the development of firms' innovation ability and output through direct ownership or industry policy (Choi et al. 2011; Kollmann and Roeger 2011; Guo at al. 2016; Zhan and Zhu 2020) or hinder innovation by imposing high taxes. We find that government intervention mitigates the impact of terrorism through state ownership and industry policy but exacerbates the impact by imposing a high tax burden and strict censorship.

The remainder of this paper is organized as follows. Section 2 presents the related literature. Section 3 describes the data sources and variable construction. Section 4 presents the identification strategy, empirical results, mechanisms, and heterogeneity analysis. Section 5 concludes.

2. Hypotheses Development

2.1 Safety Uncertainty and Innovation

The consequence of safety uncertainty from terrorism is a controversial topic in macro and micro research (Abadie and Gardeazabal 2003; Chen and Siems 2004; Abadie and Gardeazabal 2008; Llussá and Tavares 2011; Enders et al. 2013; He et al. 2020). Although some studies argue that localized terrorism destroys only a fraction of capital stock in a country and, thus, should not affect economic activity (Becker and Murphy 2001), most studies have shown that safety uncertainty from terrorism hurts national economic activities and growth (Blomberg et al. 2004; Abadie and Gardeazabal 2008; Meierrieks and Gries 2013), specifically private consumption and investment, leading to economic recession (Llussá and Tavares 2011).

In addition to macro-level economic activities, other studies focus on the impact of safety uncertainty and terrorism on investment decisions and capital factors (Chen and Siems 2004; Bloom 2007; Abadie and Gardeazabal 2008; Enders et al. 2013). For example, Abadie and Gardeazabal (2008) document how terrorism affected international investment decisions, while Enders et al. (2013) show the impact of terrorism and security uncertainty on foreign direct investment in the context of the United States, emphasizing human and non-human capital loss. Investors would take capital out of markets as news of terrorist events broke, and would also be influenced by expectations of uncertainty (Chen and Siems 2004).

Recent studies have explored the effects of uncertainty from terrorism at the firm level. Dai et al. (2019) found that safety uncertainty from terrorism lead to higher labor costs. Antoniou et al. (2017) argued that terrorist incidents induced companies to make more conservative decisions. Expectation uncertainty is likely to prompt companies to halt high-risk, long-term R&D investments. However, there is hardly any empirical evidence on terrorism lowering corporate spending on R&D and corporate innovation. Following Bloom's (2007) theoretical model, this study proposes that firms' R&D spending responds to uncertainty from terrorism via adjustment costs, which in turn affect corporate innovation, given the effects of terrorism on capital input and investment decisions. Therefore, we propose the following hypothesis:

H1: Uncertainty from terrorism impedes firm innovation.

2.2 Moderating Effects of Government Intervention

2.2.1 The Mitigating Effect of Government Intervention

Despite government intervention, an administrative monopoly with Chinese characteristics remains intriguing. Irrespective of whether political interference augments firm innovation activities, existing studies offer two competing arguments. Government intervention may benefit firm innovation by increasing public expenditures and optimizing resource allocation. The Chinese government faithfully implements an innovation-driven strategy, funding supporting R&D activities and exerting an important effect on firm innovation activities, especially in coping with inadequate innovative investment (Guo et al. 2016). The generation of information or knowledge via an innovative process is often accompanied by market failure, which is the main basis for government intervention. The cost of technological innovation is beyond the reach of private firms, which is a major reason for the scarcity of firm innovation investment (Wang 2018). Hence, government intervention in guiding market players to participate in innovation activities makes sense, especially because firms need to ward against negative external shocks (Blomberg et al. 2004). Therefore, firm innovation may be less sensitive to safety uncertainties from terrorism through government intervention by way of two arrangements: state ownership and industry policy.

First, the Chinese government maintains a dominant presence in most areas through state-controlled entities. It is easier for the government to implement policy intervention through SOEs to significantly affect the development of firms' innovation ability, innovation output, and efficiency (Choi et al. 2011; Zhan and Zhu 2020). As Piotroski and Wong (2012) suggest, SOEs possess inherent advantages in policy preference and resource endowment relative to non-SOEs (Piotroski and Wong 2012), which are conducive to firms trying to cope with the harsh external environment. Thus, we expect that the effects of external uncertainty from terrorism on firm innovation are relatively weak for SOEs.

Second, industry policy through which governments extend a helping hand (Kollmann and Roeger 2011; Guo et al. 2016) could be effective. Combined with the changes and adjustment of industry structure, the Chinese government gives priority and support to favored and important industries during resource allocation, including subsidies, tax privileges, R&D funding, and investment opportunities, to realize performance objectives (Ayyagari et al. 2011; Guo et al. 2016). This directive intervention is largely based on the government's perception that motivated industries are more important to China's industrial strategy (Guo et al. 2016). As the government concentrates resources in favored industries for strategic considerations of independent innovation acceleration and industrial upgrade (Guo et al. 2016; Liu et al. 2018), firm innovation activities also benefit from government industrial policy support. Thus, we expect that policy support alleviates the negative effects of safety uncertainty from terrorism on innovation in affected firms. Hence, we propose the following hypothesis:

H2a: Government interventions attenuate the negative impact of safety uncertainty on firm innovation.

2.2.2 The Exacerbating Effect of Government Intervention

Government intervention exerts negative externalities over corporate innovation. Neoliberalism advocates the leading role of the market and posits that innovation in the market economy is mainly determined by the invisible hand of market demand (Mowery 1979; Hurley and Hult 1998). Government intervention may lead to a deadweight loss in social welfare, which distorts market efficiency in resource allocation (Wang 2018; Gerring and Thacker 2005) and generates unexpectedly negative impacts on private R&D inputs (Wallsten 2000; David et al. 2000; Chen et al. 2011; Guo et al. 2016; Acemoglu et al. 2018; Huang and Yuan 2019). Thus, government intervention may exacerbate the impact of safety uncertainty on corporate innovation in affected firms. This study explores two government interventions (a high tax burden and strict internet censorship) to see how they moderate the relationship between safety uncertainty and corporate innovation.

First, the government extracts resources from firms via taxes to redistribute national income (Che 2002). A higher tax burden accompanies higher government intervention, especially in emerging markets (Zhang at al. 2016). At the legal level, China unified the tax rate. However, the jurisdictional tax competition among local governments generates obvious regional differences regarding the actual tax burden of enterprises, thus contributing to identifying the extent of government intervention. A high tax burden fails to create a favorable business environment for enterprise innovation since R&D investment and innovation outputs are restricted to a firm's tax burden (Mukherjee et al. 2017). This situation may make the situation worse for firms affected by negative shocks. Hence, firm innovation activities are expected to be more responsive to safety uncertainty under a higher degree of government intervention via tax burden.

Second, the study sheds light on government intervention via information censoring intensity. Government engages in strict censorship to ostensibly maintain social stability. However, it creates unintended consequences on corporate innovation; the rise in internet censorship following the emergence of the social media produced profound changes to the enterprise management environment. As China has the world's most complex internet filtering system ("Great Firewall of China"), the Chinese regional web filter is considered a reasonable proxy to measuring the censoring intensity degree (Kong et al. 2018). In filtering blocked keywords,[7] international knowledge spillovers may be subject to interference from web filter devices. Further, we argue that the strong position of the government in censorship aggravates the influence of terrorism (Meierrieks and Gries 2013) and makes local firms' innovative activities more sensitive to safety uncertainty. Thus, provinces with high censoring capacity

[7] The Great Firewall of China operates by inspecting Transmission Control Protocol (TCP) packets for filtering blocked keywords. The keyword-based blocking occurs within routers, which use devices based on intrusion detection system (IDS) technology to determine whether the content is acceptable. If the content is to be blocked, the IDS equipment will issue TCP reset packets to cause the offending connection to be closed.

experience pronounced negative external uncertainty effects from terrorism on firm innovation. Hence, we propose the following hypothesis:

H2b: Government interventions exacerbate the negative impact of safety uncertainty on firm innovation.

3. Data and Variable Construction

3.1 Data and Sample

First, this study obtains data on terrorist attacks from the GTD managed by START. From this database, we collect information on geographic coordinates and target groups of each terrorist attack event in China from 2003 to 2014. Second, we obtain data on firm innovation activities from the State Intellectual Property Office of China (SIPO). Third, we collect financial information on listed firms from the China Stock Market and Accounting Research (CSMAR) database.

Since the regulation and disclosure rules in the financial sector are different from those in other sectors, the study excludes listed companies in the financial industry. We then delete abnormal observations with negative net assets. Further, to minimize the confounding effect of extreme values, we winsorize all continuous variables at the 1% and 99% percentiles. Finally, the study employed a sample of 19,715 firm-year observations spanning 2003 to 2014.

3.2 Variable Construction

3.2.1 Firm Innovation

Following previous innovation studies (He and Tian 2013; Balsmeier et al. 2017), we construct two variables to capture the innovation outputs and quality from firm creative activities. The first measure is the total number of eventually-granted patent applications filed by a firm in a given year. We employ patent application year rather than that of grants to match other financial proxies since it better captures the actual time of firms' innovation activities (Griliches et al. 1986; Hall et al. 2001).

The patent data, however, are subject to truncation problems (Hall et al. 2001, 2005). Given the lag in granting applications, an application may not be granted in the period of the database coverage. Therefore, we employ several approaches to adjust the data on the raw patent count. First, the average application-grant lag in China is about three years.[8] To alleviate the truncation problem, we restrict our sample to 2015. Second, we adjust the raw patent count data in our data coverage (2003–2014) via the application-grant lag distribution of the 1984–2002 period. Specifically, we adjust patent counts as follows:

$$NumPat_y^{adj} = \frac{NumPat_y^{raw}}{\sum_{i=0}^{Endyr-y} frac_i},$$

where y is the application year, $frac_i$ is the fraction of patents granted in i years ($2003 \leqslant i \leqslant 2014$), and *Endyr* is the last year of the data sample (e.g., 2014 in our sample). The denominator represents the fraction of (successful) patent applications in year y that are expected to have been granted by the end year (*Endyr*) of the sample based on historical patterns.

Due to the right skewness of the patent and citation counts, we calculate the natural logarithm value of one plus the patent counts (*LnPat*) to measure the innovation quantity. To consider the innovation quality, we calculate the natural logarithm value of one plus the number of citations (*LnCite*). Since innovation is a long-term risky investment, the study adopts the one-year-ahead value of *LnPat* and *LnCite* in all analyses.

3.2.2 Terrorist Attacks

In this study, the main independent variable is *Attack_50km*, which takes the value of 1 if a terrorist attack occurs within 50 km of the firms' headquarters and 0 otherwise.[9] Moreover, we construct two variables to measure the severity of terrorist attacks regarding fatality (Luo et al. 2019; Nguyen et al. 2019). In particular, *Attack_Kill* is a dummy variable that takes the value of 1 for affected firms if death occurs and 0 otherwise. Affected firms are headquartered within 50 km of terrorist attacks. Following Nguyen et al. (2019), terrorism intensity is the sum of the number of deaths and 50% of the number of injuries. *Attack_Terrorism* is a dummy variable that takes the value of 1 for affected firms if the terrorism intensity is above the sample median and 0 otherwise.

[8] From *The Long Wait for Innovation: The Global Patent Pendency Problem*, published by the Center for the Protection of Intellectual Property (CPIP).

[9] Per the Baidu Map, no city in China has a radius larger than 50 km. Since firms may share similar traits in the same city due to local proximity, we set 50 km as the threshold to measure the safety uncertainty surrounding the firm. In the robustness check, we apply 25 km and 10 km as alternative thresholds to measure safety uncertainty surrounding the firm.

Moreover, to compare the impact of different types of terrorist attacks on corporate innovation, we constructed three variables based on the attack target. *Attack_GovArmy* takes the value of 1 if attack targets include the government, police, or military and 0 otherwise. *Attack_public* takes the value of 1 if the attack targets include airports, aircraft, or public transportation and 0 otherwise. *Attack_Private* takes the value of 1 if the attack targets are private citizens and property or business, and 0 otherwise.

3.2.3 Other Variables

Motivated by prior studies (He and Tian 2013; Cornaggia et al. 2014), the study constructs a vector of covariates reflecting firm and regional characteristics that may affect a firm's innovation outcomes. Specifically, *Cash* is cash holdings scaled by the total assets of a firm in a year. *ROA* is the ratio of net income to total assets of a firm in a year. *PPE* is the investment in plant, property, and equipment scaled by the total assets of a firm in a year. *Size* is the natural logarithm of total assets (measured in million RMB). *Leverage* is the ratio of total debt to total assets of a firm in a year. *HHI* is the sum of squares of market share measured by firm sales in a year. *Growth* is the growth rate of a firm's operating income in a year. *SOE* is a dummy variable that takes the value of 1 for SOEs and 0 otherwise. *Dual* is a dummy variable that takes the value of 1 if the chair and CEO are the same person and 0 otherwise. *IndRatio* is the fraction of independent directors on a board. *MGDP* is a city's gross domestic product per capita (measured in 10,000 RMB per person). *Sec_Industry* is the proportion of secondary industries in a city's gross domestic product. *lnSalary* is the natural logarithm of the average salary of employees measured at 10,000 RMB. *Density* is the population density in a city measured by the number of people per square kilometer. Table A1 of Appendix A provides all variable definitions.

3.3 Summary Statistics

Table 1 presents the sample description. Panel A shows that the mean value of $LnPat_{t+1}$ is 0.613, and the mean value of $LnCite_{t+1}$ is 0.402, which is similar to Kong et al. (2018). Approximately 37.8% of our sample observations are affected by terrorist attacks if we set 50 km as the threshold to measure the safety uncertainty surrounding firms. The average firm holds a significant amount of cash with a cash ratio of 16.3% of the total assets. Regarding performance, on average, a sample firm has a ROA ratio of 3.2%. The average firm is levered with a book leverage ratio of 48.3%. On average, independent directors account for approximately 36.2% of board members.

Panel B reports the distribution of terrorist attacks by province. During the sample period, there were 40 terrorist attacks within 50 km of the location of the listed firms. Guangdong and Xinjiang experienced the most frequent terrorist attacks. Panel C reports the distribution of terrorist attacks by targets, which are, mainly, private citizens and property. Panel D shows the sample distribution by industry. Approximately 58.55% of our sample observations are from the manufacturing industry.

[Insert Table 1 here]

4. Empirical Results

4.1 Multivariate DID Analysis

Following Bertrand and Mullainathan (2003), we examine the impact of safety uncertainty on corporate innovation by performing a standard DID test through the following regression:

$$Innovation_{i,t+1} = \alpha + \beta_1 Attack\_50km_{i,t} + Z_{i,t}\Theta + FirmFE + YearFE + \varepsilon_{i,t},$$

where *i* indexes the firm, and *t* indexes the year. $Innovation_{i,t+1}$ represents *the LnPat* and *LnCite* of firm *i* in year *t*+1. *Attack_50km* takes the value of 1 if a terrorist attack has ever occurred within 50 km of the firms' headquarters and 0 otherwise. $Z_{i,t}$ is the set of control variables that may affect a firm's innovation output. Specifically, we include *cash*, *PPE*, *Size*, *ROA*, *Leverage*, *Growth*, *HHI*, SOE, *lndRatio*, and *Dual* in our baseline regression. Further, to control for regional factors, we include *MGDP*, *Sec_Industry*, *lnSalary*, and *density* in the baseline regression. We also include the year-fixed effect to control for time-specific shocks to innovation output. Moreover, we add the firm-fixed effect to account for time-invariant firm unobservable characteristics that may affect corporate innovation. We cluster the standard errors at the firm level to account for the potential correlation of error terms.

Attack_50km is the coefficient of interest, which captures the innovation difference between terrorism-affected firms before and after terrorist attacks and compares the difference with a similar before-after difference in terrorism-unaffected firms. The DID estimate enables us to remove biases in the post-attack comparison between the affected and unaffected firms. These biases could be the result of either a permanent difference between the two groups or a possible time trend effect (Imbens and Wooldridge 2009). If safety uncertainty leads to a larger decrease in innovation output among terrorism-affected firms, this coefficient should be negative and statistically significant.

Table 2 reports the results of the multivariate DID analysis. In all specifications in Columns 1, 2, 4, and 5, the coefficient of *Attack_50km* is negative and statistically significant at the 1% level, indicating that, relative to unaffected firms, terrorism leads to a larger decrease in innovation quantity and quality among affected firms. Particularly, in Column 2, relative to unaffected firms, terrorism leads to a 10.0% (=$e^{0.095}$-1) decrease in the number of patents among affected firms. Further, in Column 5, relative to unaffected firms, terrorism leads to a 7.7% (=$e^{0.074}$-1) decrease in the number of citations among the affected firms. Thus, the economic significance of the impact of the safety uncertainty on corporate innovation output is also significant.

[Insert Table 2 here]

4.2 Identification Issues

4.2.1 Trend Analysis

An important assumption regarding the DID estimation validity is the parallel trend, which requires the average change in corporate innovation to be the same in affected and unaffected firms. Thus, given a parallel trend, DID estimation may generate biased results.

Hence, to address such concerns, we follow Bertrand and Mullainathan (2003) to examine the dynamics of innovation output surrounding terrorist attacks by estimating the following equation:

$$Innovation_{i,t+1} = \alpha + \beta_1 Before3_{i,t} + \beta_2 Before2_{i,t} + \beta_3 Before1_{i,t} + \beta_4 Current_{i,t} + \beta_5 After1_{i,t} + \beta_6 After2_{i,t} + \beta_7 After3_{i,t} + \beta_8 After4_{i,t} + \beta_9 After5_{i,t} + \beta_{10} {After^{6+}}_{i,t} + Z_{i,t}\Theta + FirmFE + YearFE + \varepsilon_{i,t},$$

where *Beforek* (k=1, 2, 3) is a dummy variable that is equal to 1 if the observation of the affected firm occurs k (k=1, 2, 3) year(s) before the terrorist attack and 0 otherwise. *Current* is a dummy variable that is equal to 1 if the observation of the affected firm occurs in the year of the terrorist attack and 0 otherwise. Therefore, *k* (*k*=1, 2, 3, 4, 5) is a dummy variable that is equal to 1 if the observation of the affected firm occurs k (k=1, 2, 3, 4, 5) year(s) after the terrorist attack and 0 otherwise. *After6*$^{+}$ is a dummy variable that is equal to 1 if the observation of the affected firm occurs at least six years after the attack and 0 otherwise. All other variables are the same as those described in the baseline DID regression.

The coefficients of interest are β_1, β_2, and β_3 for *Before1, Before2,* and *Before3*, respectively. Any pre-trend in innovation between the affected and unaffected firms should generate statistically significant coefficients of β_1, β_2, and $\beta 3$. We report the dynamic DID results in Columns 3 and 6 of Table 2. The coefficients of β_1, β_2, and β_3 are insignificant, indicating that the parallel assumption of DID holds. The absence of any pre-trend implies that the negative impact of safety uncertainty on corporate innovation is not due to omitted variable bias, which somewhat mitigates the reverse causality concern.

We show that the coefficient estimates of β_4 for *Current* and β_5 for *After1* are small in magnitude and statistically insignificant in both regressions. Moreover, the coefficients of β_6 are larger in magnitude and statistically significant, suggesting that the impact of safety uncertainty on corporate innovation emerges two years after the terrorist attacks. Consistent with the existing literature that corporate innovation is a long-term process (Hall et al. 2001; Manso 2011), the dynamic DID estimations show that the effect of safety uncertainty on innovation activities is long-lasting.

4.2 Placebo Tests

Another potential concern is that our DID analysis results may be driven purely by chance. Thus, we conducted two placebo tests to address this concern. The first placebo test was conducted by constructing pseudo-attack years. If terrorist attacks truly influence corporate innovation via increased safety uncertainty, we should not find similar results by replacing real attack years with pseudo-attack years. Thus, we randomly generate pseudo-attack years during our sample period. We denote *FakePost* as a dummy variable to define whether an observation is from years after the pseudo-attack year. We define *Treat* as a dummy variable to indicate whether a firm is located within 50 km of terrorist attacks. We then interact *FakePost* with *Treat* to replace *Attack_50km* in our baseline regression. Columns 1 and 3 in Panel A of Table 3 show the regression results of the placebo test with fake-attack years. The coefficients of *FakePost*Treat* are statistically insignificant.

Moreover, we design the second placebo test by randomly assigning the sample firms as either affected firms or terrorism-unaffected firms. If terrorist attacks truly influence corporate innovation due to increased safety uncertainty, we should not find similar results by replacing affected firms with pseudo-affected firms. Specifically, we denote the random pseudo-affected firms as *FakeTreat*. We further define *Post* as the indicator to measure whether an observation is from years after the terrorist attacks. We then replace *Attack_50km* with the interaction term between *FakeTreat* and *Post* in our baseline model. Columns 2 and 4 in Panel A of Table 3 show the regression results of the placebo test with pseudo-affected firms. The coefficients of *FakeTreatt*Post* are statistically insignificant.

Finally, we repeat the simulation process for pseudo-attacked years and pseudo-affected firms by 1,000 times. In Panel B of Table 3, we summarize the distribution of the coefficients of interaction terms from the DID regressions by reporting the mean, 5th percentile, 25th percentile, median, 75th percentile, 95th percentile, and standard deviation of the placebo estimates. The coefficients of *FakePost*Treat* on *LnPat* (*LnCite*) ranged from −0.028 (−0.033) to 0.029 (0.034) with a mean value of 0. The coefficients of *FakeTreat*Post* on *LnPat* (*LnCite*) range from −0.009 (−0.011) to 0.009 (0.010) with a mean value of 0.[10] Moreover, the corresponding *t*-statistics are small and insignificant, which suggests that it is improbable that the results from our baseline model are purely driven by chance.

[Insert Table 3 here]

4.3 Propensity Score Matching

Our empirical evidence clarifies the negative relationship between safety uncertainty and firm innovation. However, selection bias due to unobservable firm characteristics may bias our results (Lambert et al. 2017; Qian 2019). Ideally, firms in the sample should be identical in all respects, except that treated firms are affected by terrorist attacks and the controls are not. In reality, however, we cannot find such firms in observational data. Thus, to address this concern, we match each affected firm with two unaffected firms using propensity score matching (PSM) with replacement.

In particular, we estimate the logit model to predict the probability of being an affected firm in the year prior to the terrorist attacks. In the logit regression, we include all control variables in the main regression model represented by the control variables $Z_{i,t}$. We conduct the PSM for the whole sample, where the likelihood of a company located in regions affected by terrorist attacks is determined by a set of observed attributes. From the logit estimates, we obtain the propensity score for a company located

[10] Since the magnitude of coefficients is very small, we multiply the coefficients by 1,000.

in affected regions (i.e., the predicted value of the logit model). Based on this score and using one-to-two nearest neighbor matching, we choose two other companies in the same city and industry that were unaffected by terrorist events but had a similar likelihood of being attacked.[11] Thus, we match each observation (treated group) with two other observations (matched group) from unaffected observations. As the matched group is only a subset of unaffected observations, the PSM sample (i.e., the treated group plus the matched group) is a subset of the whole sample.

Table 4 reports the PSM-DID results. All coefficients of *Attack_50km* remain negative and statistically significant in the regressions. Moreover, the magnitude of *Attack_50km* is larger than that in the baseline results, suggesting that our main findings are robust to alternative samples. In Column 1, relative to unaffected firms, the safety uncertainty from terrorism leads to a 39.4% ($=e^{0.332}-1$) decrease in the number of patents among affected firms. In Column 2, relative to unaffected firms, the safety uncertainty from terrorism leads to a 31.9% ($=e^{0.277}-1$) decrease in the number of citations among affected firms.

[Insert Table 4 here]

4.4 Economic Mechanisms

This section explores two plausible underlying economic channels through which safety uncertainty affects innovation output: decreased R&D investment and a drain of talent or human capital.

4.4.1 R&D Investment

Real options theory implies that firms cannot fully redeploy their investment without cost when facing negative uncertainty shocks. It is challenging for firms to evaluate future cash flows generated from investment due to high uncertainty. Thus, firms tend to be increasingly prudent and hold back on investment until the uncertainty is resolved. As innovation input, R&D investment and innovation output go hand in hand (Audretsch and Feldman 1996; Parisi et al. 2006). Therefore, safety uncertainty caused by terrorist attacks leads firms to cut R&D investment, which worsens firm innovation output. Thus, we compare the difference in R&D investment between affected and unaffected firms before and after the terrorist attacks. Specifically, we run our baseline model by adopting R&D investment as the

[11] For the balance test of our matched sample, please see Appendix B.

dependent variable (Kong and Qin 2019; Xu 2020). Column 1 of Table 5 presents the regression results. The coefficient of *Attack_50km* is negative and statistically significant at the 1% level, indicating that safety uncertainty caused by terrorist attacks leads to decreased corporate R&D investment.

4.4.2 Inventor Mobility

Since technology innovation and breakthroughs are dominated by inventors (Byun et al. 2020), safety uncertainty may result in inventor turnover in a firm, resulting in a drain of human capital. Thus, we investigate the impact of safety uncertainty on inventor outflow. Following Bernstein (2015), we measure inventors' mobility across firms based on patent filing assignees. We identify whether an inventor moves to a new firm per the change in patent filing assignees. We then calculate the net inventor outflow at a firm (i.e., the difference between the number of inventors entering the company and that of those leaving) denoted by variable *NetOut*. We expect that the potential impact channels can be explained by the turnover of innovative inventors. Specifically, we run our baseline model by adopting inventor outflow as the dependent variable (Kong and Qin 2019; Xu 2020). Column 2 of Table 5 present the regression results. The coefficient of *Attack_50km* is negative and statistically significant at the 5% level, indicating that terrorism impedes innovation outcomes by driving valuable inventors to quit the affected company.

[Insert Table 5 here]

4.5 Tests on Moderating Effects of Government Intervention

4.5.1 The Mitigating Effect of Government Intervention

Given that the real effect of government intervention on the economy is controversial (Wang 2018), we test H2a from two distinct perspectives: stated ownership and industry policy.

First, given that SOEs possess inherent advantages in policy preference and resource endowment relative to non-SOEs (Piotroski and Wong 2012), which is conducive to firms in coping with the harsh external environment, we first test whether the effects of external uncertainty from terrorism on firm innovation are relatively weak due to state ownership.

We divide the sample into two groups according to state ownership and compare the differences in the effect of terrorism on the firm's innovativeness between SOEs and non-SOEs. Panel A of Table

6 shows the results for the negative effects of terrorism on corporate innovation by SOEs and non-SOEs, respectively. In Column 1 (3) of Table 6, we find that the coefficient of *Attack_50km* on *LnPat* (*LnCite*) is insignificant in the subsample of SOEs. Meanwhile, the coefficient of *Attack_50km* is significantly negative, as shown in Column 2 (4), and the number of granted patents (patent citations) in non-SOEs, felled by about 12.2% (=$e^{0.115}$-1) (12.4% [=$e^{0.117}$-1]) after experiencing the threat of uncertainty arising from the external environment, indicating that the negative impacts are more obvious in non-SOEs, consistent with our expectation. Government ownership somewhat restrains the negative effects of terrorist attacks on corporate innovation.

[Insert Table 6 here]

Second, since the Chinese government selects favored and important industries for support during resource allocation to realize performance objectives, we test whether the policy support mitigates the negative effects of safety uncertainty from terrorism on innovation in affected firms.

Similarly, we split all industries into two groups based on different levels of policy support for industries, that is, those more favored by the government and those less favored. Favored industries, such as mining, construction, technology, culture, and conglomerate industries, are encouraged and supported in the Government Working Report (Liu et al. 2018). Panel B of Table 6 shows that companies that benefit from industrial policy support are less sensitive to terrorist attacks. Accordingly, the number of granted patents (patent citations) in affected firms reduces by 15.3% (=$e^{0.142}$-1) (13.5% [=$e^{0.127}$-1]) in less-favored industries. The findings suggest that government support significantly alleviates the impact of terrorism on firm innovation through industrial policies. Thus, government intervention is conducive to offsetting the negative impact of safety uncertainty on the innovation activities of affected enterprises.

4.5.2 The Exacerbating Effect of Government Intervention

In addition to the mitigating effect of government intervention, government intervention also exerts negative externalities over corporate innovation. We test H2b from two distinct perspectives: imposing a high tax burden and engaging in strict censorship.

First, given higher corporate taxes, since firms are more likely to reduce R&D investment and innovation outputs (Mukherjee et al. 2017), we test whether firm innovation activities are more responsive to safety uncertainty under a higher degree of government intervention via a tax burden.

The sample is divided into two groups per the external tax burden index (Wang et al. 2016) to explore whether the taxation burden exacerbates the negative effects of safety uncertainty on corporate innovation. Panel B of Table 8 shows that the number of granted patents in affected firms reduces by 9.9% (=$e^{0.094}$-1), and that of patent citations decreased by approximately 10.4% (=$e^{0.099}$-1) in provinces with a higher degree of government intervention. This finding shows that excessive tax burden exaggerates the negative impact of safety uncertainty shocks via terrorism on firm innovation activities.

[Insert Table 7 here]

Second, given that the rise in internet censorship produces profound changes to the management environment of the enterprise, we test whether strict internet censorship exacerbates the negative effects of safety uncertainty from terrorism on innovation in affected firms. Hence, we test whether firm innovation activities are more responsive to safety uncertainty under a higher degree of government intervention via government engagement in strict censorship.

Following Xu et al. (2011), 17 provinces are found to have local filtering devices and experience stronger censoring intensity.[12] We further divide our samples into two groups based on whether a firm is located in a province with a local web filter. Panel B reports the results. Specifically, treated firms in areas with web filters produce 9.2% (=$e^{0.088}$-1) and 10.2% (=$e^{0.097}$-1) fewer granted and cited patents, respectively, than control firms in the same areas after terrorist attacks. It indicates that the negative effects of external uncertainty from terrorist attacks on firm innovation are more pronounced in provinces with high censoring capacity. The strong position of the government in censorship aggravates the influence of terrorism (Meierrieks and Gries 2013) and makes local firms' innovative activities more sensitive to safety uncertainty.

4.6 Cross-Sectional Analysis

The influence of the knowledge spillover effect on corporate innovation varies according to

[12] The 17 provinces are Guangdong, Fujian, Hunan, Hubei, Sichuan, Yunnan, Guangxi, Jiangsu, Zhejiang, Guizhou, Jiangxi, Hainan, Chongqing, Anhui, Xinjiang, Tibet, and Shanghai.

region disparity in different nations (Fritsch and Franke 2004; Tödtling and Trippl 2005), which are closely related to patent activities in China with significant regional disparities (Liu and White 2001). In this subsection, we explore whether the effects of safety uncertainty from terrorism on innovation vary in the degree of market development and regional stability.

4.6.1 Market Development

Given the important role of the institutional environment in promoting innovation activities and stimulating R&D investment (Hou et al. 2017; Moshirian et al. 2020), we further explore whether firm innovation is less sensitive to terrorist attacks in regions with better marketization and institutional environments. The results provide further evidence for our baseline argument that the stability of the external environment is conducive to innovative development strategies.

Based on the province product marketization index (Wang et al. 2016), the sample is divided into two sub-samples to compare the moderating effects of market economy development. Following Meierrieks and Gries (2013), we assume that the regulatory role of the market in resource allocation dilutes the negative impact of safety uncertainty from terrorism in regions with a higher level of marketization. Table 7 presents the results. In the sample group with a lower level of marketization, the number of granted patents falls by 13.0% (=$e^{0.122}$-1), and that of patent citations decreases by about 9.5% (=$e^{0.091}$-1). The negative response of corporate innovation from terrorism is less significant in areas with a higher level of marketization, consistent with prior empirical studies (Hou at al. 2017; Moshirian et al. 2020).

[Insert Table 8 here]

4.6.2 Regional Stability

In the wake of the September 11 terrorist attacks in the United States (Birkland 2004), Chinese policymakers and the media focused on regional stability. Hence, we explore whether regional stability affects the negative impacts of external uncertainty. Given the crime rate, measured by the arrest and sue rates in the province, we separated the samples into two groups and examined whether there was a significant difference in the influence of terrorism on corporate innovation between high- and low-crime regions. Panels A and B of Table 9 represent the results. In the sample group with a higher crime rate, the number of granted patents falls from 12.0% (=$e^{0.113}$-1) to 13.3% (=$e^{0.125}$-1) and that of patent citations decreases by about 8.8% (=$e^{0.084}$-1). However, the external environment uncertainty from terrorism has no significant impact on corporate innovation in regions where social security is guaranteed.

[Insert Table 9 here]

4.7 Robustness Tests

4.7.1 Other Measurement of Terrorist Attacks

The study further conducts a series of robustness tests. First, it employs alternative cutoff values to repeat the baseline regression to check the robustness of the findings. In particular, we use 10 km and 25 km. We then use *Attack_25km* and *Attack_10km* to denote firms near the terrorist attack (i.e., within 25 or 10 km). Table 10 reports the results using alternative indicators of terrorism. In Columns 1 (2), the coefficient (β_1) of *Attack_25km* (*Attack_10km*) on *LnPat* is –0.124 (–0.151), which is significantly negative at 1%. When examining changes in the number of patent citations (*LnCite*), as shown in Columns 5 and 6, the results remain consistent with our main results. In addition to the distance limit, we also consider the casualty consequences of each terrorist attack.

Given that the consequences vary considerably, we attempt to measure the degree of safety uncertainty by death and injury from terrorist attacks. Thus, we construct two other measures of terrorist attacks based on the casualties from each attack (Luo et al. 2019; Nguyen et al. 2019): *Attack_Kill* and *Attack_Terrorism*. The cutoff of attack proximity is consistent with the main analysis. *Attack_Kill* indicates affected firms after a terrorist attack where death has occurred—it is 0 prior to the event. The results in Columns 3 and 4 suggest that if there is a terrorist attack resulting in deaths within 50 km of a company's headquarters, the firm's future patent applications and citations decline significantly. *Attack_Terrorism* indicates affected firms after a terrorist attack with a high level of terrorism intensity.[13] Similarly, Columns 7 and 8 in Table 10 illustrate that the higher the degree of casualties in terrorist attacks, the greater the negative impact on the innovation of nearby companies.

[Insert Table 10 here]

[13] The impact of deaths on safety uncertainty is significantly greater than that of injuries.

4.7.2 Different Target Groups of Terrorist Attacks

The study also explores the degree to which different types of terrorist attacks affect corporate innovation, depending on the target group. It then employs the following three variables to identify the target of a terrorist attack. *Attack_GovArmy* indicates affected firms after a terrorist attack that targets the government, police, or military. *Attack_public* indicates affected firms after a terrorist attack that targets airports, aircraft, or public transportation. *Attack_Private* indicates affected firms after a terrorist attack targeting private citizens, property, and business. Table 11 reports the results. Further, to ensure comparability, the control groups in the six regressions are firms that have never been affected by terrorist attacks.

The results are consistent with our expectations. When terrorist attacks against government departments, police, or the military occur, the innovation activities of listed companies nearby are the most affected. Columns 1 and 4 show that the number of patents filed by companies fell by 28.0% (=$e^{0.247}$-1), and that of patent citations decreased by 17.4% (=$e^{0.16}$-1). Terrorist attacks targeting airports or public transportation have also exerted a significant negative impact on companies' innovative activities (Columns 2 and 5). However, when terrorist attacks target private individuals or property, no significant impact on innovation is observed (Columns 3 and 6).

[Insert Table 11 here]

4.7.3 Alternative Sample

This section performs four robustness tests by imposing more restrictions on our sample. First, to rule out the possibility that some firms located in areas where terrorist attacks are frequent dominate our overall results, we excluded observations in Guangdong and Xinjiang Uygur Autonomous Region from the sample. Panel A of Table 12 shows that the results remain robust. We delete the companies located in Guangdong in Columns 1 and 4 and omit the firms located in Xinjiang in Columns 2 and 5. Further, all firms located in both are deleted in Columns 3 and 6.

Second, people may also be concerned that terrorist attacks in ethnic-minority autonomous regions may involve more complex ethnic conflicts and disputes, which may interfere with the effects of safety uncertainty on firm innovation (Parrotta et al. 2014; Lee 2015). Thus, we exclude observations in autonomous regions populated by ethnic minorities: the Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Tibet Autonomous Region, Xinjiang Uygur Autonomous Region, and Ningxia Hui Autonomous Region. Panel B of Table 12 presents the results after filtering the effects of ethnic minority autonomous regions. The findings were highly consistent with the main results.

Third, our findings may be biased due to unobservable local factors. To alleviate the concern, we matched the treated and control groups in adjacent provinces. Specifically, we match a control firm in a province adjacent to the treated firm location. Hence, our treated and control firms are more likely to share similar local characteristics. We impose distance restrictions on the geographic location of control companies for comparability. In Panel C, unaffected firms have their headquarters between 51 km and 100 km from the location of the terrorist incident. After limiting the distance to the control company, the innovation activities of affected companies are found to be more sensitive to terrorist attacks. Column 1 of Panel C shows that the number of firms granted patents decreased by approximately 15.3% (=$e^{0.142}$-1) under the impact of a dangerous external environment. Column 2 of Panel C shows that the number of citations for corporate innovation patents also declined significantly.

Fourth, another potential issue arising from our finding is that since a firm's R&D department might be located in a place far away from the headquarters, the safety uncertainty surrounding the headquarters may not affect the R&D department. Although it can be argued that executives at the headquarters make all important financial decisions and the chaos around the headquarters affect all departments of the firm regardless of where they are located, we conduct empirical tests to alleviate this concern. Specifically, we exclude firms with a high degree of spatial diversification. We then set the proportion of subsidiaries in a province different from that of the parent company to be more than 50%, thereby making the firm highly diversified. Panel D of Table 12 shows the estimation results after eliminating the interference of spatial diversification and indicates that the finding is highly consistent with the main results.

[Insert Table 12 here]

5. Conclusion

This study provides novel evidence on the effect of terrorism on firm innovation. Inspired by prior studies on the costs of terrorism and its effect on firm policy and labor cost, we posit that negative shocks from the external environment impede corporate innovation. Using the DID approach, we find that corporate innovation capacity declined after the threat of a terrorist attack. Further, examining the channels by which terrorism affects firm innovation activities showed that external uncertainty from terrorism drives firms to cut R&D development, resulting in drain of innovator talent, which hampers corporate innovation.

Considering the moderating effects of government intervention, we find that firm innovation activities benefit from government ownership and industry policy, restraining the negative effects of terrorism on corporate innovation. Moreover, firm innovation output is negatively responsive to safety uncertainty under a higher degree of government intervention measured via tax burden and internet censorship. Further, cross-sectional analyses reveal that the effects of terrorism on firm innovation weaken due to market development and regional stability.

This study offers clear policy implications for regulators. When innovation activities in firms exposed to safety uncertainty from terrorist attacks are hampered, it constrains the implementation of an innovation-driven strategy for emerging markets. Thus, when firms are exposed to negative external shocks, government intervention can induce firm innovation via resource allocation through SOEs and industrial policies. However, government intervention also exerts negative externalities over corporate innovation. Specifically, a high tax burden and strict censorship negatively affect firm innovation given safety uncertainty from terrorist attacks. Therefore, the findings indicate that it is a complex trade-off to evaluate the role of government intervention in corporate innovation.

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Table 1. Descriptive statistics

Panel A: Descriptive statistics of main variables

variable	N	Mean	S.D.	P5	P25	P50	P75	P95
$LnPat_{t+1}$	19,129	0.613	1.230	0	0	0	0.693	3.403
$LnCite_{t+1}$	19,129	0.402	1.080	0	0	0	0	3.286
Attack_50km	19,129	0.378	0.485	0	0	0	1	1
Attack_25km	19,129	0.329	0.470	0	0	0	1	1
Attack_10km	19,129	0.136	0.343	0	0	0	0	1
Cash	19,129	0.163	0.134	0.021	0.069	0.125	0.215	0.445
ROA	19,129	0.032	0.065	-0.074	0.011	0.032	0.0610	0.123
PPE	19,129	0.263	0.180	0.018	0.121	0.231	0.378	0.610
Size	19,129	21.66	1.238	19.91	20.81	21.52	22.33	24
Leverage	19,129	0.483	0.227	0.116	0.318	0.486	0.635	0.832
HHI	19,129	0.010	0.0470	0	0	0	0.001	0.033
Growth	19,129	0.217	0.590	-0.320	-0.018	0.129	0.304	0.875
SOE	19,129	0.540	0.498	0	0	1	1	1
Dual	19,129	0.179	0.383	0	0	0	0	1
IndRatio	19,129	0.362	0.0540	0.333	0.333	0.333	0.375	0.444
MGDP	19,129	8.922	9.565	1.119	2.898	5.892	11.35	33.34
Sec_Industry	19,129	47.15	10.01	24	42.45	48.30	53.46	61.59
lnSalary	19,129	10.53	0.590	9.540	10.20	10.60	10.92	11.35
Density	19,129	797.2	559.1	162.7	430.1	691.9	956.8	2209

Panel B: The distribution of terrorist attacks by province

Province	Frequency of terrorist attacks	Percent
Beijing	3	7.5
Fujian	1	2.5
Guangdong	6	15
Guangxi	3	7.5
Heilongjiang	2	5
Henan	1	2.5
Hubei	2	5
Inner Mongolia	2	5
Ningxia Hui	1	2.5
Qinghai	1	2.5
Shaanxi	2	5
Shandong	2	5
Shanghai	3	7.5
Shanxi	1	2.5
Sichuan	1	2.5
Tibet	1	2.5
Xinjiang Uyghur	5	12.5
Yunnan	1	2.5
Zhejiang	2	5
Total	**40**	**100**

Panel C: The distribution of terrorist attacks by target groups

Target groups	Frequency of terrorist attacks	Percent
Airports & Aircraft	4	10
Business	9	22.5
Government (General)	1	2.5
Military	1	2.5
Police	3	7.5
Private Citizens & Property	13	32.5
Transportation	8	20
Unknown	1	2.5
Total	**40**	**100**

Panel D: The distribution of observations by industry

Industry	Freq.	Percent
Agriculture, forestry, animal husbandry, and fishery	271	1.420
The mining industry	613	3.200
Manufacturing	11,200	58.55
Production and supply of electricity, heat, gas, and water	900	4.700
The construction industry	501	2.620
Wholesale and retail	1,407	7.350
Transportation, warehousing, and postal services	748	3.910
Accommodation and catering	115	0.600
Information transmission, software, and information technology services	837	4.380
The real estate industry	1,344	7.030
Leasing and business services	277	1.450
Scientific research and technical services	66	0.350
Water, environmental, and public utility management industries	202	1.060
Education	24	0.130
Health and social work	41	0.210
Culture, sports, and entertainment	293	1.530
Comprehensive and others	291	1.520
Total	**19,175**	**100**

Notes. This table reports the summary statistics of the key variables, frequency of terrorist attacks, and the distribution of observations in our analysis. Panel A reports the summary statistics of the key variables. Panel B reports the distribution of terrorist attacks by province. Panel C reports the distribution of terrorist attacks by target groups. Panel C reports the distribution of observations by industry. Variable definitions are reported in Appendix A.

Table 2**.** Multivariant DID analysis

Dep Var.	*LnPat*$_{t+1}$			*LnCite*$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Attack_50km	-0.102***	-0.095***		-0.080***	-0.074**	
	(-3.15)	(-2.78)		(-2.80)	(-2.42)	
Before3			0.019			0.015
			(0.47)			(0.34)
Before2			-0.005			0.003
			(-0.10)			(0.07)
Before1			0.003			-0.013
			(0.07)			(-0.27)
Current			-0.043			-0.069
			(-0.90)			(-1.43)
After1			-0.066			-0.051
			(-1.20)			(-0.98)
After2			-0.122**			-0.114**
			(-2.17)			(-2.23)
After3			-0.143**			-0.073
			(-2.33)			(-1.36)
After4			-0.169***			-0.102*
			(-2.71)			(-1.86)
After5			-0.162**			-0.095*
			(-2.41)			(-1.70)
After6^{+}			-0.241***			-0.140**
			(-3.26)			(-2.26)
Cash		-0.128*	-0.121*		0.026	0.029
		(-1.84)	(-1.74)		(0.38)	(0.41)
ROA		0.049	0.050		0.024	0.025
		(0.57)	(0.58)		(0.31)	(0.31)
PPE		0.166***	0.171***		0.046	0.047
		(2.67)	(2.74)		(0.86)	(0.88)
Size		0.073***	0.073***		0.051***	0.051***
		(4.20)	(4.21)		(3.59)	(3.61)
Leverage		0.045	0.045		0.012	0.012
		(0.87)	(0.87)		(0.26)	(0.27)
HHI		0.310	0.317		0.278	0.280
		(1.14)	(1.17)		(1.48)	(1.49)
Growth		-0.014**	-0.014**		-0.009	-0.009
		(-2.05)	(-2.02)		(-1.46)	(-1.41)
SOE		0.099***	0.098***		0.064*	0.064*
		(2.91)	(2.83)		(1.84)	(1.82)
Dual		-0.029	-0.029		0.017	0.017
		(-1.14)	(-1.15)		(0.66)	(0.66)
IndRatio		0.038	0.034		0.014	0.014
		(0.19)	(0.18)		(0.08)	(0.08)
MGDP		-0.003	-0.001		-0.003	-0.002
		(-0.49)	(-0.18)		(-0.58)	(-0.40)
Sec_Industry		0.001	-0.001		0.000	-0.000
		(0.29)	(-0.24)		(0.21)	(-0.04)
lnSalary		-0.032***	-0.037***		-0.020**	-0.022**

		(-2.84)	(-3.21)		(-2.15)	(-2.28)
Density		-0.000*	-0.000		-0.000	-0.000
		(-1.71)	(-1.07)		(-1.49)	(-1.19)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	19,129	19,129	19,129	19,129	19,129	19,129
Adj. R^2	0.820	0.821	0.822	0.707	0.708	0.708

Notes. This table reports the results of the dynamic DID analysis designed to investigate the impact of terrorism on corporate innovation. In Columns 1 through 3, the dependent variable is $LnPat_{t+1}$, which is the natural logarithm of one plus the number of eventually-granted patents filed by a firm in year *t+1*. In Columns 4 through 6, the dependent variable is $LnCite_{t+1}$, which is the natural logarithm of one plus the number of forward citations made to the eventually-granted patents filed by a firm in year t+1; citations are adjusted for truncation bias. *Attack_50km* is a dummy variable that takes the value of 1 for affected firms after a terrorist attack and 0 prior to the event. The affected firms are firms headquartered within 50 km of the location of the terrorist events. *Beforek* (k=1, 2, 3) is a dummy that is equal to 1 if the observations of the affected firm in a year are from k (k=1, 2, 3) year(s) before the terrorist attack and 0 otherwise. Current is a dummy that is equal to 1 if the affected firm in a year is from the year of the terrorist attack and 0 otherwise. *Afterk* (k=1, 2, 3, 4, 5) is a dummy that is equal to 1 if the observations of the affected firm in a year are from k (k=1, 2, 3, 4, 5) year(s) after the terrorist attack and 0 otherwise. $After6^{+}$ is a dummy that is equal to 1 if the affected firm in a year is at least six years after the attack, and 0 otherwise. Variable definitions are presented in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Placebo tests

Panel A: Regression analysis

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	(1)	(2)	(3)	(4)
*FakePost*Treat*	0.011		0.031	
	(0.70)		(1.54)	
*FakeTreat*Post*		-0.000		-0.000
		(-0.90)		(-1.06)
Cash	-0.127*	-0.127*	0.027	0.027
	(-1.82)	(-1.82)	(0.39)	(0.39)
ROA	0.053	0.054	0.027	0.028
	(0.62)	(0.63)	(0.34)	(0.35)
PPE	0.168***	0.169***	0.047	0.048
	(2.70)	(2.70)	(0.88)	(0.89)
Size	0.073***	0.073***	0.051***	0.051***
	(4.19)	(4.19)	(3.59)	(3.58)
Leverage	0.053	0.053	0.018	0.018
	(1.03)	(1.03)	(0.41)	(0.40)
HHI	0.316	0.313	0.282	0.279
	(1.17)	(1.16)	(1.51)	(1.49)
Growth	-0.014**	-0.014**	-0.009	-0.009
	(-2.09)	(-2.10)	(-1.49)	(-1.50)
SOE	0.097***	0.097***	0.063*	0.063*
	(2.86)	(2.86)	(1.80)	(1.81)
Dual	-0.027	-0.027	0.018	0.019
	(-1.08)	(-1.08)	(0.70)	(0.71)
IndRatio	0.038	0.039	0.014	0.016
	(0.19)	(0.20)	(0.08)	(0.09)
MGDP	-0.003	-0.003	-0.003	-0.003
	(-0.50)	(-0.49)	(-0.59)	(-0.58)
Sec_Industry	0.002	0.002	0.001	0.001
	(0.69)	(0.70)	(0.56)	(0.58)
lnSalary	-0.029***	-0.029***	-0.018*	-0.018*
	(-2.60)	(-2.60)	(-1.92)	(-1.93)
Density	-0.000*	-0.000*	-0.000	-0.000
	(-1.74)	(-1.74)	(-1.52)	(-1.52)
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	19,129	19,129	19,129	19,129
Adj. R^2	0.821	0.821	0.708	0.708

Panel B: Simulation results

Dependent variable: $LnPat_{t+1}$	N	Mean	S.D.	P5	P25	P50	P75	P95
*FakePost*Treat*	1,000	0	0.017	-0.028	-0.011	0.001	0.012	0.029
t-value	1,000	0.028	1.034	-1.635	-0.638	0.057	0.705	1.679
*FakeTreat*Post*1000*	1,000	0	0.006	-0.009	-0.004	-0.000	0.004	0.009
t-value	1,000	0.018	1.002	-1.623	-0.697	-0.034	0.710	1.686
Dependent variable: $LnCite_{t+1}$	N	Mean	S.D.	P5	P25	P50	P75	P95

*FakePost*Treat*	1,000	0	0.021	-0.033	-0.015	0	0.014	0.034
t-value	1,000	-0.01	1.016	-1.584	-0.737	-0.014	0.676	1.652
*FakeTreat*Post*1000*	1,000	0	0.007	-0.011	-0.005	0	0.004	0.010
t-value	1,000	-0.052	1.010	-1.653	-0.748	-0.072	0.664	1.610

Notes. This table presents the outcomes of the placebo test. Panel A reports the results of two placebo tests. Panel B reports the descriptive statistics of the placebo coefficients of *FakePost*Treat* and *FakeTreat*Post* and their t-values for 1,000 placebo tests. *Treat* is a dummy variable that takes the value of 1 for the affected firms, including firms that are affected by the attacks, specifically, firms that are headquartered within 50 km of the location of the terrorist events; otherwise, it is 0. *Post* is a time indicator that takes the value of 1 for the affected firms in or after terrorist events and 0 otherwise. In Panel A, Columns 2 and 4 report the results of the placebo test for *FakePost*. *FakePost* is a pseudo-post indicator that takes the value of 1 if the pseudo-year is in or after terrorist events and 0 otherwise. Columns 2 and 4 report the results of the placebo test for *FakeTreat*. *FakeTreat* is a pseudo-treat indicator that takes the value of 1 if the pseudo-firm is headquartered within 50 km of the location of the terrorist events and 0 otherwise. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. PSM-DID analysis

Dep Var.	$LnPat_{t+1}$	$LnCite_{t+1}$
	(1)	(2)
Attack_50km	-0.332**	-0.277**
	(-2.37)	(-2.13)
Cash	-0.995***	-0.732**
	(-2.84)	(-2.08)
ROA	0.005	0.062
	(0.02)	(0.28)
PPE	-0.344	-0.325
	(-1.13)	(-1.59)
Size	-0.096**	-0.204**
	(-2.21)	(-2.37)
Leverage	-0.234*	0.411
	(-1.66)	(1.61)
HHI	-0.154	0.521
	(-0.20)	(0.70)
Growth	0.017	0.010
	(1.26)	(0.66)
SOE	0.215**	-0.167
	(2.06)	(-1.18)
Dual	0.159*	0.418**
	(1.66)	(2.12)
IndRatio	0.182	0.101
	(0.43)	(0.22)
MGDP	0.022*	0.009
	(1.75)	(1.07)
Sec_Industry	-0.004	-0.011
	(-0.45)	(-1.28)
lnSalary	0.006	0.221
	(0.02)	(0.70)
Density	0.000	-0.000
	(0.65)	(-0.03)
Intercept	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	5,021	5,021
Adj. R^2	0.872	0.752

Notes. This table reports the results of the dynamic DID analysis designed to investigate the impact of terrorist attacks on corporate innovation via the PSM method. In Column 1, the dependent variable is $LnPat_{t+1}$. In Column 2, the dependent variable is $LnCite_{t+1}$. The independent variable is *Attack_50k*. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Economic mechanisms

Dep Var.	RD_{t+1}	$NetOut$
	(1)	(2)
Attack_50km	-0.008***	0.222**
	(-2.71)	(2.53)
Cash	0.023	-0.243
	(1.32)	(-1.07)
ROA	-0.002	-0.170
	(-0.14)	(-0.69)
PPE	0.016	0.131
	(1.45)	(0.85)
Size	-0.007	0.098
	(-1.38)	(1.35)
Leverage	0.025	-0.064
	(1.31)	(-0.58)
HHI	0.005	0.067
	(0.37)	(0.07)
Growth	-0.002	-0.000
	(-0.81)	(-0.02)
SOE	0.001	-0.219
	(0.48)	(-1.48)
Dual	0.005*	0.005
	(1.94)	(0.09)
IndRatio	0.035	0.142
	(1.33)	(0.27)
MGDP	0.000	0.002
	(0.51)	(0.14)
Sec_Industry	-0.000	0.001
	(-1.39)	(0.11)
lnSalary	-0.007	-0.018
	(-1.08)	(-0.25)
Density	0.000	-0.000
	(0.84)	(-0.44)
Intercept	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	5,711	19,129
Adj. R^2	0.655	0.655

Notes. This table examines the potential mechanism through which terrorist attacks affect corporate innovation. In Column 1, the dependent variable is RD_{t+1}, which is the R&D expenses scaled by the total assets of a firm in year $t+1$. In Column 2, the dependent variable is *NetOut*, which is the net inflow of inventors, the difference between the number of inventors entering the company, and the number of inventors leaving the company. The independent variable was *Attack_50km*. *Exp* is a dummy variable that takes the value of 1 for firms' inventors with more experience (specifically, longer than the industry median average level) and 0 otherwise. Variable definitions are presented in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6. The mitigating effect of government intervention

Panel A: State Ownership

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	SOEs	Non-SOEs	SOEs	Non-SOEs
	(1)	(3)	(2)	(4)
Attack_50km	-0.074	-0.115**	-0.041	-0.117***
	(-1.54)	(-2.33)	(-0.96)	(-2.62)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	10,276	8,780	10,276	8,780
Adj. R^2	0.826	0.828	0.731	0.698

Panel B: Favored industry

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	More-favored Industry	Less-favored Industry	More-favored Industry	Less-favored Industry
	(1)	(2)	(3)	(4)
Attack_50km	-0.027	-0.142***	-0.028	-0.107***
	(-0.47)	(-3.36)	(-0.55)	(-2.88)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	9,818	9,311	9,818	9,311
Adj. R^2	0.824	0.818	0.698	0.721

Notes. This table presents the mitigating effects of government intervention on innovation. Panels A and B show the heterogeneous effects of terrorist attacks on corporate innovation through state ownership and favored industry policy, respectively. In Columns 1 and 3, the dependent variable is $LnPat_{t+1}$. In Columns 2 and 4, the dependent variable is $LnCite_{t+1}$. *Attack_50km* indicates the affected firms after a terrorist attack; it is 0 prior to the event. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. The exacerbating effect of government intervention

Panel A: Tax burden

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	Higher tax burden	Lower tax burden	Higher tax burden	Lower tax burden
	(1)	(2)	(3)	(4)
Attack_50km	-0.094**	-0.063	-0.108***	-0.051
	(-2.50)	(-1.39)	(-2.76)	(-1.04)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	4,058	4,232	4,058	4,232
Adj. R^2	0.837	0.882	0.779	0.797

Panel B: Web filter devices

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	With Web filter	Without Web filter	With Web filter	Without Web filter
	(1)	(2)	(3)	(4)
Attack_50km	-0.088*	-0.066	-0.097**	-0.026
	(-1.65)	(-1.32)	(-1.97)	(-0.61)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	10,949	8,169	10,949	8,169
Adj. R^2	0.804	0.847	0.700	0.723

Notes. This table presents the exacerbating effects of government intervention on innovation. Panels A and B show the heterogeneous effects of terrorist attacks on corporate innovation through the tax burden and information censorship, respectively. In Columns 1 and 3, the dependent variable is $LnPat_{t+1}$. In Columns 2 and 4, the dependent variable is $LnCite_{t+1}$. *Attack_50km* indicates the affected firms after a terrorist attack; it is 0 prior to the event. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Market development

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	Well marketization	Weak marketization	Well marketization	Weak marketization
	(1)	(2)	(3)	(4)
Attack_50km	-0.042	-0.122**	-0.012	-0.091**
	(-1.06)	(-2.20)	(-0.28)	(-1.98)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	8,959	9,407	8,959	9,407
Adj. R^2	0.843	0.825	0.743	0.716

Notes. This table presents the heterogeneous effects of terrorist attacks on corporate innovation from government efforts on marketization development. In Columns 1 and 3 of each panel, the dependent variable is $LnPat_{t+1}$. In Columns 2 and 4 of each panel, the dependent variable is $LnCite_{t+1}$. *Attack_50km* indicates the affected firms after a terrorist attack; it is 0 prior to the event. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Regional stability

Panel A: Crime rate measured by arrest rate

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	High arrest rate	Low arrest rate	High arrest rate	Low arrest rate
	(1)	(2)	(3)	(4)
Attack_50km	-0.113**	-0.109	-0.084**	-0.032
	(-2.45)	(-1.39)	(-2.17)	(-0.50)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	8,256	8,832	8,256	8,832
Adj. R^2	0.846	0.803	0.733	0.700

Panel B: Crime rate measured by sue rate

Dep Var.	$LnPat_{t+1}$		$LnCite_{t+1}$	
	High prosecute rate	Low prosecute rate	High prosecute rate	Low prosecute rate
	(1)	(2)	(3)	(4)
Attack_50km	-0.125***	-0.104	-0.084**	-0.035
	(-2.69)	(-1.41)	(-2.16)	(-0.58)
Controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	8,035	8,719	8,035	8,719
Adj. R^2	0.850	0.805	0.735	0.704

Notes. This table presents the heterogeneous effects of terrorist attacks on corporate innovation from regional stability. In Columns 1 and 3 of each panel, the dependent variable is $LnPat_{t+1}$. In Columns 2 and 4 of each panel, the dependent variable is $LnCite_{t+1}$. *Attack_50km* indicates the affected firms after a terrorist attack; it is 0 prior to the event. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Other measurements of terrorist attacks

Dep Var.	$LnPat_{t+1}$				$LnCite_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attack_25km	-0.124***				-0.093***			
	(-3.62)				(-3.01)			
Attack_10km		-0.151***				-0.077**		
		(-4.29)				(-2.35)		
Attack_Kill			-0.111**				-0.076**	
			(-2.44)				(-1.97)	
Attack_Terrorism				-0.077*				-0.066*
				(-1.85)				(-1.72)
Cash	-0.128*	-0.126*	-0.128*	-0.129*	0.026	0.028	0.026	0.025
	(-1.83)	(-1.81)	(-1.83)	(-1.85)	(0.38)	(0.40)	(0.38)	(0.37)
ROA	0.050	0.050	0.046	0.049	0.025	0.026	0.022	0.024
	(0.59)	(0.59)	(0.54)	(0.57)	(0.32)	(0.33)	(0.28)	(0.30)
PPE	0.162***	0.162***	0.167***	0.165***	0.043	0.044	0.046	0.044
	(2.61)	(2.61)	(2.67)	(2.65)	(0.80)	(0.83)	(0.86)	(0.83)
Size	0.073***	0.073***	0.074***	0.073***	0.051***	0.051***	0.051***	0.051***
	(4.21)	(4.24)	(4.25)	(4.20)	(3.60)	(3.61)	(3.63)	(3.60)
Leverage	0.044	0.045	0.047	0.050	0.011	0.014	0.014	0.015
	(0.85)	(0.88)	(0.92)	(0.97)	(0.25)	(0.31)	(0.31)	(0.34)
HHI	0.305	0.304	0.316	0.318	0.275	0.277	0.283	0.285
	(1.12)	(1.12)	(1.18)	(1.18)	(1.46)	(1.47)	(1.51)	(1.52)
Growth	-0.014**	-0.014**	-0.014**	-0.014**	-0.009	-0.009	-0.009	-0.009
	(-2.06)	(-2.03)	(-2.07)	(-2.07)	(-1.46)	(-1.45)	(-1.47)	(-1.47)
SOE	0.101***	0.099***	0.098***	0.098***	0.065*	0.064*	0.063*	0.063*
	(2.95)	(2.91)	(2.88)	(2.87)	(1.88)	(1.83)	(1.82)	(1.82)
Dual	-0.029	-0.029	-0.028	-0.028	0.017	0.018	0.018	0.018
	(-1.16)	(-1.13)	(-1.11)	(-1.09)	(0.65)	(0.68)	(0.69)	(0.69)
IndRatio	0.042	0.049	0.036	0.039	0.017	0.020	0.013	0.015
	(0.22)	(0.25)	(0.19)	(0.20)	(0.10)	(0.11)	(0.07)	(0.09)
MGDP	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002	-0.002
	(-0.49)	(-0.55)	(-0.43)	(-0.44)	(-0.57)	(-0.62)	(-0.52)	(-0.52)
Sec_Industry	0.001	0.001	0.002	0.002	0.000	0.001	0.001	0.001
	(0.21)	(0.22)	(0.58)	(0.61)	(0.15)	(0.29)	(0.48)	(0.48)

lnSalary	-0.032***	-0.032***	-0.032***	-0.031***	-0.020**	-0.019**	-0.019**	-0.019**
	(-2.86)	(-2.80)	(-2.80)	(-2.76)	(-2.15)	(-2.04)	(-2.11)	(-2.10)
Density	-0.000*	-0.000*	-0.000*	-0.000*	-0.000	-0.000	-0.000	-0.000
	(-1.68)	(-1.69)	(-1.66)	(-1.70)	(-1.46)	(-1.49)	(-1.45)	(-1.47)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,129	19,129	19,129	19161	19,129	19,129	19,129	19161
Adj. R^2	0.821	0.821	0.821	0.821	0.708	0.708	0.708	0.708

Note. This table presents coefficients from DID regressions designed to investigate the impact of terrorist attacks on corporate innovation via other terrorist measurements. In Columns 1 through 4, the dependent variable is $LnPat_{t+1}$. In Columns 5 through 8, the dependent variable is $LnCite_{t+1}$. *Attack_25km* (*Attack_10km*) is a dummy variable that takes the value of 1 for affected firms after a terrorist attack and 0 prior to the event. The affected firms are headquartered within 25 (10) km of the location of the terrorist events. *Attack_Kill* is a dummy variable that takes the value of 1 for affected firms after a terrorist attack where death has occurred and 0 prior to the event. The affected firms are headquartered within 50 km of the location of the terrorist events. *Attack_Terrorism* is a dummy variable that takes the value of 1 for affected firms after a terrorist attack with a higher level of terrorism intensity and 0 prior to the event. According to Nguyen et al. (2019), the terrorism measure intensity is the sum of the number of deaths and 50% of the number of injuries. The affected firms are headquartered within 50 km of the location of the terrorist events. Variable definitions are presented in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Different target groups of terrorist attacks

Dep Var.	$LnPat_{t+1}$			$LnCite_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Attack_GovArmy	-0.237***			-0.160***		
	(-5.19)			(-3.22)		
Attack_public		-0.091**			-0.085*	
		(-2.34)			(-1.96)	
Attack_Private			-0.050			-0.019
			(-1.41)			(-0.49)
Cash	-0.120	-0.162**	-0.123**	-0.025	-0.017	0.010
	(-1.63)	(-2.31)	(-2.05)	(-0.32)	(-0.22)	(0.15)
ROA	0.009	0.008	0.041	-0.014	0.006	-0.011
	(0.08)	(0.07)	(0.43)	(-0.12)	(0.05)	(-0.11)
PPE	0.157**	0.129**	0.198***	0.040	0.005	0.072
	(2.49)	(2.14)	(3.75)	(0.59)	(0.07)	(1.22)
Size	0.084***	0.094***	0.076***	0.063***	0.068***	0.054***
	(6.75)	(7.80)	(7.34)	(4.68)	(5.09)	(4.70)
Leverage	0.001	0.057	0.019	-0.002	0.056	-0.015
	(0.02)	(1.18)	(0.43)	(-0.03)	(1.04)	(-0.31)
HHI	0.411	0.278	0.346	0.206	0.210	0.284
	(1.50)	(1.06)	(1.61)	(0.69)	(0.72)	(1.18)
Growth	-0.014	-0.013	-0.014*	-0.006	-0.006	-0.009
	(-1.50)	(-1.43)	(-1.69)	(-0.61)	(-0.56)	(-0.98)
SOE	0.054*	0.070**	0.103***	0.014	0.033	0.070**
	(1.81)	(2.40)	(4.04)	(0.44)	(1.01)	(2.47)
Dual	-0.059***	-0.046**	-0.037**	-0.021	-0.006	0.020
	(-2.68)	(-2.17)	(-1.97)	(-0.87)	(-0.26)	(0.97)
IndRatio	0.170	0.095	0.034	0.166	0.137	-0.021
	(1.18)	(0.69)	(0.28)	(1.06)	(0.89)	(-0.16)
MGDP	-0.005	-0.005	-0.006*	0.000	-0.001	-0.004
	(-1.13)	(-1.12)	(-1.92)	(0.06)	(-0.16)	(-1.21)
Sec_Industry	0.002	0.003	-0.000	0.003*	0.004*	0.000
	(0.83)	(1.41)	(-0.10)	(1.65)	(1.92)	(0.12)
lnSalary	-0.034*	-0.030	-0.036**	-0.016	-0.015	-0.021
	(-1.81)	(-1.62)	(-1.98)	(-0.79)	(-0.71)	(-1.06)
Density	-0.000	-0.000	-0.000**	-0.000	-0.000	-0.000
	(-0.52)	(-1.56)	(-2.12)	(-0.06)	(-0.66)	(-1.49)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	12,403	13,370	16,974	12,403	13,370	16,974
Adj. R^2	0.794	0.801	0.821	0.689	0.685	0.715

Notes. This table presents the robustness results of different types of terrorist attack target groups. In Columns 1 through 3, the dependent variable is $LnPat_{t+1}$. In Columns 4 through 6, the dependent variable is $LnCite_{t+1}$. *Attack_GovArmy* indicates the affected firms after a terrorist attack that targets the government, police, or military; it is 0 prior to the event. *Attack_public* indicates the affected firms after a terrorist attack that targets airports, aircraft, or transportation; it is 0 prior to the event. *Attack_Private* indicates the affected firms after a terrorist attack that targets private citizens, property, business; it is 0 prior to the event. All other variables are defined in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Alternative samples

Panel A: Exclude province Guangdong or Xinjiang

Dep Var.	$LnPat_{t+1}$			$LnCite_{t+1}$		
	Exclude firms located in Xinjiang	Exclude firms located in Guangdong	Exclude firms located in Xinjiang or Guangdong	Exclude firms located in Xinjiang	Exclude firms located in Guangdong	Exclude firms located in Xinjiang or Guangdong
	(1)	(2)	(3)	(4)	(5)	(6)
Attack_50km	-0.118***	-0.105***	-0.132***	-0.070**	-0.078**	-0.074**
	(-2.95)	(-3.04)	(-3.29)	(-2.11)	(-2.49)	(-2.19)
Cash	-0.072	-0.128*	-0.072	0.069	0.024	0.067
	(-0.97)	(-1.84)	(-0.97)	(0.93)	(0.34)	(0.90)
ROA	0.017	0.063	0.031	0.007	0.029	0.011
	(0.18)	(0.73)	(0.34)	(0.08)	(0.36)	(0.13)
PPE	0.144**	0.165***	0.142**	0.046	0.047	0.048
	(2.25)	(2.64)	(2.21)	(0.86)	(0.88)	(0.89)
Size	0.076***	0.072***	0.076***	0.060***	0.050***	0.060***
	(4.25)	(4.15)	(4.20)	(4.26)	(3.53)	(4.19)
Leverage	0.073	0.043	0.071	0.043	0.007	0.038
	(1.39)	(0.83)	(1.35)	(0.94)	(0.15)	(0.82)
HHI	0.399	0.362	0.463	0.248	0.301	0.279
	(1.31)	(1.32)	(1.49)	(1.14)	(1.55)	(1.25)
Growth	-0.017**	-0.014**	-0.016**	-0.010	-0.009	-0.010
	(-2.38)	(-2.01)	(-2.32)	(-1.53)	(-1.39)	(-1.46)
SOE	0.072**	0.100***	0.073**	0.035	0.065*	0.036
	(2.49)	(2.93)	(2.52)	(1.24)	(1.84)	(1.24)
Dual	-0.041	-0.030	-0.043	-0.007	0.014	-0.012
	(-1.53)	(-1.19)	(-1.58)	(-0.27)	(0.53)	(-0.44)
IndRatio	-0.002	0.044	0.004	-0.014	0.026	-0.000
	(-0.01)	(0.22)	(0.02)	(-0.08)	(0.15)	(-0.00)
MGDP	-0.006	-0.003	-0.006	-0.001	-0.003	-0.000
	(-0.71)	(-0.48)	(-0.68)	(-0.09)	(-0.57)	(-0.06)
Sec_Industry	-0.000	0.001	-0.000	0.001	0.000	0.001
	(-0.05)	(0.22)	(-0.15)	(0.51)	(0.18)	(0.47)
lnSalary	-0.030***	-0.032***	-0.029***	-0.016*	-0.020**	-0.016*
	(-2.65)	(-2.83)	(-2.62)	(-1.81)	(-2.13)	(-1.78)
Density	-0.000*	-0.000*	-0.000*	-0.000	-0.000	-0.000
	(-1.88)	(-1.71)	(-1.86)	(-1.09)	(-1.48)	(-1.07)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	16,610	18,899	16,380	16,610	18,899	16,380
Adj. R^2	0.815	0.821	0.815	0.702	0.708	0.702

Panel B: Excluding ethnic minority autonomous regions

	(1) $LnPat_{t+1}$	(2) $LnPat_{t+1}$	(3) $LnCite_{t+1}$	(4) $LnCite_{t+1}$
Attack_50km	-0.116***	-0.102***	-0.084***	-0.072**
	(-3.52)	(-2.97)	(-2.79)	(-2.30)
Cash		-0.133*		0.028
		(-1.87)		(0.39)
ROA		0.043		0.020
		(0.49)		(0.24)
PPE		0.181***		0.071
		(2.89)		(1.31)
Size		0.071***		0.050***
		(3.96)		(3.41)
Leverage		0.007		-0.014
		(0.13)		(-0.31)
HHI		0.322		0.229
		(1.19)		(1.28)
Growth		-0.013*		-0.008
		(-1.76)		(-1.26)
SOE		0.099***		0.056
		(2.76)		(1.55)
Dual		-0.032		0.013
		(-1.24)		(0.49)
IndRatio		0.030		0.033
		(0.15)		(0.18)
MGDP		-0.004		-0.004
		(-0.65)		(-0.88)
Sec_Industry		0.001		0.001
		(0.35)		(0.28)
lnSalary		-0.032***		-0.021**
		(-2.82)		(-2.27)
Density		-0.000		-0.000
		(-1.44)		(-1.13)
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	18,695	18,356	18,695	18,356
Adj. R^2	0.823	0.824	0.708	0.709

Panel C: Imposing more distance restrictions in control groups

Dep Var.	$LnPat_{t+1}$ (1)	$LnCite_{t+1}$ (2)
Attack_50km	-0.142***	-0.081**
	(-3.38)	(-2.30)
Cash	-0.151**	0.015
	(-1.97)	(0.18)
ROA	0.062	0.093
	(0.58)	(0.88)
PPE	0.232***	0.118*
	(2.88)	(1.75)
Size	0.069***	0.049**
	(2.95)	(2.55)
Leverage	0.038	-0.002
	(0.59)	(-0.04)

HHI	0.024	0.252
	(0.05)	(0.76)
Growth	-0.023**	-0.019**
	(-2.51)	(-2.31)
SOE	0.047	0.052
	(1.43)	(1.55)
Dual	-0.014	0.029
	(-0.37)	(0.78)
IndRatio	-0.069	0.056
	(-0.26)	(0.21)
MGDP	-0.013**	-0.008
	(-2.00)	(-1.56)
Sec_Industry	-0.004	-0.003
	(-1.30)	(-0.92)
lnSalary	-0.107	-0.039
	(-1.61)	(-0.65)
Density	-0.000**	-0.000
	(-1.96)	(-1.02)
Intercept	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	10,498	10,498
Adj. R^2	0.831	0.704

Panel D: Excluding firms with spatial diversified business

	(1) $LnPat_{t+1}$	(2) $LnPat_{t+1}$	(3) $LnCite_{t+1}$	(4) $LnCite_{t+1}$
Attack_50km	-0.105***	-0.107***	-0.082**	-0.080**
	(-2.83)	(-2.75)	(-2.45)	(-2.28)
Cash		-0.133*		0.043
		(-1.79)		(0.58)
ROA		0.081		0.059
		(0.89)		(0.68)
PPE		0.158**		0.043
		(2.27)		(0.72)
Size		0.077***		0.052***
		(4.17)		(3.45)
Leverage		0.059		0.053
		(1.11)		(1.13)
HHI		0.317		0.321
		(1.13)		(1.65)
Growth		-0.014*		-0.010
		(-1.84)		(-1.54)
SOE		0.104***		0.080**
		(2.71)		(2.07)
Dual		-0.018		0.025
		(-0.63)		(0.92)
IndRatio		0.049		0.053
		(0.23)		(0.27)
MGDP		-0.000		-0.001
		(-0.05)		(-0.22)
Sec_Industry		-0.000		-0.000
		(-0.10)		(-0.14)
lnSalary		-0.034**		-0.022**
		(-2.57)		(-2.07)

Density		-0.000		-0.000
		(-1.43)		(-1.04)
Intercept	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	16,316	15,845	16,316	15,845
Adj. R^2	0.831	0.832	0.723	0.725

Notes. This table presents the results of the subsample regression. In Panel A, we perform a robustness test by excluding provinces with a high frequency of terrorist attacks from full samples. In Panel B, we perform a robustness test by removing samples from ethnic autonomous regions. In Panel C, we perform a robustness test by imposing more distance restrictions on unaffected firms. In Panel D, we perform a robustness test by eliminating firms with a spatially diversified business. In Columns 1 and 4 of Panel A, we exclude firms located in Guangdong. In Columns 2 and 5 of Panel A, we exclude firms located in Xinjiang. In Columns 3 and 6 of Panel A, we exclude firms located in Guangdong and Xinjiang. The dependent variables are $LnPat_{t+1}$ and $LnCite_{t+1}$. The independent variable was *Attack_50km*. Variable definitions are presented in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix A: Variable Definition

Variables	Definition	Data Source
	Patent-based Measures of Innovation	
LnPat	The natural logarithm of one plus the number of eventually-granted patents filed by a firm in a year	PATSTAT and SIPO
LnCite	The natural logarithm of one plus the number of forward citations made to the eventually-granted patents filed by a firm in a year; citations are adjusted for truncation bias	PATSTAT and SIPO
	Terrorist Attack	
Treat	Dummy variable that takes the value of 1 for the affected firms, including firms affected by the attacks, specifically, firms that are headquartered within 50 km of the location of the terrorist events; otherwise, it is 0.	GTD
Post	Time indicator that takes the value of 1 for the affected firms in (after) the year of terrorist events; otherwise, it is 0.	GTD
Attack_50km	Dummy variable that takes the value of 1 for affected firms after a terrorist attack and 0 prior to the event. The affected firms are headquartered within 50 km of the location of the terrorist events. Alternatively, *Attack_50km* is equal to *Treat* multiplied by *Post*.	GTD
Attack_25km	Dummy variable that takes the value of 1 for affected firms after a terrorist attack has occurred and 0 prior to the event. The affected firms are headquartered within 25 km of the location of the terrorist events.	GTD
Attack_10km	Dummy variable that takes the value of 1 for affected firms after a terrorist attack has occurred and 0 prior to the event. The affected firms are headquartered within 10 km of the location of the terrorist events.	GTD
Attack_Kill	Dummy variable that takes the value of 1 for affected firms after a terrorist attack where death has occurred and 0 prior to the event. The affected firms are headquartered within 50 km of the location of the terrorist events.	GTD
Attack_Terrorism	Dummy variable that takes the value of 1 for affected firms after a terrorist attack with a higher level of terrorism intensity and 0 prior to the event. According to Nguyen et al. (2019), we define the terrorism intensity measure as the sum of the number of deaths and 50% of the number of injuries. The affected firms are headquartered within 50 km of the location of the terrorist events.	GTD
Attack_GovArmy	Dummy variable that takes the value of 1 for affected firms after a terrorist attack that targets the government, police, or military and 0 prior to the event.	GTD
Attack_public	Dummy variable that takes the value of 1 for affected firms after a terrorist attack that targets airports, aircraft, or public transportation and 0 prior to the event.	GTD
Attack_Private	Dummy variable that takes the value of 1 for affected firms after a terrorist attack that targets private citizens, property, or business and 0 prior to the event.	GTD
	Firm Characteristics	
RD	R&D expenses scaled by the total asset of a firm in a year	CSMAR
NetOut	The net inflow of inventors in the next year; the difference between the number of inventors entering the company and the number of inventors leaving the company	PATSTAT and SIPO
Cash	Cash holdings scaled by the total asset of a firm in a year	CSMAR
ROA	The ratio of net income over the total asset of a firm in a year	CSMAR
PPE	Investment in plant, property, and equipment scaled by the total asset of a firm in a year	CSMAR

Size	The natural logarithm of the total asset; the total asset is measured in million RMB.	CSMAR
Leverage	The ratio of total debt over the total asset of a firm in a year	CSMAR
HHI	The sum of the squares of market share measured via sales of a firm in a year	CSMAR
Growth	The growth rate of the operating income of a firm in a year	CSMAR
SOE	Dummy variable that takes the value of 1 for state-owned enterprises and 0 otherwise.	CSMAR
Dual	Dummy variable that takes the value of 1 if the chair and CEO are the same person and 0 otherwise	CSMAR
IndRatio	The ratio of the number of independent directors to the board directors	CSMAR
	City Characteristics	
MGDP	City's gross domestic product per capita, measured in 10,000 RMB per people	CSMAR
Sec_Industry	The proportion of the secondary industry in a city's gross domestic product	CSMAR
lnSalary	The natural logarithm of the average salary of employees; the average salary of employees is measured in 10,000 RMB.	CSMAR
Density	The population density in a city, measured in people per square kilometer	CSMAR

Note. This table provides a detailed definition of all the variables used in the analysis. Variables are categorized into four groups: patent-based measures of innovation, terrorist attack, firm characteristics, and city characteristics.

Appendix B: Balance Test of PSM matched sample

Variable	Treated	Control	Difference	t-statistic
Cash	0.173	0.178	-0.005	0.013
ROA	0.033	0.033	-0.001	0.348
PPE	0.235	0.240	-0.004	0.062
Size	21.759	21.738	0.021	0.224
Leverage	0.481	0.480	0.001	0.728
HHI	0.011	0.012	-0.001	0.146
Growth	0.229	0.236	-0.007	0.435
Dual	0.187	0.194	-0.007	0.165
IndRatio	0.366	0.366	0.000	0.677

Note. This appendix reports univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics after PSM matching. The treatment group includes all firms that are affected by the attacks, specifically, firms that are headquartered within 50 km of the location of the terrorist events; otherwise, it is 0.