The Effects of Terrorist Attacks on Inventor Productivity and Mobility

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Abstract
We examine the causal effects of terrorism on inventor productivity and mobility. During the five-year window after terrorist attacks, inventors close to the strikes are more likely to move to distant companies. While the inventors that continue working for firms near the attacks exhibit a drastic productivity decline, those that relocate to faraway companies become very productive. These results prove robust to alternative specifications and numerous controls including the influence of the 9/11 attacks. Our findings provide novel insights about the impact of shocks that distort human capital productivity and promote the mobility and reallocation of specialized resources among firms.

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1. Introduction

In the wake of the September 11, 2001 terrorist attacks, Becker and Murphy (2001) proposed that "nations recover quickly [from national disasters and the ravages of war] as long as they retain their knowledge and skills, the prime engines of economic growth". In a related context, Abadie and Gardeazabal (2008) theorize that terrorism distorts human capital productivity and may promote the mobility and allocation of productive capital in an open economy.

With this backdrop, this paper empirically examines the causal effects of terrorism on inventor productivity and mobility for US firms. The choice of inventor productivity and mobility as the main output proxies for productive (human) capital is natural given that their success depends on the work of creative individuals with exceptional knowledge and skills.

We propose two hypotheses on the effects of terrorism on inventor productivity and mobility. The first is based on the *innovation disruption* theorized by Abadie and Gardeazabal (2008). The empirical predictions from this hypothesis are that inventors in the affected firms should be more likely to move to faraway companies. Moreover, while inventor productivity in firms near terrorist strikes should experience a non-trivial decline, the productivity of inventors that relocate should not. The alternative hypothesis is rooted on research in psychology documenting resilient behavior that leads individuals to thrive after traumatic events (e.g., Bonnano 2004). Under the *resilience* alternative, inventors in firms affected by a terrorism event will become more productive at their existing firms as they will be motivated to work harder in order to increase job security, to heed calls for regional unity, or both.

To distinguish the innovation disruption hypothesis from the resiliency alternative, we construct a dataset consisting of innovating firms located near terrorist attacks and matching firms located at least 400 miles away from these events. Using inventor-level data from the USPTO database, which leads to over 1.1 million inventor-year observations during our sample period, we examine the effects of terrorism on innovation using as outcome variables those used in previous studies: the number of patents generated, and the number of patent citations.[1] We also assess the quality (value) of the innovation with the method outlined by Kogan, Papanikolaou, Seru, and Stoffman (2017), and the novelty of innovation with the Trajtenberg, Henderson, and Jaffe (1997) measures. The latter measures identify patents that start a citation stream (Originality) and those that impact a wide range of succeeding patent classes (Generality). Patents that cite a wider range of technology classes have a higher originality value, whereas those that are cited by patents in a wider set of technology classes have a higher generality value.

Given the lifecycle of innovation, we follow other studies (e.g., Brav, Jiang, Ma, and Tian 2018) and evaluate changes in inventor productivity and mobility during the five-year window subsequent to a terrorist attack. We construct two proxies of terrorism based on a firm's proximity to an attack. The first flags cases in which the distance between a firm's headquarters and the strike's site is within 100 miles. The second proxy indicates whether corporate headquarters and the terrorist strike are in the same metropolitan statistical area (MSA). The rationale for these measures rests on the idea that the effect of terrorism increases as the distance from the attack's scene decreases (Ahern 2018).

Using difference-in-differences estimation, we find that within five years from a strike, patents per employee and per inventor decline by 8.88% and 2.66%, respectively, for the average firm located within 100 miles from the terrorism scene. Confirming the results on inventor productivity at the firm level, we find a robust negative association between terrorism activity and corporate innovation at the inventor level. According to our regression estimates, within a five-year period after a terrorist attack, inventors in local firms afflicted by a strike are associated with a decline in patents and citations of 2.76% and 5.82%, respectively. Additionally, the value of the patents generated by the same inventors drops by 7.69%, while inventors generate patents that integrate existing knowledge from *fewer* dissimilar areas and, as a result, have a lower originality value. These

[1] See, for example, Atanassov (2013) and Seru (2014).

findings do not support the view that resilience will improve the productivity of inventors near the stricken scenes. Instead, the findings appear consistent with the idea that the attacks disrupt innovation. Additionally, on average, firms located within 100 miles of a strike are associated with an 11.93% reduction in the pool of inventors, a 7.13% decline in new inventors hired, and a 6.40% increase in inventors leaving the area. This last result also supports the innovation disruption hypothesis.

To gain further insights on the effect of terrorism on inventor productivity, we study the inventors who move from a firm in a terrorism stricken area to a different firm located far from the attacks' scene. We find that these inventors innovate more in their new firms relative to their former co-workers who remain employed by (or other inventors who move to other) terrorism-affected firms. The evidence related to the inventors that relocate to distant companies, together with our earlier results, provides compelling support for the innovation disruption hypothesis. That is, in line with the theoretical model of Abadie and Gardeazabal (2008), our empirical evidence indicates that terrorism distorts human capital productivity and promotes the mobility and reallocation of productive resources among firms.

We are aware that the location of a terrorism event is not necessarily random. Terrorists might favor attacks in growing cities with diverse populations and these characteristics might also influence innovation activity. If the location choice is indeed correlated with innovation activity, then we cannot attribute the change in innovation to terrorist attacks. This issue, however, is unlikely to affect our findings because, in our sample, matched firms are just as (demographically) likely to be located near an attack as their treated counterparts. Indeed, before the attacks, both our treated and matching sample firms exhibit similar characteristics in terms of the average number of employees and their location's population.

We check whether our data plausibly satisfy parallel trends, a condition necessary to ensure the internal validity of difference-in-differences models. For this purpose, we estimate trends in our inventor productivity and mobility outcome variables before and after a terrorist strike. These tests also shed light on whether other events drive our results, on the likelihood that the attack was somehow anticipated, and on the possibility of reverse causality. Our results mitigate concerns related to these issues because the trend in every outcome variable changes *after* the attack, but not before.

At first glance, the lingering (three year) effect of terrorism on innovation we find appears in conflict with evidence indicating a quick *overall* economic recovery from terrorist attacks. According to Bloom (2009), for example, the 9/11 attacks caused a rapid economic decline and recovery, with a loss of about 1 million jobs and investment equivalent to 3% of GDP during the 4 months after the attack, but little longer run impact. Our results suggest that, at least with respect to innovation activity, recovery in the terrorism-stricken areas is not as rapid. This inference is bolstered by our findings on inventor mobility: During the five years after an attack, firms in stricken areas are less likely to hire new employees and more likely to see some of their inventors move to companies located farther from the attack scenes. The latter result helps us reconcile our evidence with the earlier literature. Specifically, since the outgoing inventors become more productive at those remote new firms, the effects of terrorism on innovation might take less time to dissipate when measured at the country level.

We are mindful of concerns related to the magnitude of the attack, to analogous events not necessarily classified as acts of terrorism, to the general level of economic stability, to the prevailing level of personal security, and to the assistance afforded to individuals that lose their jobs. In this regard, we note that our findings continue to hold when we: (i) exclude the 9/11 terrorist attacks from the analyses; (ii) augment our terrorism data with data on mass shootings; (iii) control for VIX; (iv) account for the local crime rate; and (v) control for the availability of unemployment benefits.

We are also sensitive to the criticism that there might be other ways to evaluate the impact of disruptive shocks on inventor productivity and mobility. Bhattacharya, Hsu, Tian, and Xu (2017), for example, find that *policy* uncertainty (captured by close presidential elections) is associated with a decline in corporate innovation activity. In contrast, Atanassov, Julio, and Leng (2019) show that uncertainty over government policy (proxied by close gubernatorial elections) stimulates firm-level R&D investment. Moreover, consistent with higher-than-normal R&D investment in the gubernatorial election year, Atanassov et al. (2019) also find an increase in lagged patent activity. The evidence by Atanassov et al. (2019) suggests that policy uncertainty can attenuate or promote innovation depending on the properties of the investment and the degree of product market competition. In contrast with scheduled political elections, terrorist attacks produce unanticipated unambiguous negative shocks to the environment where entities operate.

The central contribution of this paper is to provide new evidence on how terrorism affects inventor productivity and mobility.[2] In this vein, our findings deliver empirical support for the theoretical predictions by Abadie and Gardeazabal (2008) that terrorism unsettles the productivity and triggers the reallocation of specialized human capital in an open economy. In addition, it is likely that some of our results are due, at least in part, to the detrimental psychological impact of terrorism (e.g., drop in innovation productivity at firms near the attacks and inventors moving to faraway companies). As result, our paper is also related to the work by Ahern (2018) in which he conjectures that terrorism's key channel of influence must be psychological and by Becker and Rubinstein (2011) in which they posit that exposure to terror causes intense personal uncertainty about future attacks leading to reduced job satisfaction, participation, effort, learning, and creativity.[3] This study also contributes to the strand of the literature showing that uncertainty adversely affects investment

[2] Other characteristics known to affect innovation include: competition (Aghion, Bloom, Blundell, Griffith, and Howitt 2005); bankruptcy laws (Acharya and Subramanian 2009); private equity involvement (Lerner, Sorensen, and Strömberg 2011); analyst coverage (He and Tian 2013); institutional ownership (Aghion, Van Reenen, and Zingales 2013); anti-takeover provisions (Atanassov 2013); labor laws (Acharya, Baghai, and Subramanian 2013, 2014); venture capital (Chemmanur, Loutskina, and Tian 2014); investors' attitudes toward failure (Tian and Wang 2014); stock liquidity (Fang Tian, and Tice 2014); firm boundaries (Seru 2014); public offering decisions (Bernstein 2015); employee stock options (Chang, Fu, Low, and Zhang 2015); banking competition (Cornaggia, Mao, Tian, and Wolfe 2015); lending relationships (Hombert and Matray 2017); corporate taxes (Mukherjee, Singh, and Žaldokas 2017); independent directors (Balsmeier, Fleming, and Manso 2017), employment non-discrimination acts (Gao and Zhang 2017); and hedge fund activism (Brav et al. 2018).

[3] This is also consistent with medical research which shows that, after terrorist attacks, emotional disorders weaken the productivity and economic stability of a firm's workforce (North and Pfefferbaum 2002).

(e.g., Alesina and Perotti 1996, Bloom, Bond, and Van Reenen 2007, Julio and Yook 2012, Gulen and Ion 2016). Notably, work in this area considers *tangible* investment whereas we evaluate innovation which represents an *intangible* investment due to its longer duration and higher risk.

Possibly motivated by recent terrorist events in the US (e.g., the 2013 Boston Marathon bombing, the 2015 San Bernardino, CA shootings, the 2017 Charlottesville, VA vehicle ramming attack, the 2018 Pittsburgh Synagogue killings, and the 2019 Walmart massacre in El Paso, TX), there is renewed academic interest in assessing the financial consequences of terrorism. In this regard, our work complements recent studies using the underlying exogeneity of terrorist attacks to establish the causal effect of these incidents on investors' risk preferences (Wang and Young 2020), on the sentiment and forecasts of sell-side equity analysts (Cuculiza, Antoniou, Kumar, and Maligkris 2020), and on CEO compensation (Dai, Rau, Stouraitis, and Tan 2020).[4] The latter paper, for instance, shows that after a terrorist strike, CEOs of firms located near the attack's scene get a sizable cash compensation increase. To the extent that CEOs and inventors are hard to redeploy assets, our evidence on inventor mobility suggests that the post-terrorism pay increases documented by Dai et al. (2020) might be aimed at preventing CEOs (e.g., specialized human capital) from leaving their firms. More generally, our paper advances this literature by relating terrorism to innovation. Understanding the dynamics between these two activities is of first-order importance given that innovation is vital for sustaining economic growth in general and firm value in particular.

The paper continues as follows. Section 2 describes our data and the measures of terrorist attacks, inventor productivity and mobility, and corporate innovation. Section 3 presents our main empirical analyses at both the firm and inventor level. Section 4 presents the robustness checks. Section 5 concludes. The Appendix provides the definition for all the variables we use in this study.

[4] Other papers studying the financial effects of terrorism include the work by Burch, Emery, and Fuerst (2003) considering closed-end fund discounts and investor sentiment after the 9/11 attacks; by Poteshman (2006) looking at option trading after the 9/11; by Arin, Ciferri, and Spagnolo (2008) examining the effect of terrorism on stock market volatility; by Karolyi and Martell (2010) examining the stock price impact of terrorism during 1995-2002 with a list of 75 attacks compiled by the US Department of State; by Procasky and Ujah (2016) studying whether terrorism affects the cost of debt; by Kim and Kung (2017) determining how terrorism-induced uncertainty affects corporate investment under varying degrees of asset redeployability; and by Brodeur (2018) showing that terrorist strikes boost consumer pessimism.

2. Data and Experimental Design

2.1. Terrorism

We collect data on the date, location, and number of victims of each terrorist attack in the US between 1985 and 2007. This information is drawn from the Global Terrorism Database (GTD) maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). The GTD contains systematic records on domestic and international terrorism events. The attacks most often target businesses, private citizens, and property. According to START, to be included in the GTD, events must involve a deliberate act of violence or threat of violence and, additionally, meet two of the following three criteria: (1) the attack aimed at attaining a political, economic, religious, or social goal; (2) the attack intended to coerce, intimidate, or deliver some other message to a larger audience (other than the immediate victims); and (3) the violent act was outside the precepts of International Humanitarian Law (particularly the warning against intentionally targeting civilians or non-combatants).

We verify all the attacks and the accuracy of the data pertaining to each event (e.g., location, casualties, perpetrators, etc.) by performing a manual search in US newspapers through Lexis-Nexis. During our sample period, we record information for 761 different terrorist attacks. These events produce 3,261 deaths and 22,908 injuries. The 9/11 World Trade Center attack accounts for 2,770 deaths and 10,878 injuries.

Table 1 presents the temporal distribution and attack classification for the 761 terrorism events in our sample. Attacks are categorized by either the type of incident (e.g., explosion) or by the characteristics of the target (e.g., airplane hijacking). At 319, attacks of facility/infrastructure (e.g., the October 9, 1995 Palo Verde, AZ train derailment with a toll of 1 killed and 78 injured individuals) is the most common type of terrorism event. There are only two kidnapping events in the sample. The year 1993 shows no incidents. In contrast, 1995 is the year with most terrorist attacks (at 60) which includes the Oklahoma City bombing in which 168 persons died and 650 others were injured.

Existing work notes that the impact of terrorist attacks is stronger for individuals closer to the incident's location (e.g., Ahern, 2018). With this logic in mind, we create an indicator variable, labeled "*attack vicinity within 100 miles*" that is set to one if firm *i* is headquartered within 100 miles of terrorism scene *j*.[5] We match company location data with information from the US Census Bureau's Gazetteers and Zip Code Database to obtain details on the latitude and longitude of the firms and terrorist incidents sites. Following the procedure in Vincenty (1975), we use this information to calculate the distance between a firm's headquarters and a terrorist attack location. To increase the likelihood that innovations are generated at the headquarter site, we follow Almazan, De Motta, Titman, and Uysal (2010) and retain companies for which a high percentage of their assets and employees are in the firm's headquarters.

Our *attack vicinity within 100 miles* variable is vulnerable to the concern that the event could have occurred in areas in which some firms are part of a general business zone but are, nevertheless, domiciled more than 100 miles from the stricken location. Under this possibility, the 100 miles-related variable might miss the effects accruing to these companies. To address this issue, we also define local firms as those headquartered in the same Metropolitan Statistical Area (MSA) as the attack. We identify MSAs with information provided by the US Census Bureau. According to the Office of Management and Budget (OMB), an MSA consists of a "core area that contains a substantial population nucleus, together with adjacent communities that have a high degree of social and economic integration with that core."

2.2. Inventor productivity and mobility

We evaluate the effects of terrorism on both inventor productivity and mobility at the firm and inventor level. Following the extant literature (e.g., Aghion et al. 2013, Seru 2014, Brav et al. 2018),

[5] Using distances of 50 or 200 miles from the attack's site does not alter our results.

a firm's patenting activity captures innovation output. Therefore, to measure inventor productivity at the firm level, we collect patent characteristics from the dataset created by Kogan et al. (2017) which contains information for all patent applications filed with (and eventually granted by) the US Patent and Trademark Office (USPTO) from 1926 to 2010. Their dataset provides identifiers for each filing firm which enable us to merge the patent data with CRSP and Compustat. We focus our analyses on the patent filing year because, as Griliches, Pakes, and Hall (1987) note, the filing (rather than the grant) year better captures the actual time of innovation. Moreover, focusing on the filing date addresses the concern of potential anomalies that may arise due to lags between the application and granting dates (two years, on average).

We track patent output (the number of patents granted) as it is a widely accepted measure of innovation (Hall, Jaffe, and Trajtenberg 2001). We are concerned that this metric varies over time and across scientific fields and because it is vulnerable to a truncation bias. The latter distributional issue arises since patents only appear in the dataset after they are granted and due to the time it takes before a granted patent is eventually cited. To address this concern, we follow Hall et al. (2001, 2005) and adjust patent counts by weighting each patent by the mean number of patents granted in the same year and technology class. Hence, patents granted in fields with more patent activity receive less weight. To further address the distributional concern, we exclude 2009 and 2010 because the truncation bias is the most severe in these two years of the patent dataset (Hall et al. 2005). As a result, our innovation sample spans the period 1986 to 2008.[6]

We use two measures to track innovation productivity within the firm, which are like those in Acharya et al. (2014) and Mukherjee et al. (2017): i) the natural logarithm of the number of patents per 1,000 firm employees, plus one; and ii) the natural logarithm of the number of patents scaled by the number of inventors, plus one, which captures the people more likely to be involved in the

[6] There is a one-year lag between the terrorism sample and the innovation sample because we examine the response of the inventor variables in year *t+1* to a terrorist attack that occurs during *t*.

innovation process. We define inventors as the individuals who apply for a patent on behalf of their firm in the current year and have not filed a patent for a different firm during the same year.

To measure inventor mobility at the firm level, we follow Brav et al. (2018) and employ three different proxies. Specifically, we use: i) the natural logarithm of the number of inventors plus one, adding inventors in a firm's staff in a given year; ii) the natural logarithm of the number of new hires plus one, tracking inventors hired from another firm in a given year; and iii) the natural logarithm of the number of leavers plus one, counting inventors who move to another firm in a given year. We identify new hires and leavers by verifying subsequent patents filed by the same inventor within one year.

To measure innovation productivity at the inventor level, we create a time-series for inventors, using data from the USPTO covering approximately 4.2 million patent records and 3.1 million inventors from 1975 until 2010.[7] We start by identifying the first and last year an inventor appears in the patent database. We then assign a value of zero to the inventor's innovation output variables for the years in between and without any patent record.[8] Every inventor is also matched to a patent's assignee (the firm listed in the patent's application). This procedure generates over 1.1 million inventor-year observations during our sample period.

Some of our analyses use five innovation productivity outcome variables at the inventor level. To define them, we collect patent and citation characteristics from the dataset created by Kogan et al. (2017). We track patent output (the number of patents granted) as it is a widely accepted measure of innovation (Hall, Jaffe, and Trajtenberg 2001). However, this measure does not inform whether the patent is associated with a revolutionary innovation or an incremental discovery (e.g., Griliches 1990). Consequently, we also assess the novelty of a patent with the number of citations it receives after the grant date. We finally follow the Hall et al. (2001, 2005) process of adjustment and

[7] Please see Li, Lai, D'Amour, Doolin, Sun, Torvik, Amy, and Fleming (2014). These data along with accompanying programs are available from the UC-Berkeley Fung Institute for Engineering Leadership
[8] Baghai et al. (2019) use a similar procedure.

truncation described above excluding also the last two years of the dataset when the truncation bias is most severe.

As in Kogan et al. (2017), we measure the quality of innovation (or patent's dollar value) with the firm's market-adjusted stock return estimated from the day of the patent approval announcement date until two days after (t, t+2), multiplied by the firm's market capitalization on the day prior to the announcement (t-1). We also assess the importance of the innovation with the Trajtenberg et al. (1997) measures of Originality and Generality. The first measure identifies patents that start a citation stream. The second measure captures patents that influence an extensive range of succeeding patent classes. Specifically, patents citing a wider assortment of technology classes have a higher originality value while those cited by patents in a broader set of technology classes have a higher generality value.

Finally, in the spirit of Hombert and Matray (2017), we focus on inventors who move to a different company after a terrorist attack to create three different variables under the premise that an inventor has moved if she filed a patent for company *A* and later files a patent for company *B*. We use three variables to measure mobility at the inventor level. The first variable is the "*Ln (Distance of the Move + 1)*", which is the natural logarithm of inventor's distance of the move in miles to a new employer from her previous employer. The second variable is an indicator variable, "*Over-100-Miles Move"*, which equals one if companies *A* and *B* are located more than 100 miles from one another. The indicator is set to zero whenever the distance between companies *A* and *B* is less than 100 miles. The third variable, "*Out-of-MSA Move,"* is set to one if companies *A* and *B* are in different MSAs and set to zero if they are in the same MSA.

2.3. Sample Overview

We merge the databases described in the previous sections to form our main sample. Using criteria similar to that in Brav et al. (2018), our sample includes potentially innovative firms which requires that the firm: i) files at least one patent that is eventually granted prior to the year of a terrorist attack; and ii) experiences at least one positive R&D expenditure within the five-year window before the attack.

Our main analyses rely on the pooled sample of innovative (treated) firms that experience a terrorist attack and innovative (control) firms matched by propensity scores. Aside from being innovative, firms become candidates to enter the control group if, in the year of the attack, they are located at least 400 miles away from the strike and operate in the same 2-digit SIC industry as the treated firm. To create the control group, we first estimate propensity scores through probit regressions, p(Y=1/X=x), based on the probability of receiving the treatment, Y, conditional on a vector of firm characteristics, x. These characteristics include size, Tobin's Q, cash holdings, leverage, return on assets (ROA), tangible assets, capital expenditures, the natural logarithm of firm age, H-index, and H-index^2. As noted earlier, detailed definitions for these and other variables appear in the Appendix.

For each terrorism-affected firm-year, we then use the propensity score to find a control firm-year based on the nearest-neighbor method (i.e., one-to-one matching) without replacement.[9] Following Brav et al. (2018), the event year for a terrorism-afflicted firm also serves as the "pseudo-event" year for its matched firm. To ensure the adequacy of the matching estimation, the absolute difference in propensity scores among pairs cannot exceed 0.05. If there are multiple control firms-years that meet this criterion, we retain the firm-year with the *smallest* propensity score difference.

Table 2 reports the mean, standard deviation, 25th, 50th, and 75th percentile for several firm characteristics of treated firms and matched firms (measured during the year before the attack). For every characteristic, the last two columns in the table respectively report the differences in means for the two samples and the associated *t*-statistics for mean equality.

[9] To be thorough, we also use 3- and 5-nearest-neighbors matching estimators and obtain similar results.

Table 2, Panel A reports summary statistics for observations related to attacks within 100 miles away from the firm's headquarters, whereas Panel B presents the statistics related to attacks in the same MSA as the firm's headquarters. As is the case for all other firm characteristics, including the average number of employees and the location's population, none of the differences in the firm-level inventor or inventor innovation variables are either economically or statistically significant even though these variables are not part of the matching criteria.[10] The pre-attack similarity in the summary statistics for the inventor-level innovation variables suggests that our data satisfies the "parallel trends" condition which is necessary to ensure internal validity of difference-in-differences estimates. Section 3.6 describes other tests related to parallel trends. In addition, the similarity in the number of employees and in the population statistics between the treated and control samples alleviates the concern that terrorists deliberately perpetrate attacks in locations in which a strike has a better chance to produce many casualties.

2.4. Experimental Design

The sample consists of firm-year level observations of innovative firms that are subject to a terrorist attack and their matched firms. Our primary interest is to evaluate how terrorist attacks affect inventor productivity and mobility. To do so, equation (1) presents our difference-in-differences regression framework which is similar to that in Brav et al. (2018).

$$\text{Inventor Productivity (Mobility)}_{i,\,l,\,t+1} = \tag{1}$$

$$= \alpha_t + \alpha_i + \beta_1\, \mathit{Attack\ Vicinity}_{i,\,l,,\,t} * \mathit{Post}_{i,\,l,\,t} + \beta_2\, \mathit{Post}_{i,\,l,\,t} + \gamma\, X_{i,\,l,\,t} + \in_{i,\,l,\,t+1}$$

where i indexed firms, l indexes the location of the firm, and t indexes time. $\mathit{Attack\ Vicinity}_{i,\,l,\,t}$ is an indicator variable that equals one if a firm is located within 100 miles (or within the MSA) of the

[10] Innovation samples like ours have been extensively used in previous studies, so we refrain from discussing descriptive statistics but verify that they are in line with prior studies (see, for example, Chang et al. 2015, Cornaggia et al. 2015, Balsmeier et al. 2017, Mukherjee et al. 2017).

attack. *Post* $_{i, l, t}$ is a dummy equal to one if the firm-year (i, t) observation is within [$t+1$, $t+5$] years of a terrorist attack (for treated firms) or a pseudo-event year (for matched firms). The results are robust if we instead use the three-year period following the event. Our main variable of interest is the interaction term *Attack Vicinity* $_{i, l, t}$ * *Post* $_{i, l, t}$, which captures the differential change in inventor productivity and mobility for firms subject to terrorist attacks, compared to that for matched firms. Following the extant innovation literature (e.g., Atanassov 2013, Acharya et al. 2014) we also control for a series of firm-specific characteristics in our model, represented by $X_{i, l, t}$.[11] We winsorize all independent variables at the 1st and 99th percentiles.

Since we analyze firm-year observations, the question is whether inventor productivity and mobility change after a local terrorist attack. Therefore, our test must identify the change in inventor productivity and mobility for the same firm before and after a terrorist attack, compared to other firms that are not located near an attack. For this purpose, equation (1) controls for time-invariant unobservable firm characteristics with firm fixed effects, α_i. Equation (1) also includes year indicator variables α_t to control for economy-wide shocks.

Following Gormley and Matsa (2014), we also estimate equation (1) with higher order fixed effects to control for unobserved firm heterogeneity, time-varying differences across regions, and time-varying differences across industries by including firm (α_i) and year (t), region-by-year ($\omega_{p,t}$), and 2-digit SIC industry-by-year ($\lambda_{z,t}$) fixed effects for a firm i, located in region p, operating in industry z, at time t. As in Acharya et al. (2014, p. 322), we distinguish 4 US regions (Northeast, South, Midwest, and West) following the classification of the US Census Bureau. Angrist and Pischke (2009) and Gormley and Matsa (2014) argue that including control variables in the presence of fixed effects may lead to biased parameter estimates. Therefore, in the estimations that use the high order fixed effects, we suppress all control variables.[12] In all tests, we follow Petersen's (2009)

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[11] Specifically, $X_{i, l, t}$ is a vector of control variables which include size, Tobin's Q, cash holdings, leverage, ROA, tangible assets, capital expenditures, ln (firm age), H-index, and H-index^2.

[12] Our baseline results are unaltered when we repeat all our empirical tests in regressions that simultaneously use all control variables and high-order fixed effects. These analyses are available upon request.

advice to control for serial correlation with robust Rogers (1993) standard errors clustered at the firm level.[13]

3. Empirical results

3.1. Employee and inventor productivity (Firm-level analysis)

Table 3 reports eight difference-in-differences regressions based on equation (1) to evaluate the effect of terrorism on employee and inventor productivity. The key independent variable, *Attack Vicinity * Post Attack*, follows from equation (1) and we estimate it for firms located within 100 miles of the attacked site and for those within a stricken MSA. The dependent variable in models (1)-(4) is the natural logarithm of the number of patents per 1,000 firm employees, plus one. The dependent variable in models (5)-(8) is the natural logarithm of the number of patents scaled by the number of inventors, plus one. The odd-numbered tests omit the controls and use standard and multiplicative fixed effects while the even-numbered models include control variables and standard fixed effects.

According to Table 3, both patents/employees and patents/inventors decrease significantly during the five-year period that follows a terrorist attack. An average firm headquartered within 100 miles from a terrorist attack location is related to an 8.88% decline in patents/employee and a 2.66% drop in patents/inventor in the five-year period after the attack. These effects rely on the *Attack Vicinity within 100 miles * Post* coefficients in columns (2) and (6), respectively. The estimates for terrorist attacks within an MSA lead to analogous inferences.

3.2. Inventor Productivity (Inventor-level analysis)

In this section we study the effect of terrorist attacks on inventor productivity with data at the inventor level (rather than at the firm level). This alternative specification allows examining the

[13] The results are similar if we use the suggestions by Bertrand et al. (2004) and cluster the standard errors at the state of location level or allow for correlated error terms at the state of incorporation level.

effect of terrorist attacks on conventional innovation outcome variables such as patents, citations, innovation value, generality and originality. The dependent variable is the natural logarithm of the number of patents plus one in models (1) and (2), the natural logarithm of the number of patent citations plus one in models (3) and (4), the natural logarithm of the innovation's value plus one in models (5) and (6), the patent's generality in models (7) and (8), and the patent's originality in models (9) and (10).

The inventor-level analyses appear in Table 4. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e., inventor and year fixed effects, region-by-year fixed effects, and industry-by-year fixed effects), while the even-numbered columns include control variables and standard fixed effects (i.e., inventor and year fixed effects). Panel A reports results for inventors working within 100 miles of the terrorist attack, whereas Panel B analyzes inventors located within a stricken MSA. Our results with the inventor-level data confirm the findings we obtain with firm-level data: inventors who work in terrorism-afflicted areas exhibit lower innovation productivity following the strikes. Specifically, terrorist attacks reduce patenting, citations, innovation value, and patent originality. Using the estimates in columns (1) and (3) of Panel A, during the five-year window following a terrorist attack, inventors in local firms afflicted by a strike are associated with a decline in patents and citations of 2.76% and 5.82%, respectively. According to the estimates in column (5), the value of the patents generated by the same inventors drops by 7.69%., which provides further evidence of reduction in inventor productivity after terrorist attacks. Results for the remaining tests in Table 5 show that the Originality (but not the Generality) of patents is curtailed after a terrorist attack.

Overall, the results in Tables 3 and 4 provide support for the *innovation disruption* hypothesis but not for the *resilience* alternative. After terrorist attacks, inventors in firms near the attacks exhibit material declines in various metrics of innovation productivity.

3.3. Inventor Mobility (Firm-level analysis)

Next, we examine whether terrorism promotes employee mobility. To consider this issue, we follow Brav et al. (2018) and use three different proxies to measure inventor mobility. Specifically, the dependent variables in Table 5 are: the natural logarithm of the number of inventors plus one in models (1)-(4), adding inventors in a firm's staff in a given year; the natural logarithm of the number of new hires plus one in models (5)-(8), tracking inventors hired from another firm in a given year; and the natural logarithm of the number of leavers plus one in models (9)-(12), counting inventors who move to another firm in a given year. We identify new hires and leavers by verifying subsequent patents filed by the same inventor within one year.

Looking at Table 5, both the number of inventors in a firm's staff and the number of new inventor hires decline during the five years subsequent to a terrorist attack. Conversely, after the same event and during the same period, the number of inventors who move to other firms increases. To illustrate the magnitude of the results, on average, a firm located within 100 miles from an attack's scene is associated with an 11.93% decline in staff inventors, a 7.13% decrease in the number of new inventor hires, and a 6.40% increase in the number of inventors who leave to work elsewhere in the five-year period after the attack. These effects are based on the *Terrorist Attack within 100 miles * Post* coefficients in columns (1), (5), and (9), respectively. Defining local firms with MSAs yields comparable results.

3.4. Labor Market Relocation (Inventor-level analysis)

To provide further insights on the effects of terrorism on inventor mobility, we track *inventors* over time and across the firms for which they file patents. We use three dependent variables to measure labor market relocation. The first variable is the "*Ln (Distance of the Move + 1)*", the second is an indicator variable, "*Over-100-Miles Move"*, and the third variable is an indicator labeled "*Out-of-MSA Move"*.

In the regressions reported in Table 6, *Ln (Distance of the Move + 1)* is the dependent variable in columns (1) and (2), *Over-100-Miles Move* is the dependent variable in columns (3)-(4) and *Out-of-MSA Move* is the dependent variable in columns (5)-(6). The results strongly suggest that, during the five-year period following a terrorist attack, some inventors are significantly more likely to relocate to faraway companies if they had worked near the strike's scene. The OLS estimates in column (1) indicate that terrorist attacks lead to a 21.02% increase in the distance of the move. Similarly, the estimates from a probit regression in column (3) suggest that, inventors in firms within 100 miles from the strike are 3.01 percentage points more likely to move to a firm located more than 100 miles from their previous firm. Additionally, according to the results in column (5), inventors in a stricken MSA are 3.68 percentage points more likely to relocate to a firm in a different MSA. These findings suggest that inventors in firms near terrorist strikes get new jobs farther away relative to other inventors who leave firms not located near an attack.

Overall, the results in Tables 5 and 6 are consistent with another key prediction of the *innovation disruption* hypothesis that terrorist attacks promote mobility of human capital.

3.5. Innovation Productivity for Inventors that Relocate from the Attacked Areas

Our previous tests show that inventors who remain at firms located near the scenes of a terrorist attack exhibit a decline in patenting and other measures of innovation productivity. Other analyses show that, some inventors move from firms near the attacks to different firms located far away from the attacks. In this section, we investigate the innovation productivity of the cohort of inventors that relocate to those remote firms. For this purpose, we use the dataset from Li et al. (2014), which contains disambiguated inventor names and unique inventor IDs that enables us to track inventors across firms. For example, an inventor that files a patent with firm A in 1999 and one with firm B in 2000 is designated as an employee of firm A in 1999 and as an employee of firm B in 2000. If more than one year elapse between two patent filings, we assume that the employment transition between the two firms occurs at the midpoint between the patent application years. For example, if an inventor employed by firm A is granted a patent in 1995 and a different patent while employed by firm B in 2000 and has no other patents granted in the interim, we assume that the inventor is employed by firm A until 1997 and by firm B from 1998 onwards. In the analysis, we identify an inventor's employer with the Compustat GVKEY recorded in the patent.

Table 7 presents the ten regressions with dependent variables similar to those in Table 4 in which the key independent variable is *Relocated Inventors * Post*. Panel A reports the estimates for inventors who relocate from stricken areas and file patents in firms domiciled outside the 100 miles radius from the terrorist attack, whereas Panel B analyzes inventors who relocate away from a stricken MSA. The benchmark group is the cohort of treated inventors who remain employed by a firm located in a terrorism-affected area and those who move to another firm located in a terrorism-stricken area.

We find that inventors who relocate away from the stricken sites experience a significant increase in innovation productivity in terms of the number of patents, citations, innovation value, patent generality and originality. To provide insights about the economic magnitude of the terrorism impact, inventors who move to companies domiciled more than 100 miles from the location of the terrorist attack are associated with an increase of 39.98% in the number of patents and of 156.25% in the number of citations. These economic effects are based on the estimates reported in columns (2) and (4) of Panel A. This evidence provides support for the remaining prediction of the innovation disruption hypothesis, that terrorism promotes the reallocation of productive human capital among firms in an open economy.

3.6. Anticipation and Persistence of the Terrorism Effect

Our baseline tests use difference-in-differences methods, that enable us to compare changes in inventor productivity and mobility among firms in areas subject to a terrorist attack with changes in inventor productivity and mobility among firms located elsewhere. A valid concern with this setting is whether events other than the terrorist attack might be driving our results. A related issue is whether the terrorist attack is anticipated. Another concern is whether there is reverse causality. To evaluate these possibilities, we perform tests to ensure that the changes in inventor productivity and mobility we document in the preceding analyses occur only *after* the attacks, but not *before*.

Figure 1 presents 5 separate plots of the average response functions during the pre- and post-attack periods for each of the 5 outcome variables we study at the firm level.[14] For every plot, we use the attack vicinity within 100 miles estimates from 9 different regressions with independent variables that capture the trend on the outcome variable 3 years before and 5 years after the terrorist attack as in Brav et al. (2018). As mentioned above, using a window of (*t-3, t+3*) years around the terrorist attack leads to similar conclusions. Specifically, we run falsification tests in which each terrorism event is assigned a placebo date one year (*t* - 1), two years (*t* - 2), and three years (*t* - 3) *before* the year of the actual attack (i.e., year *t*). We use these placebo dates to construct our attack vicinity measures and re-estimate baseline regressions like those in Tables 3 and 5. We also run the regressions in these tables with dependent variables that capture the effect of terrorism on inventor productivity and mobility over one, two, three, four and five years *after* the actual attack. For every outcome variable, we repeat this procedure to trace the effect corresponding to Attack Vicinity within MSA.

To facilitate visual inspection of the trends in our variables, we overlay a vertical line in each plot to denote the year of the terrorist attack and report the actual regression coefficient estimates along with their respective *p*-values. According to Figure 1, the significant downward (upward) trend for the inventor productivity, the inventor mobility, number of employees, and number of new hires (leavers) starts on the year of the attacks but not earlier. These patterns remain when local firms are defined within 100 miles or within the MSA of the attack. These findings lessen concerns of reverse

[14] Figure 1 presents 5 different plots for our respective 5 outcome variables organized as follows. Panel A presents the plot for ln (#Patents/Employees +1), Panel B for ln (#Patents/Inventors+1), Panel C for ln (#Inventors+1), Panel D for ln (#Leavers+1), and Panel E for ln (#New Hires+1).

causality or possible anticipation of the attacks which would have affected inventor productivity and mobility ex-ante. Moreover, the absence of pre-trends suggests that our data plausibly satisfy the parallel trends condition which is essential to ensure the internal validity of difference-in-differences models.

The plots in Figure 1 also show that both the per-employee and per-inventor measures reveal that the drop in patenting lasts for 3 years after a terrorist attack. The plots also illustrate that, during the three years after the terrorist strike, firms in the vicinity of the attack keep losing inventors and not hiring new ones. Altogether, the post-trend evidence in Figure 1 suggests that terrorism generates effects that linger for some time after an attack. This evidence compares favorably with the results by Dai et al. (2020). They find that the effects of terrorism on executive compensation do not vanish right away, lasting for up to two years after the incident.

4. Robustness Tests

With additional data, and different samples, we perform supplementary analyses to probe the robustness of our baseline findings.

4.1. Including Mass Shootings and Other Control Variables

We augment the terrorist attacks data with 41 mass shootings. We collect this information from the US Mass Shootings Mother Jones Database (MJD) for events that occur during our sample period. For each mass shooting, we verify the reported information with a manual search in major US newspapers through Lexis-Nexis. Notably, the MJD contains some events that do not meet the GTD criteria to be classified as terrorist attacks (e.g., the Virginia Tech shooting in April of 2007).[15] We add these events to the analyses because they could also affect the productivity of employees working near the shootings.

To help contextualize the firm responses to a terrorist attack, we include three control variables

[15] Seung-Hui Cho, a VA Tech student and a U.S. resident of South Korean origin, killed 32 people and wounded 17 others with two semi-automatic pistols. Six others were injured jumping out of windows to escape Cho.

that may either attenuate or exacerbate the impact of the strike. First, it is possible that the responses we estimate occur because economic volatility in the stricken location is already high. To address this possibility, we include VIX as a control variable. Second, under the same logic, our results might be the byproduct of attacks in locations where grave concerns about personal safety are prevalent. We add Crime Rate (as reported by the FBI) as a control to partially account for this issue. Lastly, voluntary or involuntary employee departures might depend on the current level of unemployment benefits. To consider this matter, we add Unemployment Insurance Benefit as an additional independent variable.

To conserve space, in Table 8 we report only the coefficients for *Attack Vicinity* * *Post* and the additional control variables from regressions based on the augmented dataset. These tests are otherwise like those reported in Tables 3 through 6. The results echo our previous findings: Attacks stifle inventor productivity and corporate innovation, promote inventor mobility, and prevent firms in areas near the attacks from hiring new inventors. In unreported tests, like those in Panel B, we obtain similar results when the Vicinity variable is based on the MSA.

4.2. Excluding the 9/11 Terrorist Attacks

The 9/11 terrorist attacks comprise three incidents in New York, Virginia, and Pennsylvania which resulted in 3,201 deaths and 6,106 injuries. To eliminate potential concerns that this important outlier might drive our results, we drop the 9/11 terrorist attacks from the analyses. Table 9 presents the results of regressions that exclude the 9/11 events but are otherwise like those reported in Tables 3 through 6. For brevity, we only report the coefficients for our *Attack* Vicinity * *Post* interaction variable. These tests yield qualitatively similar inferences to those drawn from our baseline analyses. We again find comparable results in untabulated MSA tests similar to those reported in Panel B.

5. Conclusions

We consider two hypotheses to study the causal effects of terrorism on inventor productivity and mobility for US firms. The *innovation disruption* hypothesis is rooted on theoretical work by Abadie and Gardeazabal (2008). Their model predicts that terrorism disrupts the productivity of specialized resources and promotes their reallocation in an open economy. The alternative is the *resilience* hypothesis which is based on research in psychology showing that individuals tend to thrive after traumatic events (e.g., Bonnano 2004).

Using difference-in-differences estimation, we find robust evidence that, during the five-year period after a terrorism event, inventors working in firms located near an attack's site exhibit material declines in various measures of innovation productivity. In addition, firms geographically close to terrorism-afflicted areas are less likely to hire new inventors and more likely to have inventors move to firms located far away from the stricken scenes. Importantly, once they relocate to their new (faraway) firms, inventors become more productive (e.g., generate more patents).

Our results are consistent with the view that terrorism distorts the productivity of human capital and rearranges specialized resources among firms. In this regard, our findings help reconcile the evidence in Bloom (2009) that even large terrorism events such as the 9/11 attacks are not associated with long-lasting economic effects. According to our evidence, the detrimental effects of terrorism on corporate innovation persist for at least three years after the attacks, particularly in firms located near the strikes. However, because the same attacks promote inventor mobility to firms in distant locations, innovation activity at those remote firms thrives. Overall, our evidence on the effects of terrorism on inventor productivity and mobility are of first-order importance given the centrality of innovation activity for sustaining long-run economic growth in general and firm value in particular.

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Figure 1

Trends in the Relation between Terrorist Attacks and Inventor Productivity, and Inventor Mobility

This figure shows the trends in the relation between terrorist attacks and inventor productivity, and inventor mobility over the 3-year period before and 5-year period after the terrorist attacks. The y-axis plots the estimated coefficients after regressing on inventor productivity variables (Panel A for ln (#Patents/Employees +1) and Panel B for ln (#Patents/Inventors+1)), and inventor mobility variables (Panel C for ln (#Inventors+1), Panel D for ln (#Leavers+1), and Panel E for ln (#New Hires+1)), as well as on the control variables and firm and year fixed effects used in Table 3 (for Panels A and B), and in Table 5 (for Panels C through E). The x-axis shows the time relative to terrorist attacks for the 3-year period before and 5-year period after the terrorist attacks. The red dotted line corresponds to the attack vicinity within 100 miles and the blue solid line corresponds to the attack vicinity within MSA. The symbols ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

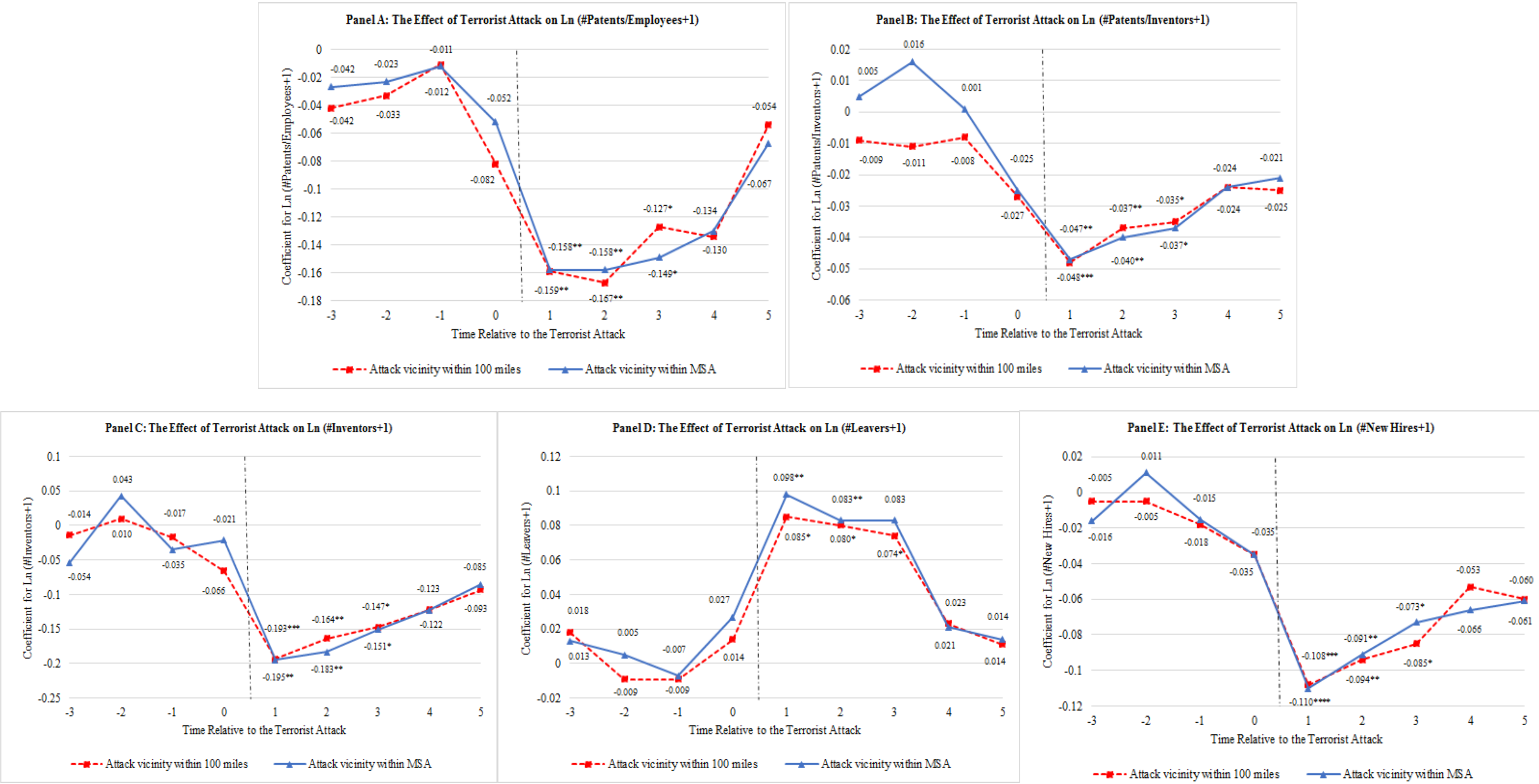

Table 1
Sample Description.
This table presents the annual distribution by attack type (columns (1) through (9)), and total number of attacks (column (10)).

	Assassination (1)	Armed Assault (2)	Bombing/ Explosion (3)	Hijacking (4)	Barricade Incident (5)	Kidnapping (6)	Facility/ Infrastructure (7)	Unarmed Assault (8)	Unknown (9)	Total Attacks (10)
1985	3	0	25	0	0	0	11	1	0	40
1986	2	1	32	0	0	0	13	1	0	49
1987	0	0	18	0	0	0	16	0	0	34
1988	0	0	15	0	1	0	11	0	0	27
1989	6	0	16	0	0	0	20	0	0	42
1990	4	0	15	0	0	0	13	0	0	32
1991	2	1	7	0	0	0	20	0	0	30
1992	5	1	3	0	1	0	22	0	0	32
1993	0	0	0	0	0	0	0	0	0	0
1994	8	7	8	0	10	0	21	0	1	55
1995	2	6	15	0	8	0	28	1	0	60
1996	2	3	14	0	0	0	15	1	0	35
1997	2	1	19	0	0	1	19	0	0	42
1998	0	2	9	0	0	0	19	1	0	31
1999	0	8	7	0	0	1	23	14	0	53
2000	0	9	5	0	1	0	25	2	0	42
2001	0	6	4	4	0	0	21	12	0	47
2002	0	2	20	1	0	0	10	0	0	33
2003	0	0	7	0	0	0	24	2	0	33
2004	0	0	0	0	0	0	9	0	0	9
2005	0	0	9	0	0	0	11	1	0	21
2006	0	1	2	0	0	0	2	1	0	6
2007	0	0	2	0	0	0	6	0	0	8
Total	**36**	**48**	**252**	**5**	**21**	**2**	**359**	**37**	**1**	**761**

Table 2

Summary Statistics for Innovating Firms and the Matched Control Sample.

This table reports firm characteristics at the firm-year level for the subsample of innovating firms defined as firms that filed for at least one patent that was eventually granted prior to the year of the terrorist attack with at least one positive R&D expenditure within the five-year window prior to the attack and for the control sample. A firm enters the treatment group if it is headquartered within 100 miles (MSA) of the location of the terrorism event that occurs at time *t* and has not experienced other terrorist attacks during the previous five years. The matching control group consists of innovative firms which, during the year of the attack, are located at least 400 miles away from the strike and operate in the same 2-digit SIC industry as its corresponding treated firm. The event year for a terrorism-afflicted firm also serves as the "pseudo-event" year for its matched firm. We match firms using one-to-one nearest neighbor propensity score matching without replacement, where the propensity score is estimated using size, Tobin's Q, cash holdings, leverage, return on assets (ROA), tangible assets, capital expenditures, ln (firm age), H-index, and H-index^2. Panel A reports statistics for the cohort in which treated firms are within 100 miles from an attack and Panel B for the cohort in which treated firms are located in the same MSA of an attack. The detailed definitions of all variables are provided in the Appendix. The variable values are measured as of the year prior to the terrorist attack. For each variable, we report the mean, standard deviation, 25th, 50th, and 75th percentiles. We also report the *t*-statistics for the differences in mean values between the treated and matched control firms.

Panel A: Attack Vicinity within 100 miles

	Treatment (N=733)					Control (N=733)					Difference	
	Mean	**Std. dev.**	**p25**	**p50**	**p75**	**Mean**	**Std. dev.**	**p25**	**p50**	**p75**	**Mean**	***t*-statistic**
Firm and Industry Variables												
Size	5.262	2.076	3.747	5.053	6.654	5.138	1.999	3.606	4.881	6.376	0.124	1.165
Tobin's Q	2.405	2.276	1.196	1.641	2.761	2.555	3.088	1.198	1.675	2.835	-0.151	-1.063
Cash Holdings	0.220	0.228	0.034	0.140	0.336	0.229	0.260	0.035	0.147	0.404	-0.009	-1.283
Leverage	0.197	0.228	0.017	0.143	0.311	0.184	0.233	0.008	0.135	0.293	0.013	1.106
ROA	0.059	0.233	0.024	0.115	0.173	0.053	0.283	-0.012	0.103	0.167	0.006	0.652
Tangible Assets	0.471	0.320	0.241	0.420	0.622	0.451	0.292	0.222	0.379	0.594	0.02	1.512
Capital Expenditures	0.049	0.041	0.021	0.039	0.065	0.048	0.053	0.019	0.037	0.061	0.001	0.457
Ln (Firm Age)	2.620	0.889	2.079	2.708	3.219	2.583	0.933	2.079	2.708	3.219	0.037	0.782
H-Index	0.188	0.154	0.084	0.123	0.264	0.181	0.150	0.085	0.120	0.255	0.006	0.768
H-Index^2	0.059	0.113	0.007	0.015	0.070	0.055	0.115	0.007	0.015	0.065	0.003	0.562
Number of Employees	7.424	25.418	0.180	0.752	3.994	7.542	21.813	0.219	0.884	4.268	-0.117	0.095
Location Variables												
Population	1,279,925	1,575,332	296,232	788,500	1,454,868	1,221,559	1,412,685	446,276	859,718	1,510,515	58,366	0.743
Population Density	2,868.619	6,050.993	693.395	1,870.431	2,752.020	2,758.495	9,405.525	416.873	892.026	1,332.507	110.124	0.266
Firm-level Inventor Variables												
Ln (#Patents/Employees+1)	1.016	1.230	0.000	0.756	1.864	0.920	1.207	0.000	0.266	1.540	0.096	1.057
Ln (#Patents/Inventors+1)	0.277	0.284	0.000	0.288	0.494	0.267	0.309	0.000	0.182	0.499	0.010	0.618
Ln (#Inventors+1)	1.450	1.675	0.000	1.137	2.482	1.327	1.711	0.000	0.693	2.197	0.123	1.379
Ln (#Leavers+1)	0.306	0.710	0.000	0.000	0.000	0.388	0.867	0.000	0.000	0.000	-0.083	-1.686
Ln (#New Hires+1)	0.341	0.762	0.000	0.000	0.000	0.375	0.824	0.000	0.000	0.000	-0.034	-0.815
Inventor-level Innovation												
Ln (#Patents+1)	0.512	0.468	0.000	0.642	0.642	1.064	0.543	0.642	1.017	1.284	0.002	0.018
Ln (#Citations+1)	1.422	1.558	0.000	1.115	2.671	2.783	1.635	1.701	2.840	4.029	-0.197	-1.395
Ln (Innovation Value+1)	1.492	1.429	0.000	1.429	2.522	2.671	1.297	1.650	2.627	3.559	-0.001	-0.005
Generality	0.311	0.345	0.000	0.157	0.647	0.431	0.280	0.231	0.465	0.654	-0.009	-0.569
Originality	0.360	0.346	0.000	0.365	0.687	0.522	0.247	0.380	0.564	0.720	-0.017	-1.237

Table 2 (Continued)

Panel B: Attack Vicinity within MSA												
	Treatment (N=662)					Control (N=662)					Difference	
	Mean	**Std. dev.**	**p25**	**p50**	**p75**	**Mean**	**Std. dev.**	**p25**	**p50**	**p75**	**Mean**	***t*-statistic**
						Firm and Industry Variables						
Size	5.147	1.911	3.458	4.549	5.912	5.215	1.844	3.863	5.013	6.438	-0.068	-1.574
Tobin's Q	2.321	2.468	1.158	1.616	2.575	2.443	3.035	1.204	1.650	2.648	-0.121	-0.797
Cash Holdings	0.259	0.258	0.043	0.175	0.415	0.246	0.262	0.033	0.128	0.404	0.012	0.865
Leverage	0.175	0.211	0.005	0.120	0.284	0.189	0.205	0.011	0.146	0.300	-0.015	-1.275
ROA	0.018	0.284	-0.012	0.097	0.164	0.036	0.253	0.002	0.107	0.167	-0.018	-1.214
Tangible Assets	0.436	0.353	0.202	0.369	0.594	0.434	0.291	0.212	0.367	0.596	0.001	0.071
Capital Expenditures	0.050	0.051	0.019	0.036	0.063	0.047	0.050	0.019	0.036	0.060	0.003	1.069
Ln (Firm Age)	2.477	0.948	2.079	2.565	3.135	2.446	0.985	1.792	2.565	3.178	0.031	0.577
H-Index	0.192	0.177	0.083	0.117	0.272	0.184	0.157	0.083	0.123	0.256	0.008	0.889
H-Index^2	0.068	0.141	0.007	0.014	0.074	0.059	0.124	0.007	0.015	0.066	0.010	1.304
Number of Employees	5.729	15.457	0.206	0.810	4.300	4.766	15.575	0.152	0.508	2.293	0.963	1.123
						Location Variables						
Population	1,443,075	1,601,700	378,547	1,020,286	1,891,328	1,321,495	1,664,644	403,164	891,356	1,561,366	121,580	1.354
Population Density	2,487.773	4,851.008	419.147	3,014.673	3,557.917	2,317.008	4,510.491	588.572	1,357.130	2,104.428	170.765	0.660
						Firm-level Inventor Variables						
Ln (#Patents/Employees+1)	1.115	1.206	0.000	0.789	1.848	0.990	1.261	0.000	0.000	1.528	0.125	1.265
Ln (#Patents/Inventors+1)	0.268	0.281	0.000	0.282	0.485	0.227	0.290	0.000	0.000	0.435	0.041	1.558
Ln (#Inventors+1)	1.351	1.563	0.000	1.099	2.303	1.069	1.496	0.000	0.000	1.792	0.282	1.312
Ln (#Leavers+1)	0.307	0.767	0.000	0.000	0.000	0.286	0.690	0.000	0.000	0.000	0.021	0.517
Ln (#New Hires+1)	0.307	0.747	0.000	0.000	0.000	0.256	0.653	0.000	0.000	0.000	0.051	1.299
						Inventor-level Innovation						
Ln (#Patents+1)	0.534	0.474	0.000	0.642	0.648	1.112	0.550	0.648	1.017	1.296	0.042	1.095
Ln (#Citations+1)	1.293	1.477	0.000	0.948	2.441	2.762	1.552	1.792	2.840	3.808	-0.091	-1.028
Ln (Innovation Value+1)	1.788	1.585	0.000	1.908	3.007	3.067	1.349	2.260	3.126	3.953	-0.069	-0.643
Generality	0.236	3.014	0.000	0.000	0.542	0.387	0.275	0.192	0.390	0.594	0.025	1.394
Originality	0.363	0.335	0.000	0.389	0.675	0.524	0.243	0.380	0.564	0.715	0.012	0.810

Table 3
Terrorist Attacks and Inventor Productivity.
This table presents the effects of terrorist attacks on innovation productivity of employees and inventors. The main variables of interest are the *Attack vicinity within 100 miles * Post* and the *Attack vicinity within MSA * Post*, respectively. In columns (1) through (4), the dependent variable is defined as the natural logarithm of the number of patents per 1,000 firm employees (EMP) plus one and measures innovation productivity of firm employees in a given year. In columns (5) through (8), the dependent variable is defined as the natural logarithm of the number of patents/inventors plus one and measures innovation productivity of firm inventors in a given year. All control variables are lagged by one year. The detailed definitions of all variables are provided in the Appendix. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e., firm and year fixed effects, region*year fixed effects, and industry*year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e., firm and year fixed effects, whose coefficients are suppressed). The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Patents/Employees+1)				**Ln (#Patents/Inventors+1)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Attack vicinity within 100 miles*Post	-0.115**	-0.093**			-0.031***	-0.027**		
	(0.047)	(0.042)			(0.011)	(0.010)		
Attack vicinity within MSA*Post			-0.133**	-0.103**			-0.033***	-0.037***
			(0.052)	(0.048)			(0.012)	(0.012)
Post	-0.058	-0.036	-0.058	-0.024	0.002	-0.005	-0.002	-0.005
	(0.035)	(0.032)	(0.039)	(0.037)	(0.009)	(0.008)	(0.010)	(0.010)
Size		-0.007		-0.005		0.027***		0.017*
		(0.038)		(0.044)		(0.009)		(0.009)
Tobin's Q		0.012		0.021**		0.002		0.002
		(0.008)		(0.009)		(0.002)		(0.002)
Cash Holdings		0.556***		0.726***		0.035		0.049*
		(0.140)		(0.160)		(0.030)		(0.029)
Leverage		-0.150*		-0.214		-0.007		-0.024
		(0.077)		(0.143)		(0.016)		(0.022)
ROA		0.072		0.055		0.000		0.003
		(0.071)		(0.093)		(0.014)		(0.015)
Tangible Assets		-0.135		-0.105		-0.030		-0.011
		(0.116)		(0.122)		(0.027)		(0.030)
Capital Expenditures		0.368		0.304		0.156*		0.181**
		(0.329)		(0.393)		(0.084)		(0.086)
Ln (Firm Age)		-0.193***		-0.239***		0.040***		0.063***
		(0.053)		(0.062)		(0.012)		(0.010)
H-Index		-0.617		0.331		-0.033		-0.035
		(0.531)		(0.667)		(0.196)		(0.207)
H-Index^2		0.470		-0.198		-0.146		-0.046
		(0.519)		(0.641)		(0.226)		(0.203)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	12,524	12,524	10,580	10,580	12,524	12,524	10,580	10,580
Adjusted R^2	0.620	0.608	0.618	0.606	0.521	0.497	0.508	0.476

Table 4

The Effect of Terrorist Attacks on Corporate Innovation at the Inventor Level.

This table presents the effects of terrorist attacks on corporate innovation using inventor-level data. Panel A reports the results for the effect of terrorist attacks on treated firms that are located within 100 miles from an attack and Panel B for the effect of terrorist attacks on treated firms that are located in the same MSA of an attack. The dependent variable in columns (1) and (2) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (3) and (4) is the natural logarithm of citation counts plus one. The dependent variable in columns (5) and (6) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. The dependent variable in specifications (7) and (8) is the patent generality score. The dependent variable in specifications (9) and (10) is the patent originality score. We use the same control variables as in Table 3. All control variables are lagged by one year. The detailed definitions of all variables are provided in the Appendix. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e., inventor and year fixed effects, region*year fixed effects, and industry*year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e., inventor and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at inventor level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Attack vicinity within 100 miles

	Ln (#Patents+1)		Ln (#Citations+1)		Ln (Innovation Value+1)		Generality		Originality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attack vicinity within 100 miles*Post	-0.028***	-0.024***	-0.060***	-0.049***	-0.080***	-0.062***	-0.001	-0.002	-0.007*	-0.011***
	(0.006)	(0.005)	(0.018)	(0.015)	(0.018)	(0.015)	(0.006)	(0.007)	(0.004)	(0.004)
Post	-0.006	-0.005	-0.011	-0.007	-0.014	0.005	-0.009**	-0.005	-0.006*	-0.001
	(0.005)	(0.004)	(0.014)	(0.012)	(0.014)	(0.012)	(0.004)	(0.004)	(0.003)	(0.003)
Control Variables of Table 3	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	342,246	342,246	342,246	342,246	342,246	342,246	312,909	312,909	281,381	281,381
Adjusted R^2	0.423	0.419	0.404	0.398	0.406	0.397	0.212	0.21	0.341	0.337

Panel B: Attack vicinity within MSA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attack vicinity within MSA*Post	-0.054***	-0.026***	-0.182***	-0.074***	-0.114***	-0.068***	-0.021	-0.007	-0.028***	-0.013***
	(0.008)	(0.007)	(0.025)	(0.021)	(0.025)	(0.021)	(0.016)	(0.006)	(0.006)	(0.005)
Post	0.001	-0.009	0.028	-0.007	-0.001	0.011	-0.004	-0.005	-0.010*	-0.004
	(0.007)	(0.006)	(0.022)	(0.017)	(0.023)	(0.018)	(0.005)	(0.005)	(0.005)	(0.004)
Control Variables of Table 3	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	201,614	201,614	201,614	201,614	201,614	201,614	183,873	183,873	160,268	160,268
Adjusted R^2	0.465	0.458	0.433	0.426	0.445	0.436	0.310	0.305	0.358	0.351

Table 5
Terrorist Attacks and Inventor Mobility.
This table presents the effects of terrorist attack on inventor mobility. In columns (1) through (4) the dependent variable is the natural logarithm of the number of firm's inventors in a given year plus one. In columns (5) through (8) the dependent variable is the natural logarithm of the number of firm's newly hired inventors in a given year plus one. In columns (9) through (12) the dependent variable is the natural logarithm of the number of firm's inventors who leave for other firms in a given year plus one. All control variables are lagged by one year. The detailed definitions of all variables are provided in the Appendix. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e., firm and year fixed effects, region*year fixed effects, and industry*year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e., firm and year fixed effects, whose coefficients are suppressed). The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (#Inventors+1)				**Ln (#New Hires+1)**				**Ln (#Leavers+1)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Attack vicinity within 100 miles*Post	-0.113**	-0.127***			-0.048*	-0.074***			0.095***	0.067**		
	(0.051)	(0.048)			(0.025)	(0.028)			(0.027)	(0.027)		
Attack vicinity within MSA*Post			-0.105**	-0.144***			-0.052**	-0.078***			0.095***	0.062**
			(0.052)	(0.048)			(0.024)	(0.023)			(0.028)	(0.026)
Post	0.007	-0.008	0.021	0.016	0.020	0.021	0.019	0.027	-0.016	-0.015	0.004	0.003
	(0.038)	(0.034)	(0.041)	(0.038)	(0.020)	(0.022)	(0.017)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)
Size		0.258***		0.227***		0.077***		0.066***		0.122***		0.092***
		(0.039)		(0.040)		(0.021)		(0.022)		(0.022)		(0.022)
Tobin's Q		0.007		0.010*		0.004		0.005*		0.002		0.003
		(0.005)		(0.006)		(0.003)		(0.003)		(0.003)		(0.003)
Cash Holdings		0.128		0.227**		0.034		0.060		0.049		0.032
		(0.103)		(0.111)		(0.057)		(0.057)		(0.061)		(0.062)
Leverage		-0.105		-0.238***		-0.043		-0.041		-0.050		-0.033
		(0.067)		(0.081)		(0.036)		(0.037)		(0.035)		(0.037)
ROA		-0.099**		-0.127**		-0.056**		-0.021		-0.102***		-0.057**
		(0.044)		(0.055)		(0.022)		(0.026)		(0.026)		(0.025)
Tangible Assets		-0.018		0.005		0.017		0.043		0.119**		0.091
		(0.102)		(0.094)		(0.045)		(0.048)		(0.055)		(0.056)
Capital Expenditures		0.461*		0.321		0.338**		0.456***		0.109		0.138
		(0.278)		(0.304)		(0.152)		(0.144)		(0.153)		(0.139)
Ln (Firm Age)		0.182***		0.280***		0.030		0.054***		0.086***		0.098***
		(0.055)		(0.060)		(0.023)		(0.019)		(0.025)		(0.025)
H-Index		-0.938		-0.210		-0.011		0.050		-0.173		-0.381
		(0.639)		(0.781)		(0.369)		(0.286)		(0.387)		(0.430)
H-Index^2		0.305		-0.141		0.161		0.148		0.409		0.531
		(0.753)		(0.862)		(0.381)		(0.287)		(0.384)		(0.389)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	12,524	12,524	10,580	10,580	12,524	12,524	10,580	10,580	12,524	12,524	10,580	10,580
Adjusted R^2	0.815	0.809	0.795	0.786	0.772	0.757	0.713	0.693	0.769	0.758	0.715	0.698

Table 6
Terrorist Attacks and Inventor Relocation.

This table examines the effect of terrorist attacks on labor market relocation using inventor-level data. In columns (1) and (2) the dependent variable "Ln (Distance of the Move+1)" is the natural logarithm of inventor's distance of the move to a new employer from her previous employer. In columns (3) and (4) the dependent variable "Over-100 mile Move" is an indicator variable that takes the value of one if an inventor moves to another employer located over 100 miles away from her previous employer, and zero otherwise. In columns (5) through (6) the dependent variable, "Out-of-MSA Move" is an indicator variable that takes the value of one if an inventor moves to another employer located in a different MSA than her previous employer, and zero otherwise. All control variables are lagged by one year. Detailed definitions of all variables appear in the Appendix. All specifications include year and industry fixed effects, whose coefficients are suppressed. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Ln (Distance of the Move+1)		**Over-100-Mile Move**		**Out-of-MSA Move**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Attack vicinity within 100 miles*Post	0.236**		0.167*		0.191**	
	(0.108)		(0.094)		(0.092)	
Attack vicinity within MSA*Post		0.278**		0.226**		0.238**
		(0.136)		(0.102)		(0.105)
Post	-0.194*	-0.171*	-0.103	-0.138	-0.107	-0.164*
	(0.103)	(0.095)	(0.095)	(0.084)	(0.093)	(0.086)
Size	-0.010	-0.026	-0.009	-0.022	-0.017	-0.021
	(0.037)	(0.032)	(0.025)	(0.024)	(0.025)	(0.025)
Tobin's Q	0.035	0.065**	0.024	0.046**	0.025	0.042**
	(0.025)	(0.028)	(0.018)	(0.019)	(0.017)	(0.018)
Cash Holdings	-0.297	-0.463	-0.194	-0.482**	-0.191	-0.400*
	(0.293)	(0.321)	(0.195)	(0.222)	(0.188)	(0.223)
Leverage	-0.051	0.125	0.113	0.085	0.100	0.167
	(0.258)	(0.295)	(0.174)	(0.201)	(0.173)	(0.204)
ROA	0.011	0.431	0.089	0.327	0.058	0.285
	(0.334)	(0.313)	(0.210)	(0.207)	(0.209)	(0.210)
Tangible Assets	-0.591***	-0.759***	-0.456***	-0.600***	-0.455***	-0.551***
	(0.135)	(0.160)	(0.117)	(0.133)	(0.113)	(0.132)
Capital Expenditures	0.850	1.673	0.696	1.345*	0.563	1.375*
	(0.805)	(1.021)	(0.690)	(0.784)	(0.618)	(0.741)
Ln (Firm Age)	-0.272***	-0.259***	-0.176***	-0.170***	-0.200***	-0.173***
	(0.056)	(0.053)	(0.039)	(0.036)	(0.038)	(0.039)
H-Index	1.288	0.931	1.201*	0.980	1.509**	0.868
	(0.956)	(0.977)	(0.661)	(0.704)	(0.655)	(0.728)
H-Index^2	-1.627	-0.721	-1.470*	-0.929	-1.939**	-0.917
	(1.188)	(1.342)	(0.796)	(0.977)	(0.799)	(0.979)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	11,363	7,878	11,363	7,878	11,363	7,878
Adjusted R^2 (Pseudo R^2)	0.052	0.059	(0.068)	(0.077)	(0.068)	(0.077)

Table 7
The Impact of Relocation on the Productivity of Treated Inventors.

This table examines the impact of relocation on the productivity of inventor affected by terrorist attacks using inventor-level data. The sample includes all inventors who work in firms affected by terrorist attacks. Relocated Inventors is a dummy variable that takes the value of one, if the inventor moves to a firm non-affected by a terrorist attack, and zero otherwise. Post is an indicator variable that takes the value of one in the years post relocation, and zero otherwise. Panel A reports the results for the effect of terrorist attacks on treated firms that are located within 100 miles from an attack and Panel B for the effect of terrorist attacks on treated firms that are located in the same MSA of an attack. The dependent variable in columns (1) and (2) is the natural logarithm of the number of patent counts plus one. The dependent variable in columns (3) and (4) is the natural logarithm of citation counts plus one. The dependent variable in columns (5) and (6) is the natural logarithm of the cumulative dollar value (in millions of 2005 nominal US dollars) of patents that a firm applies for in a given year plus one. The dependent variable in specifications (7) and (8) is the patent generality score. The dependent variable in specifications (9) and (10) is the patent originality score. We use the same control variables as in Table 3. All control variables are lagged by one year. The detailed definitions of all variables are provided in the Appendix. The odd-numbered columns omit the control variables and contain both standard and multiplicative fixed effects (i.e., inventor and year fixed effects, region*year fixed effects, and industry*year fixed effects whose coefficients are suppressed), while the even-numbered columns include control variables and standard fixed effects (i.e., inventor and year fixed effects, whose coefficients are suppressed). Standard errors, which are adjusted for heteroscedasticity and are clustered at inventor level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Attack vicinity within 100 miles										
	Ln (#Patents+1)		**Ln (#Citations+1)**		**Ln (Innovation Value+1)**		**Generality**		**Originality**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Relocated Inventors*Post	0.332***	0.332***	0.936***	0.941***	1.089***	1.087***	0.170***	0.174***	0.195***	0.195***
	(0.021)	(0.022)	(0.063)	(0.065)	(0.059)	(0.062)	(0.021)	(0.021)	(0.015)	(0.015)
Post	0.011	0.010	0.099*	0.122*	0.196*	0.092***	0.015	0.025*	0.002	0.010
	(0.012)	(0.011)	(0.049)	(0.066)	(0.095)	(0.034)	(0.012)	(0.014)	(0.011)	(0.009)
Control Variables of Table 3	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	74,657	74,657	74,657	74,657	74,657	74,657	67,223	67,223	62,647	62,647
Adjusted R^2	0.541	0.532	0.503	0.493	0.466	0.456	0.219	0.218	0.416	0.404
Panel B: Attack vicinity within MSA										
Relocated Inventors *Post	0.318***	0.320***	0.922***	0.898***	0.871***	0.851***	0.189***	0.190***	0.195***	0.194***
	(0.024)	(0.025)	(0.078)	(0.088)	(0.066)	(0.070)	(0.018)	(0.018)	(0.019)	(0.019)
Post	-0.011	0.028**	-0.096	-0.017	0.082*	0.095***	-0.015	0.018*	-0.013	0.008
	(0.017)	(0.012)	(0.062)	(0.056)	(0.043)	(0.035)	(0.013)	(0.010)	(0.015)	(0.010)
Control Variables of Table 3	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry*Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of Obs.	50,788	50,788	50,788	50,788	50,788	50,788	46,575	46,575	37,883	37,883
Adjusted R^2	0.571	0.561	0.510	0.538	0.498	0.485	0.395	0.385	0.428	0.414

Table 8

Robustness tests: including mass shootings and controlling for VIX, crime rate, and unemployment insurance benefit.

This table presents in Panel A the effects of terrorist attacks on inventor productivity (specifications (1) through (4)), and inventor mobility (specifications (5) through (10)) using firm-level analysis, and in Panel B the effects of terrorist attacks on corporate innovation (specifications (1) through (5)) and inventor mobility (specifications (6) through (8)) using inventor-level analysis, including in the sample mass shooting from the Mother Jones Database (MJD) and controlling for VIX, crime rate, and unemployment insurance benefit. We also use in Panel A the same control variables as in Table 3 (for specifications (1) through (4)) and as in Table 5 (for specifications (5) through (10)), and in Panel B the same control variables as in Table 4 (for specifications (1) through (5)) and as in Table 6 (for specifications (6) through (8)). The detailed definitions of all variables are provided in the Appendix. All specifications include firm and year fixed effects, whose coefficients are suppressed. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Firm-Level Variables										
	Ln (#Patents/ Employees+1)		Ln (#Patents/ Inventors+1)		Ln (#Inventors+1)		Ln (#New Hires+1)		Ln (#Leavers+1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attack vicinity within 100 miles*Post	-0.094**		-0.028***		-0.126***		-0.073***		0.067**	
	(0.042)		(0.010)		(0.048)		(0.027)		(0.026)	
Attack vicinity within MSA*Post		-0.112**		-0.039***		-0.150***		-0.077***		0.061**
		(0.048)		(0.012)		(0.048)		(0.023)		(0.026)
Post	-0.035	-0.017	-0.004	-0.004	-0.009	0.021	0.020	0.027	-0.016	0.005
	(0.032)	(0.037)	(0.008)	(0.010)	(0.034)	(0.038)	(0.022)	(0.018)	(0.018)	(0.018)
VIX	0.310***	0.256***	0.117***	0.117***	0.565***	0.580***	0.018	0.050	0.081*	0.055
	(0.072)	(0.075)	(0.020)	(0.019)	(0.076)	(0.076)	(0.040)	(0.038)	(0.043)	(0.040)
Crime Rate	0.082	0.279*	0.036	0.037	-0.041	0.183	-0.112	-0.064	-0.026	0.034
	(0.172)	(0.160)	(0.043)	(0.041)	(0.183)	(0.152)	(0.102)	(0.071)	(0.086)	(0.081)
Unemployment Insurance Benefit	0.020	-0.187	-0.029	-0.071	0.178	-0.035	-0.311***	-0.216**	-0.271***	-0.233***
	(0.189)	(0.192)	(0.049)	(0.046)	(0.160)	(0.154)	(0.098)	(0.085)	(0.100)	(0.088)
Control Variables of Table 3	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Control Variables of Table 5	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	12,524	10,580	12,524	10,580	12,524	10,580	12,524	10,580	12,524	10,580
Adjusted R^2	0.608	0.607	0.497	0.476	0.809	0.786	0.758	0.693	0.758	0.699

Table 8 (Continued)

Panel B: Inventor-Level Variables								
	Ln (#Patents+1)	**Ln (#Citations+1)**	**Ln (Innovation Value+1)**	**Generality**	**Originality**	**Ln (Distance of the Move+1)**	**Over-100-Mile Move**	**Out-of-MSA Move**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Attack vicinity within 100 miles*Post	-0.029***	-0.048***	-0.097***	-0.011	-0.018***	0.231**	0.161*	0.185**
	(0.005)	(0.015)	(0.015)	(0.007)	(0.004)	(0.110)	(0.094)	(0.092)
Post	0.001	-0.085***	0.014	-0.013***	0.008***	-0.199*	-0.108	-0.108
	(0.004)	(0.012)	(0.012)	(0.004)	(0.003)	(0.107)	(0.096)	(0.093)
VIX	-0.002***	-0.005***	-0.015***	-0.003***	-0.002***	-0.090	-0.063*	-0.052
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.065)	(0.034)	(0.033)
Crime Rate	-0.030***	-0.022	-0.059***	-0.021***	-0.032***	-0.011	-0.026	-0.029
	(0.006)	(0.019)	(0.021)	(0.005)	(0.004)	(0.040)	(0.030)	(0.029)
Unemployment Insurance Benefit	-0.016*	-1.012***	0.105***	-0.145***	0.031***	-0.084	-0.080	-0.041
	(0.010)	(0.030)	(0.030)	(0.012)	(0.007)	(0.135)	(0.098)	(0.099)
Control Variables of Table 4	Yes	Yes	Yes	Yes	Yes	No	No	No
Control Variables of Table 6	No	No	No	No	No	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	342,241	342,241	342,241	312,906	281,383	11,363	11,363	11,363
Adjusted R^2 (Pseudo R^2)	0.416	0.393	0.392	0.210	0.332	0.052	(0.068)	(0.068)

Table 9
Robustness tests: Excluding 9/11.
This table presents in Panel A the effects of terrorist attacks on inventor productivity (specifications (1) through (4)), and inventor mobility (specifications (5) through (10)) using firm-level analysis, and in Panel B the effects of terrorist attacks on corporate innovation (specifications (1) through (5)) and inventor mobility (specifications (6) through (8)) using inventor-level analysis, excluding observations affected by the 9/11 incidents (i.e., firms from New York, Virginia, and Pennsylvania in 2002). We also use in Panel A the same control variables as in Table 3 (for specifications (1) through (4)) and as in Table 5 (for specifications (5) through (10)), and in Panel B the same control variables as in Table 4 (for specifications (1) through (5)) and as in Table 6 (for specifications (6) through (8)). The detailed definitions of all variables are provided in the Appendix. All specifications include firm and year fixed effects, whose coefficients are suppressed. Standard errors, which are adjusted for heteroscedasticity and are clustered at firm level, are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Firm-Level Variables

	Ln (#Patents/ Employees+1)		**Ln (#Patents/ Inventors+1)**		**Ln (#Inventors+1)**		**Ln (#New Hires+1)**		**Ln (#Leavers+1)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Attack vicinity within 100 miles*Post	-0.104**		-0.029***		-0.134***		-0.070**		0.069**	
	(0.042)		(0.011)		(0.048)		(0.028)		(0.027)	
Attack vicinity within MSA*Post		-0.104**		-0.037***		-0.146***		-0.084***		0.059**
		(0.048)		(0.012)		(0.047)		(0.023)		(0.027)
Post	-0.028	-0.030	-0.005	-0.005	-0.001	0.011	0.018	0.027	-0.016	0.002
	(0.033)	(0.037)	(0.008)	(0.010)	(0.035)	(0.037)	(0.023)	(0.017)	(0.019)	(0.019)
Control Variables of Table 3	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Control Variables of Table 5	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	12,032	10,109	12,032	10,109	12,032	10,109	12,032	10,109	12,032	10,109
Adjusted R^2	0.604	0.612	0.497	0.482	0.810	0.787	0.759	0.697	0.759	0.702

Table 9 (Continued)

Panel B: Inventor-Level Variables								
	Ln (#Patents+1)	**Ln (#Citations+1)**	**Ln (Innovation Value+1)**	**Generality**	**Originality**	**Ln (Distance of the Move+1)**	**Over-100-Mile Move**	**Out-of-MSA Move**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Attack vicinity within 100 miles*Post	-0.020***	-0.038**	-0.067***	0.000	-0.007**	0.212**	0.156	0.180*
	(0.005)	(0.016)	(0.016)	(0.007)	(0.004)	(0.108)	(0.097)	(0.095)
Post	-0.011**	-0.020	0.009	-0.006	-0.004	-0.150	-0.071	-0.083
	(0.004)	(0.013)	(0.013)	(0.004)	(0.003)	(0.098)	(0.094)	(0.093)
Control Variables of Table 4	Yes	Yes	Yes	Yes	Yes	No	No	No
Control Variables of Table 6	No	No	No	No	No	Yes	Yes	Yes
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Obs.	325,996	325,996	325,996	298,664	267,553	10,919	10,919	10,919
Adjusted R^2 (Pseudo R^2)	0.419	0.399	0.395	0.194	0.337	0.051	(0.064)	(0.064)

Appendix: Variable Definitions

Dependent Variables

- **Ln (#Patents/Employees+1):** The natural logarithm of the number of patents per 1,000 firm employees (EMP) plus one. Patent data is from Kogan et al. (2017).
- **Ln (#Patents/Inventors+1):** The natural logarithm of the ratio of the number of patents scaled by the number of inventors who applied for a patent at the firm in a given year and have not yet filed any patent for a different firm plus one**.** Inventor data are from Li et al. (2014).
- **Ln (#Patents+1):** The natural logarithm of the total number of patents that a firm applies for (and are subsequently granted) in a given year plus one. This variable is created using data from Kogan et al. (2017). (see, *https://iu.app.box.com/v/patents*).
- **Ln (#Citations+1):** The natural logarithm of the total number of citations obtained on all patents that a firm applies for (and are subsequently granted) in a given year plus one. This variable is created using data from Kogan et al. (2017).
- **Ln (Innovation Value+1):** The natural logarithm of the cumulative dollar value of patents (in millions of 2005 nominal US dollars) that a firm applies for in a given year plus one. A patent's value is measured as the firm stock return in excess of the market over the three-day window around the date of patent approval (t, t+2), multiplied by the firm's market capitalization on the day prior to the announcement of the patent issuance. The dollar value of each patent is obtained from Kogan et al. (2017).
- **Generality:** One minus the Herfindahl concentration index of the number of patents citing across technological classes. We use the bias correction of the Herfindahl measures, described in Jaffe and Trajtenberg (2002), to account for cases with a small number of patents within technological categories. This variable is created using data from the NBER patent database *(https://www.nber.org/patents/)* and Bhaven Sampat's United States Patent and Trademark Office (USPTO) patent and citation database.
 (see, *http://thedata.harvard.edu/dvn/dv/boffindata*).
- **Originality:** One minus the Herfindahl concentration index of the number of cited patents across technological classes. We use the bias correction of the Herfindahl measures, described in Jaffe and Trajtenberg (2002), to account for cases with a small number of patents within technological categories. This variable is created using data from the NBER patent database *(https://www.nber.org/patents/)* and Bhaven Sampat's United States Patent and Trademark Office (USPTO) patent and citation database.
 (see, *http://thedata.harvard.edu/dvn/dv/boffindata).*
- **Ln (#Inventors+1):** The natural logarithm of the number of firm inventors in a given year plus one**.** We define "Inventors" as those who produce at least one patent in a firm in our sample period. This variable is created using data from Li et al. (2014).
- **Ln (#New Hires+1):** The natural logarithm of the number of newly hired inventors in a given year plus one. We define "New Hires" as those inventors who produce at least one patent at a new assignee firm in our sample within one year after producing a patent at a different assignee. This variable is created using data from Li et al. (2014).
- **Ln (#Leavers+1):** The natural logarithm of the number of inventors who leave for other firms in a given year plus one. We define "Leavers" as those inventors who stop filing patents at a sample firm where they had previously produced a patent and file at least one patent in a new firm in our sample within one year after producing a patent at the firm they were previously producing patents. This variable is created using data from Li et al. (2014).
- **Ln (Distance of the Move+1):** The natural logarithm of inventor's distance moves to a new employer from her previous employer.
- **Over 100 Miles Move:** An indicator set to one if an inventor files a new patent at a new company located more than 100 miles from the location of another company he had filed patents for, and zero otherwise. We create this variable with data from Li et al. (2014).
- **Out-of-MSA Move:** An indicator which takes the value of one, if an inventor who had filed a patent for a firm located in an MSA, files a new patent for another firm in a different MSA, and zero otherwise. This variable is created using data from Li et al. (2014) and Compustat for identifying firm's MSA.

Terrorism Variables

- **Attack vicinity within 100 miles: A**n indicator variable that equals one if a firm is located within 100 miles of the attack. We use data from the U.S. Census Bureau's Gazetteers and Zip Code Database to identify the latitude and longitude of the firms and the places where the terrorism incidents took place.
- **Attack vicinity within MSA: A**n indicator variable that equals one if a firm is located within the MSA of the attack.
- **Post:** An indicator variable equal to one if a firm-year observation is within [t + 1, t + 5] years of a terrorism event (for treated firms) or a pseudo-event year (for matched firms).

Firm Variables

- **Size:** The natural logarithm of total assets (AT). This variable is created using data from Compustat.
- **Tobin's Q:** The market value of equity (CSHO*PRCC_F) plus book value of assets (AT) minus book value of equity (CEQ) minus balance sheet deferred taxes (TXDB), scaled by total assets (AT). This variable is created using data from Compustat.
- **Cash Holdings:** Cash and short–term investments (CHE) scaled by total assets (AT). This variable is created using data from Compustat.
- **Leverage:** The sum of long-term debt (DLTT) and debt in current liabilities (DLC) scaled by total assets (AT). This variable is created using data from Compustat.
- **ROA:** Income before extraordinary items (IB) plus interest expense (item XINT) plus income taxes (item XINT), divided by total assets (item AT). This variable is created using data from Compustat.
- **Tangible Assets:** Property, plant, and equipment (PPEGT) scaled by total assets (AT). This variable is created using data from Compustat.
- **Capital Expenditures:** Capital expenditures (CAPX) scaled by total assets (AT). This variable is created using data from Compustat.
- **Ln (Firm Age):** The natural logarithm of one plus the number of years since the firm's first appearance in the Center for Research in Security Prices (CRSP). This variable is created using data from CRSP.
- **Number of Employees:** The number of people employed by the company (in thousands). This variable is created using data from Compustat.

County Variables

- **Population:** The number of residents for counties. This variable is created using data from The US Census Bureau.
- **Population density:** The number of people per square mile for counties. This variable is created using data from The US Census Bureau.

State Variables

- **Crime Rate:** The natural logarithm of the crime rate of the state. (Source: The Federal Bureau of Investigation (FBI)).
- **Unemployment Insurance Benefit:** The natural logarithm of the maximum unemployment insurance benefits that an unemployment insurance claimant can receive in a year. (Source: The US Department of Labor's ''Significant Provisions of State UI Laws'').

Market Variables

- **VIX:** The Chicago Board Options Exchange (CBOE) Volatility Index. **(**Source: http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data).

Industry Variables

- **H–Index:** This is the Herfindahl index which represents the sum of squares of the market shares of all firms in a given year and three–digit SIC industry, where market share is defined as sales of the firm divided by the sum of the sales in the industry. This variable is created using data from Compustat.
- **H–Index^2:** The squared root of the H-index.