When Political Connections Backfire: Social Protests, Asset Damage, and Firms' Response*

Navid Neshat†

October, 2025

Abstract

While the benefits of corporate political connections are well established, much less is known about their potential costs. Using data on approximately one million corporate assets, I find that firms led by former politicians are significantly more likely to sustain damage during social protests and, conditional on such damage, incur greater losses in the underlying value of their assets. The evidence further indicates that internet access facilitates the targeting of politically connected firms, as the disproportionate risk of damage to their assets disappears during internet shutdowns, while damage to corporate assets remains equally likely. In the aftermath of protests, connected firms, including those that did not sustain damage, insure additional assets, expand coverage on existing policies, and, in some cases, sever political ties by dismissing politician managers. Taken together, these findings indicate that close relationships with politicians can impose ex post costs on firms.

*I thank Anup Agrawal, Pat Akey, Daniel Andrei, Samar Ashour (discussant), Ilona Babenko, Abhishek Bhardwaj, Matt Billett, Daniel Carvalho, Jess Cornaggia, Sahand Davani (discussant), Ran Duchin (discussant), Andrew Ellul, Vivian Fang, Ted Fee, Tristan Fitzgerald, Eitan Goldman, Todd Gormley, Oleg Gredil, Nandini Gupta, Isaac Hacamo, Kristine Hankins, Larry Harris, Amanda Heitz, Ankit Kalda, Nishad Kapadia, Elisabeth Kempf (discussant), Yongseok Kim, Kristoph Kleiner, Aaron Kolb, Jordan Martel, David Matsa, John Matsusaka, Marina Niessner, Cecilia Parlatore, Alessio Piccolo, Alessandro Previtero, Robert Prilmeier, Adriano Rampini, Cayman Seagraves (discussant), Gunjan Seth, Rui Silva, Varun Sharma, Venkat Subramaniam, Edward Van Wesep, Wenyu Wang, Jun Yang, and seminar participants at the AFA, FMA, FRA, Indiana University, Nova School of Business and Economics, SFA, Tulane University, University of Alabama, and University of Southern California for their helpful comments.

†Freeman School of Business, Tulane University. Email: nneshat@tulane.edu

1 Introduction

Corporate political connections are pervasive worldwide, particularly in countries where institutions are weak and corruption is rampant (Faccio, 2006). These connections are valuable assets, conferring numerous advantages on politically connected firms, such as preferential treatment from the government, privileged access to credit, and insulation from adverse regulatory actions.[1] Notwithstanding these benefits, political connections can also entail risks when government disapproval intensifies.[2] A recent illustration is the attacks on Tesla vehicles, dealerships, and factories across the United States, attributed to CEO Elon Musk's "political affiliations."[3] Although examining the ex post costs of political connections is essential for understanding the trade-offs they entail, empirical evidence on this dimension remains scarce.

To study the potential risks associated with corporate political connections, the literature has typically examined stock price reactions to exogenous shocks that weaken or strengthen such ties.[4] This approach, however, faces limitations in isolating the costs of political connections, as declines in the equity value of connected firms may simply reflect the loss of anticipated benefits already capitalized into valuations. To address this challenge, I employ a direct empirical strategy, testing whether the tangible assets of connected firms are disproportionately likely to incur damage during anti-government social protests.

Whether the physical assets of politically connected firms are more likely to incur damage during social protests is ex ante unclear. On the one hand, such assets may be less vulnerable for two reasons. First, connected firms are often better informed about policy changes, which reduces political uncertainty (Stratmann, 1992; Coate, 2004; Pastor and Veronesi, 2012; Ovtchinnikov et al., 2020). This insider knowledge, potentially obtained from high-ranking government or military officials, can enable these firms to anticipate protests and take preventive measures to limit their exposure to damage. Second, connected firms may receive additional government support to safeguard their assets, such as increased police presence. On the other hand, connected firms could become prime targets for protesters, particularly when the government itself

[1] For examples of the benefits associated with corporate political connections, see, among others, Sapienza (2004); Khwaja and Mian (2005); Faccio et al. (2006); Claessens et al. (2008); Ferguson and Voth (2008); Cooper et al. (2010); Duchin and Sosyura (2012); Goldman et al. (2013); Amore and Bennedsen (2013); Houston et al. (2014); Fisman and Wang (2015); Acemoglu et al. (2016); Schoenherr (2019); Child et al. (2021).

[2] A review of history also indicates that maintaining political connections can carry serious negative repercussions when government disapproval escalates (Aftalion, 1990; Bodinier and Teyssier, 2000; Opper, 2018). For example, following the 1979 Revolution in Iran, thousands of businesses owned by individuals affiliated with the previous regime were seized and transferred to revolutionary forces (Amuzegar, 1992).

[3] The Escalating Attacks on Tesla Facilities, *Center for Strategic & International Studies*, March 2025.

[4] See, for example, Fisman (2001); Goldman et al. (2009); Acemoglu et al. (2018); Knill et al. (2024).

is the main focus of dissent, since these firms are frequently perceived as government allies.

To test this hypothesis, I use the 2019 social protests in Iran as the empirical setting. Drawing on a proprietary dataset of corporate insurance policies containing more than 3.1 million policy-quarter observations, I find that during the protests, the likelihood of damage to the assets of politically connected firms—defined as those led by former politicians—was 0.45 percentage points higher than that of comparable assets owned by unconnected firms within the same municipal district.[5] This effect represents an increase of more than 55 percent relative to the average likelihood of damage during the protests. Moreover, politically connected firms sustained significantly greater damages, both in absolute terms and as a share of asset value. Conditional on incurring damage, monetary losses to connected firms' assets were approximately 38 percent higher than those of unconnected firms. When scaled by asset value, damages to non-industrial properties of politically connected firms resulted in an additional 0.7 percent loss of value.

An important question is how protesters identified assets owned by politically connected firms among otherwise similar ones nearby. I hypothesize that information sharing and coordination through the internet—particularly doxing campaigns on social media—facilitated the identification of these assets. These campaigns solicited information from the public on the personal lives and careers of politicians and military personnel, which was subsequently disseminated online.[6] To examine whether internet access influenced the vulnerability of connected firms during the protests, I exploit a near-total national internet shutdown that lasted approximately five days amid the unrest.[7] The results show that while the overall likelihood of damage to corporate assets on protest days without internet access remained unchanged, the heightened risk of damage to politically connected firms' assets virtually disappeared. This pattern suggests that although corporate assets in general were equally likely to be damaged on days with internet shutdowns, the composition of the damages was more random.

After documenting the costs incurred by politically connected firms during the protests, I examine their subsequent responses. The results indicate that politically connected firms—including those that did not sustain damage—increased their insurance coverage by insuring additional assets and expanding existing policies. In the quarters following the protests, newly insured corporate assets were approximately 20 percent more likely to belong

[5] In Tehran, the median land area of municipal districts is 8.7 square miles.

[6] Much of the content from these campaigns is now inaccessible due to account suspensions by social media platforms. Nonetheless, Figure 8 provides examples from these campaigns. For an active campaign, see Efshagar Rasu.

[7] Internet Disrupted in Iran Amid Fuel Protests in Multiple Cities, *Netblocks*, November 2019.

to connected firms relative to unconnected firms of similar size, operating in the same industry, and located in the same province. On the intensive margin, the liability limits of insurance policies for connected firms' assets increased by 1.6 percent more than those for comparable assets held by unconnected firms.[8] These effects were particularly pronounced in regions that experienced more intense protests, suggesting that the protests led connected firms to expand their asset insurance.

The response of politically connected firms extends beyond the expansion of asset insurance. Drawing on approximately half a million resumes, I find that corporate officers with political backgrounds were significantly more likely to experience turnover in the year following the protests. While downsizing due to protest-related damages could partly account for this pattern, former politician officers were disproportionately likely to exit even from firms unaffected by the protests. To the best of my knowledge, this provides the first direct evidence that social protests can reduce the prevalence of close ties between firms and politicians—relationships that have been shown to distort resource allocation both within firms (Bertrand et al., 2018; Duchin and Sosyura, 2012) and across firms (Faccio and McConnell, 2020).

These findings are consistent with economic theories that view mass political actions as signals of private information to others (Lohmann, 1994b,a, 1993). Such actions, often costly, are particularly salient in less open societies where preference falsification is widespread and opponents of the status quo may refrain from openly expressing their desire for change (Kuran, 1989, 1991, 1995). Social protests can also shape political views, foster collective movements, and help citizens overcome coordination problems, thereby increasing the likelihood of future shifts in the distribution of *de jure* political power (Acemoglu and Robinson, 2008; Madestam et al., 2013; Aidt and Franck, 2015).[9] Mass political actions, such as social protests, may therefore prompt politically connected firms to reassess the expected value of their connections, leading some to sever these ties.

The 2019 social protests in Iran provide a well-suited empirical setting for several reasons. First, corporate political connections are pervasive in the country, partly due to firms competing for access to oil rents (Ades and Di Tella, 1999). Second, the protests were unexpected, triggered by a sudden government announcement to raise gasoline prices by at least 50 percent.[10] This lack

[8] The liability limit refers to the maximum amount an insurance company will pay for a loss or damage to an asset.

[9] See, among others, Acemoglu and Robinson (2000, 2001, 2006) for models in which de facto political power drives institutional change and influences the future distribution of de jure political power.

[10] Iran Abruptly Raises Fuel Prices, and Protests Erupt, *New York Times*, November 2019.

of foreknowledge strengthens the plausibility of the no-anticipation identification assumption, namely that firms were unlikely to alter their behavior in ways that would affect the outcomes prior to the treatment (Wooldridge, 2021).[11] It also reduces the likelihood of confounding interventions occurring simultaneously (Abbring and Van den Berg, 2003). Third, the protests spread to 29 of the 31 provinces, providing broad geographic variation that enables robustness analyses to ensure the results are not driven by specific localities.[12] Finally, the protests caused economically significant damages, with thousands of incidents reported and total losses estimated at roughly $0.2 billion.[13,14]

The findings from this study may extend beyond the specific empirical setting examined. Anecdotal evidence from developed countries likewise suggests that protesters often target corporations they perceive as contributing to broader social or political grievances. For example, in spring 2025, a series of violent attacks on Tesla properties—including showrooms and charging facilities—took place across the United States and were subsequently characterized as acts of "domestic terrorism" by the Attorney General and the Director of the Federal Bureau of Investigation (FBI).[15,16] Similar incidents took place in France, where protesters stormed the Paris headquarters of BlackRock, accusing the company of being "complicit" in the privatization of pensions,[17] and on the same day set fire to La Rotonde, a restaurant associated with President Emmanuel Macron.[18] A comparable pattern was evident during the 2019 protests in Iran, where media reports frequently documented demonstrators targeting assets owned by "the government and its affiliates."[19] Consistent with these reports, the insurance data show that during protests in Fardis County, Alborz Province, a franchise of a politically connected retail firm was damaged, while unconnected firms of similar size operating in the same industry (NAICS 44–45) within a 0.5-mile radius reported no damage.

A primary identification concern is that politically connected firms may own properties in

[11] To address the possibility that firms may have anticipated the protests and adjusted their behavior accordingly, I re-estimated the regressions excluding the quarter immediately preceding the protests from the analysis (Callaway and Sant'Anna, 2021). The results remain consistent, as shown in Table 24.

[12] Summary of the Bloody Protests of Aban 2019, *Human Rights Activists News Agency*, December 2019.

[13] With Brutal Crackdown, Iran Is Convulsed by Worst Unrest in 40 Years, *New York Times*, December 2019.

[14] At Least 2,333 Billion Tomans Went Up in Flames, *Iran Newspaper*, November 2019.

[15] Attorney General Bondi Statement on Violent Attacks Against Tesla Property, *U.S. Department of Justice*, March 2025.

[16] FBI Launches Tesla Threats Task Force: 'This Is Domestic Terrorism', *CNBC*, March 2025.

[17] Protesters](https://www.washingtonpost.com/world/2023/04/06/france-pension-protests-blackrock/Protesters) Storm BlackRock Building, Clash With Police Over France's Pension Reform, *Washington Post*, April 2023.

[18] France](https://www.bbc.com/news/world-europe-65200654France) Protests: La Rotonde Bistro Liked by Macron Attacked, *BBC*, April 2023.

[19] The Sixth Day of the Nationwide Uprising of the Iranian People, *Iran Efshagar*, November 2019.

more accessible locations, such as main streets, because they are less financially constrained (Khwaja and Mian, 2005; Claessens et al., 2008). Since distance to protest sites serves as an impediment to participation, protests are often organized in areas with high accessibility (Traag et al., 2017; Rotman and Shalev, 2022). As a result, the assets of connected firms could be more vulnerable to damage, even if protesters were targeting assets randomly. To address this endogeneity concern, I exploit the granularity of the corporate insurance data by comparing each asset of politically connected firms to assets of the same type and comparable value within the same municipal district. This design ensures that the assets being compared share similar characteristics, including safety features, visibility, and levels of pedestrian and vehicle traffic.

A related concern is that politically connected firms may be located in closer proximity to major government buildings, such as ministries. Extensive empirical evidence shows that politically connected firms receive preferential treatment from the government, making them more likely to be situated near such institutions (Schoenherr, 2019; Goldman et al., 2013; Claessens et al., 2008; Faccio et al., 2006). For example, these firms may have a higher probability of leasing office space adjacent to government facilities. Since protests are often geographically concentrated around government buildings, the assets of connected firms could be disproportionately vulnerable to damage even if protesters do not intentionally target them. To address this concern, I re-estimate the regression model after excluding municipal districts containing at least one major government building. The results remain both economically and statistically significant, alleviating concerns that the findings are driven by the proximity of connected firms to government institutions.[20]

In light of prior evidence that politically connected firms receive preferential treatment from regulatory entities, including those ostensibly independent (Correia, 2014; Heitz et al., 2023), a concern arises that insurance claims filed by such firms may be more likely to be approved. While this possibility does not inherently challenge my empirical design—which accounts for pre-event heterogeneity between connected and unconnected firms—it could confound the results if preferential treatment intensified specifically during protest periods.

This concern is mitigated for two reasons. First, the insurance company is neither politically connected nor state-owned; it is a publicly listed firm, which reduces the likelihood of direct government intervention. Second, this alternative explanation is inconsistent with my finding that the probability of an approved insurance claim for assets owned by politically connected

[20] See Table 22.

firms was statistically indistinguishable from that of comparable assets owned by unconnected firms within the same vicinity during protest days with an internet shutdown. Given the brevity and timing of the shutdown, it is implausible to assume that any potential government influence over claim approvals for connected firms would have temporarily ceased during this period, only to resume once internet access was restored.

The cross-sectional analysis reveals a pronounced concentration of political connections in the Oil and Gas sector (NAICS 21), where 20.3 percent of firms are led by CEOs with political or military backgrounds, compared to 4.3 percent in other sectors. This raises the concern that the results may be driven by a single industry, particularly since the 2019 protests were triggered by a sharp increase in gasoline prices. In this context, protesters angered by rising fuel costs may have specifically targeted oil and gas firms, many of which are politically connected in an oil-exporting country. This concern is unwarranted, however, as the statistical and economic significance of the results remains unchanged when restricting comparisons to firms of similar size within the same industry or when excluding the Oil and Gas sector from the sample.[21]

This paper contributes to the literature on corporate political connections in several ways. First, it identifies a novel mechanism through which political ties can generate unintended negative consequences, resulting in value destruction rather than value creation. Second, it documents systematic changes in the insurance policies of politically connected firms in the aftermath of the protests, including among those that did not sustain damage. These adjustments reflect a learning mechanism, suggesting that connected firms reassessed the risks associated with their political ties or revised their expectations regarding the likelihood of future protests.

Furthermore, the paper provides suggestive evidence on the role of the internet in shaping social protests, particularly by facilitating information sharing and coordination among participants. Exploiting a brief period of internet shutdown, the analysis shows that although the overall prevalence of corporate asset damage on protest days without internet access remained unchanged, the damages were no longer systematically targeted. This finding underscores that in today's internet-driven environment, political ties can impose ex post costs on firms, costs that may not have existed in the past.

[21] See Table 23.

2 Data

The study relies on three primary data sources. The first is a proprietary dataset of corporate insurance policies obtained from an insurance company in Iran, encompassing approximately one million policies. This dataset, recorded in the Solar Hijri calendar, spans a seven-year period from 1394 to 1400, corresponding to 2015 to 2021 in the Gregorian calendar.[22] It includes the period of the 2019 social protests, which started on November 15 and lasted for roughly two weeks, enabling analysis over 19 quarters before and 8 quarters after the protests.

To determine whether a corporate asset is owned by a politically connected firm, the first step is to identify the firm's CEO as of one quarter prior to the protests (hereafter, the reference date). This identification is based on data from the official business registry database, which provides comprehensive information on all companies incorporated within the country, including registration details, founders, CEOs, addresses, and updates to this information.[23] If a firm's name does not precisely match any record in the database, or if its CEO as of the reference date cannot be identified, all of the firm's insurance policies are excluded from the sample. A firm is classified as politically connected if its CEO as of the reference date was a former politician.

To be classified as a former politician, an individual must have held a managerial-level position within the public sector. This is defined as occupying either the highest or second-highest leadership role in a governmental entity. For example, within a ministry, the minister and their vice presidents responsible for different areas are considered politicians.[24] For robustness analyses, firms led by former military officials or individuals who previously held non-managerial roles in the public sector are also classified.

Table 1 presents descriptive statistics comparing politically connected and unconnected firms, focusing on firm-level characteristics and regional attributes of their headquarters' city as of the quarter preceding the protests. Consistent with prior literature, politically connected firms are generally larger, employing more workers and holding higher-value assets. For example, politically connected firms hold an average of 1.0 million USD in insured assets, compared to 0.7 million USD for unconnected firms. Regarding asset composition, connected firms are more likely to own industrial properties, which account for 7.1 percent of their assets, compared to 6.1 percent for unconnected firms. Despite these differences at the firm level, both connected

[22] The Solar Hijri calendar begins on the March equinox, typically falling on March 21.

[23] Iran Legal Gazette

[24] For a detailed list of managerial positions in the public sector held by non-military former politician CEOs, see Table 18.

and unconnected firms are headquartered in regions with similar political climates, population sizes, household incomes, and unemployment rates, suggesting comparable regional economic and demographic contexts.

The differences in firm characteristics do not pose challenges for the empirical design, as the corporate insurance data is recorded at the asset level. For firms insuring multiple assets across various locations, the data allows for the observation of each asset's unique characteristics and precise location. Corporate assets in the dataset are categorized into two main groups: non-industrial properties, which account for approximately 92.9 percent of policies, and industrial properties, which represent about 7.1 percent. Figure 7 provides an example of a policy, with identifying details of the insurer and the firm redacted for privacy.

Table 2 summarizes descriptive statistics for insurance policies across asset classes. Non-industrial properties include 765,225 policies with an average asset value of 910.7 thousand USD, of which 5.5 percent are held by politically connected firms. A total of 7,567 claims were filed with an average of 2.0 thousand USD per claim, constituting 1.2 percent of insured asset values. For industrial properties, there are 58,681 policies averaging 1,527.5 thousand USD in asset value. Politically connected firms account for 7.0 percent of policies, and 7.4 percent are led by a politician or military CEO. The category recorded 1,294 claims, averaging 2.5 thousand USD per claim. In both cases, averages are influenced by a few large claims.

Table 3 presents the distribution of economic sectors in which firms were active as of the reference date. The highest prevalence of corporate political connections is observed in the Mining, Quarrying, and Oil and Gas Extraction sector. In this sector, approximately 25.5 percent were led by either a former politician CEO or a former military CEO. This finding aligns with expectations, given that Iran is an oil and gas exporting country, and the presence of oil rents makes corporate political connections particularly advantageous in this sector (Ades and Di Tella, 1999). Conversely, the Arts, Entertainment, and Recreation sector exhibits the lowest frequency of corporate political connections, with only about 0.9 percent of these firms being led by either a former politician CEO or a former military CEO.

Table 19 presents the distribution of firms by workforce size. Column 1 categorizes firms into five groups: 1 to 9 employees, 10 to 49 employees, 50 to 99 employees, 100 to 499 employees, and 500 or more employees. Column 2 displays the percentage of policyholders within each size category relative to the total sample. Notably, 39.0 percent of firms belong to the smallest category (1 to 9 employees), while 4.4 percent have 500 or more employees. Columns 3 and 4

provide insights into the leadership of these firms. Column 3 shows the percentage of firms led by a former politician as CEO, while Column 4 reports the percentage of firms led by either a former politician CEO or a former military CEO. The data reveal that former politicians are more likely to assume leadership positions in larger firms after leaving public office, indicating a positive correlation between firm size and corporate political connections.

The final dataset used in this study is the entire collection of resumes sourced from a leading resume-building platform. This dataset is employed to examine whether job opportunities for politician managers declined following the protests. To increase the sample size, the analysis extends beyond CEOs to include corporate officers. The database contains 728,306 entries, although some resumes are incomplete. A resume is classified as complete if it includes entries for first name, surname, gender, and education. Based on this definition, 406,625 resumes are identified as complete.

Table 20 provides summary statistics for the complete resumes, organized into two panels. Panel A focuses on corporate officers employed in the private sector as of the reference date. Among these resumes, 4.8 percent correspond to corporate officers, defined as individuals whose job titles include the term "manager." In the local language, C-suite executive titles typically incorporate the word "manager," functioning similarly to "chief" in English.

Panel B of Table 20 presents summary statistics for the remaining 406,625 complete resumes. This group comprises individuals who were either unemployed on the reference date, employed without a "manager" title in their job description, or serving as managers in the public sector. Although gender representation in this cohort is also male-dominated, 36.3 percent of these individuals are female. On average, 81.4 percent of this group was employed as of the reference date. Among this group, 1.5 percent are former politicians, while 3.4 percent have backgrounds as either former politicians or former military officials.

Table 21 summarizes educational attainment across corporate officers and non-corporate officers in the private sector. Panel A focuses on corporate officers working in the private sector as of the reference date. Among them, 7.9 percent are high school graduates, 17.7 percent hold associate degrees, and 53.4 percent have bachelor's degrees, making it the predominant educational level. Additionally, 14.0 percent hold master's degrees, and 4.1 percent have doctoral degrees, reflecting the emphasis on advanced education in managerial roles. Panel B covers non-corporate officers. High school graduates make up 17.8 percent, and 15.7 percent hold associate degrees. Bachelor's degrees are the most common at 48.3 percent, while 9.3 percent have master's

degrees, and 4.5 percent hold doctoral degrees. Compared to corporate officers, non-corporate officers have a higher proportion of individuals with lower educational qualifications, highlighting the predominant educational standard for managerial roles.

3 Empirical Strategy & Findings

3.1 Asset Damage for Politically Connected Firms During Protests

3.1.1 Likelihood & Severity of Damage

I begin the analysis by investigating whether the assets of politically connected firms are more likely to be damaged during social protests. To test this hypothesis, I employ a canonical difference-in-differences framework. This analysis determines if the assets of politically connected firms are significantly more likely to sustain damage during social protests compared to similar assets of unconnected firms within the same calendar year, even when they are of comparable value and located within the same municipal district. To account for firm size and potential industry cycles, I also include Firm Size × Industry × Y-Quarter fixed effects in the regression specification. The most rigorous regression specification that I estimate is

$$Y_{ait} = \beta \cdot (\text{Connected}_i \times \text{Protest}_t) + \mu_a + \gamma_{srt} + \lambda_{cvdt} + \varepsilon_{ait} \tag{1}$$

where Y_{ait} denotes damage to corporate asset a owned by i in event quarter t. The independent variable, Connected_i, is an indicator set to one for firms identified as politically connected, as of the reference date. The independent variable Protest_t is an indicator set to one for the fourth quarter of 2019, during which the social protests occurred, and zero for all other quarters. μ_a represents asset fixed effects, γ_{srt} is firm size-by-industry-by-event-quarter fixed effects, and λ_{cvdt} is asset class-by-asset value-by-municipal district-by-event-quarter fixed effects. The ε_{ait} represents the error term. The observations are at the asset level on a quarterly basis. It is important to note that in the corporate insurance dataset, the unit of observation is individual insurance policies, each corresponding to a specific asset. For firms with multiple insured assets, there is a distinct policy for each asset.

The dependent variable, $\mathbb{1}\text{damage}_{ait}$, is an indicator equal to one if asset a owned by firm i is damaged at time t. The key independent variable, Connected_i, is an indicator set to one for firms identified as politically connected. A firm is considered connected if its CEO, as of the reference

date, had previously held a political office; otherwise, the firm is classified as unconnected. The variable Protest_t is an indicator set to one for the fourth quarter of 2019, during which the social protests occurred, and zero for all other quarters.

The term Asset Value is a categorical variable used as a proxy for the relative value of corporate assets. To construct this variable, I first calculate the real value of assets by adjusting for inflation, using the period from March 21, 2015, to March 19, 2016, as the base year. The nominal value of insured assets in subsequent years is discounted using yearly inflation rates. I then calculate the quartiles of the assets' real value, which form the Asset Value variable. Given the potential nonlinear relationship between the likelihood of property damage and asset value, it is more appropriate to control non-parametrically for the monetary value of insured corporate assets. The term Asset Class represents the type of corporate asset, categorized into two classes: non-industrial and industrial properties. Lastly, Municipal District denotes the municipal district where the corporate asset is located.

I measure firm size based on the estimated total number of employees as of the reference date. The variable Firm size is categorical, classifying firms into five groups based on workforce size: 1 to 9 employees, 10 to 49 employees, 50 to 99 employees, 100 to 499 employees, and 500 or more employees. The term Industry represents the sector in which the firm operates, classified by the 2-digit NAICS codes. The distribution of firms across industries is provided in Table 3.

The coefficient of interest is β. In the most rigorous specification shown in regression Equation (1), this coefficient measures whether, among firms of similar size operating within the same industry, the assets of politically connected firms were more likely to be damaged during the social protests compared to unconnected firms' similar assets of comparable value located in the same municipal district. The coefficient estimates are presented in Table 4.

The regression specification in Column 1 of Table 4 presents the standard difference-in-differences estimator. In Column 2, the specification adds Asset Value $\times$ Y-Quarter FE, Asset Class $\times$ Y-Quarter FE, and Municipal District $\times$ Y-Quarter FE to control for time-variant heterogeneity related to asset value, asset class, and municipal district. In Column 3, these fixed effects are replaced with an interacted effect. Finally, the specification in Column 4 includes Firm Size $\times$ Industry $\times$ Y-Quarter FE to account for potential industry cycles and firm size-specific heterogeneity. From this point onward, I focus exclusively on the most rigorous regression specification.

In Table 4, the estimate of the coefficient of interest, β, is statistically significant and greater

than zero across all four regression specifications. This indicates that the assets of politically connected firms were significantly more likely to sustain damage during the protests. In the most rigorous regression specification presented, the coefficient estimate is 0.0045. This implies that the likelihood of damage to the assets of connected firms was 0.45 percentage points higher compared to similar assets of unconnected firms with equivalent value located in the same municipal district. This increase represents a rise of over 55 percent relative to the average likelihood of damage to corporate assets during the protest quarter.

To investigate whether, conditional on sustaining damage during social protests, connected firms incur larger damages, I estimate regression Equation (1), where the dependent variable is the extent of damage in absolute and relative terms. The coefficient estimates are presented in Table 5. In Panel A, the dependent variable is the logarithm of the monetary value of damage, Ln(damage). In Panel B, the dependent variable is the monetary value of damage expressed as a fraction of the underlying asset value.

In Panel A, the coefficient estimates in Column 4 indicate that, conditional on sustaining damage during the social protests, the assets of politically connected firms incurred 38.2 percent larger damages. Consistent with the findings in Panel A, the results in Panel B indicate that politically connected firms experienced more severe property damage during social protests in relative terms. The coefficient estimates in the first three regression specifications are positive and statistically significant, though in the most rigorous model in Column 4, the coefficient is significant only at the $\alpha = 0.10$ level. According to this estimate, the damage to connected firms' assets during protests destroyed 0.7 percent more of the insured asset value compared to damages to similar assets of unconnected firms in the same municipal district.

3.1.2 Pre-Protest Trends in Asset Damage

It is crucial to examine the parallel trends assumption, as an unbiased estimation of the variable of interest within the difference-in-differences framework depends on the validity of both the parallel trends assumption and the no anticipation assumption (Wooldridge, 2021). In this paper, the parallel trends assumption implies that, in the absence of the protests, the likelihood of damage to assets owned by politically connected firms and comparable assets of unconnected firms would have followed a similar trajectory.

Although the parallel trends assumption cannot be directly tested, it is essential that the treated and untreated groups exhibit similar pre-treatment trends in the outcome variable. If

these groups differ systematically prior to treatment, any observed post-treatment differences could be attributed to these pre-existing differences rather than the treatment itself (Roberts and Whited, 2013). To assess whether pre-treatment trends were parallel and to illustrate the dynamics of the effect, I conduct an event study analysis. Including the full set of event leads allows for an examination of the parallel trends assumption in the pre-treatment period. Similarly, incorporating event lags enables an inspection of the temporal dynamics of the treatment effect, such as whether the effect grows or diminishes over time, and whether it is transitory or permanent.

Using the event study approach (Freyaldenhoven et al., 2021; Clarke and Tapia-Schythe, 2021), I visually illustrate the dynamics of the treatment effect over a period spanning four quarters before and after the 2019 protests. The regression equation I estimate is

$$\begin{aligned} Y_{ait} = {} & \beta_{con}\,\text{Connected}_i + \beta_{pre}\,\text{Connected}_i \times \text{Pre}_t + \sum_{\substack{q=-4 \\ q\neq -1}}^{+4} \beta_q\,\text{Connected}_i \times D_t^q + \beta_{post}\,\text{Connected}_i \times \text{Post}_t \\ & + \beta'_{pre}\,\text{Pre}_t + \sum_{\substack{q=-4 \\ q\neq -1}}^{+4} \beta'_q\,D_t^q + \beta'_{post}\,\text{Post}_t + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District FE} \\ & + \text{Firm Size} \times \text{Industry} + \varepsilon_{ait} \end{aligned} \tag{2}$$

where D_t^q are indicator variables set to one for observations in q quarters after (or before, if negative) the 2019 social protests. All other variables are defined as in regression Equation (1). The observations are at the asset level on a quarterly basis. Observations occurring at least 5 quarters after the event are denoted by Post_t, while those occurring at least 5 quarters prior are captured by Pre_t. Observations within one quarter prior to the quarter of the social protests, 2019 Q3, denoted as D_t^{-1}, are excluded to serve as the reference point.

For a given corporate asset, the lags and leads indicate the differential likelihood of damage if the firm is politically connected. The differences between the likelihood of damage to politically connected firms' assets and those of unconnected firms one quarter prior to the protests are anchored at 0 in the omitted base period (i.e., the first lead in regression Equation (2)). Thus, the lags and leads capture the difference between the treated and control groups relative to the prevailing difference in the omitted base period.

Figures 3a and 3b present visualizations of the estimated coefficients from regression Equation (2), where the dependent variables are $\mathbb{1}$damage and Ln(damage), respectively. Figure 3a

shows that the coefficients on the leads are centered around zero, supporting the absence of a pre-existing trend in the difference in the probability of damage to assets of politically connected firms compared to unconnected firms. However, during the protests, there is a notable increase in the likelihood of damage to politically connected firms' assets relative to similar unconnected firms' assets of comparable value within the same municipal district.

Figure 3b presents a similar pattern regarding the dollar value of damage. This figure illustrates the estimates and statistical significance of the event-study coefficients derived from estimating regression Equation (2). Consistent with the patterns in Figure 3a, the coefficients for the lead periods remain close to zero, indicating no significant pre-event differences in the size of damages between connected and unconnected firms prior to the protests. However, this changes during the protest periods. Conditional on sustaining damage, the dollar value of damage to connected firms was significantly higher than that sustained by similar assets of unconnected firms.

The findings on both the extensive and intensive margins, shown in Figure 3, indicate that in the quarters preceding the 2019 protests, the differential likelihood of damage to politically connected firms' assets, compared to unconnected firms' similar assets of comparable value within the same municipal district, aligns with the baseline period, the quarter immediately before the protests. Although this observation does not guarantee that the treated and control groups would have necessarily followed parallel trends during the protest period, if trends were not parallel in the pre-protest periods, it is unlikely they would have become parallel during the protests (Roberts and Whited, 2013; Kahn-Lang and Lang, 2020).

3.1.3 How Do Protesters Identify the Assets of Connected Firms?

It is puzzling how protesters were able to identify assets owned by politically connected firms. I hypothesize that information sharing and coordination via the internet, particularly doxing campaigns on social media, played a key role in disseminating this information. These campaigns often gathered and shared details about the personal lives and careers of politicians and members of the armed forces. Figure 8 illustrates some examples of the posts made by these campaigns on social media.[25] Although these social media campaigns during the protests were similar to those used to organize boycotts in developed countries, they often promoted violence, leading

[25] To explore one of these campaigns that is still online, see https://efshagarrasu.com/%d8%a8%d9%84%d8%a7%da%ag.

to their suspension or removal by account holders for personal safety concerns.[26]

Testing whether the internet contributed to the increased susceptibility of politically connected firms to asset damage during the protests is challenging. However, the temporary internet shutdown during the protests provides an ideal setting to explore this hypothesis. According to the NetBlocks internet observatory, the country experienced a "near-total national internet shutdown" from the evening of November 16 until November 21, when connectivity began to gradually improve.[27] Figure 9 illustrates the time series of internet connectivity in Iran during the 2019 protests.

I leverage this unexpected shock to test whether the likelihood of politically connected firms experiencing asset damage decreased during the internet shutdown. To investigate this, I estimate the following regression equation, restricting the analysis to the days of the protests, specifically from November 15 to November 25.

$$\begin{aligned} \mathbb{1}\text{damage}_{ait} = \beta\, \text{Connected}_i \times \text{Shutdown}_t + \alpha\, \text{Connected}_i \\ + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District} \times \text{Y-Day FE} + \varepsilon_{ait} \end{aligned} \tag{3}$$

where the independent variable Shutdown_t is a dummy variable set to one for the period from November 17 to November 21. All other variables are defined as in regression Equation (1). The observations are at the asset level on a daily basis.

The coefficient of interest is β. In the most rigorous specification, shown in regression Equation (3), this coefficient captures whether, during the protests, the assets of politically connected firms were less likely to sustain damage when the internet was shut down compared to their likelihood of sustaining damage during protests with normal internet connectivity.

Table 6 reports the coefficient estimates. Across all five regression specifications, the coefficient of interest is consistently negative and statistically significant. In the most rigorous specification, presented in Column 5, the coefficient estimate reveals that the assets of politically connected firms were significantly less likely to sustain damage during protests when the internet was shut down. This decline represents a reduction of 90.3 percent relative to the average likelihood of damage to corporate assets on protest days. Interestingly, the likelihood of damage to corporate assets remained equally prevalent on protest days without internet access. However, the composition of damages appeared more random on these days.

[26] For an example of boycott campaigns in developed countries, see https://www.ethicalconsumer.org/about-us/our-mission.

[27] See https://netblocks.org/reports/internet-disrupted-in-iran-amid-fuel-protests-in-multiple-cities-pA25L18b

3.1.4 Damage Across Asset Classes

Given that industrial properties are typically located in remote areas where land is inexpensive and are often secured within gated industrial zones, we would expect these properties to be less prone to damage during social protests. In the following analysis, I examine which classes of assets owned by politically connected firms are more likely to incur damage during social protests. For each asset class, I estimate a modified version of regression Equation (1), incorporating Asset Value × Y-Quarter FE, Municipal District × Y-Quarter FE, and Firm Size × Industry × Y-Quarter FE.

The coefficient estimates are presented in Table 7. Column 2 indicates that the probability of damage to non-industrial properties owned by politically connected firms during the protests was 0.49 percentage points higher than for comparable properties owned by unconnected firms of the same relative value. This represents an increase of over 50 percent relative to the average likelihood of damage during the protests. However, in Column 4, the coefficient estimate is not statistically significant, suggesting that the likelihood of damage to industrial properties owned by politically connected firms during the protests did not differ significantly from that for industrial properties owned by unconnected firms.

Next, I investigate which classes of assets owned by politically connected firms incurred greater damage during social protests, conditional on sustaining damage. Similar to Table 7, I estimate a modified version of regression Equation (1), with the dependent variable being the extent of damage in absolute and relative terms.

The coefficient estimates are displayed in Table 8 across two panels. In Panel A, the dependent variable is the logarithm of the monetary value of damage, Ln(damage). In Panel B, the dependent variable is the monetary value of damage as a fraction of the underlying asset value. The coefficient estimates in Column 2 of both panels are positive and statistically significant, indicating that, conditional on sustaining damage during the social protests, non-industrial properties of politically connected firms incurred 61.1 percent larger damages. In relative terms, damage to non-industrial properties of politically connected firms destroyed about 0.7 percent more of the underlying asset value.

In contrast, the extent of damage to industrial properties of politically connected firms was not significantly different from that to industrial properties of unconnected firms within the same municipal district. The coefficient estimates in Column 2 across Panels A and B in Table 8

are not statistically significant, suggesting that damages to industrial properties of politically connected firms during the protests were not significantly different in severity compared to damages to industrial properties of unconnected firms within the same municipal district.

3.1.5 Damage and Protest Intensity

Now, I examine whether the intensity of social protests is correlated with an increased probability of damage and a higher severity of damages to the assets of politically connected firms. The regression equation I estimate is

$$\begin{aligned} Y_{ait} = {} & \alpha_1 \, \text{Connected}_i + \alpha_2 \, \text{Connected}_i \times \text{Protest}_t + \alpha_3 \, \text{Connected}_i \times \text{Intensity}_p \\ & + \beta \, \text{Connected}_i \times \text{Protest}_t \times \text{Intensity}_p + \text{Firm Size} \times \text{Industry} \times \text{Y-Quarter FE} \\ & + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District} \times \text{Y-Quarter FE} + \varepsilon_{ait} \end{aligned} \tag{4}$$

where Intensity_p proxies the intensity of the protests at the provincial level. All other variables are defined as in regression Equation (1). The observations are at the corporate asset level on a quarterly basis.

The coefficient estimates are presented in Table 9. In the first three regression specifications, the dependent variable is $\mathbb{1}$damage, while in the last three, it is damage/asset value. Panel A proxies protest intensity using Death_p, an indicator set to one if at least one protester died during the protests in province p, and zero otherwise.[28] Data on protester deaths during the 2019 protests at the provincial level was sourced from a report by Amnesty International.[29] The report documents 321 protesters whom Amnesty International claims were killed by the country's security forces during the 2019 protests. Figures 2a and 2b respectively show which provinces reported at least one protest-related death and the number of deaths per million residents during the protests.

In Panel A of Table 9, the coefficient of the triple interaction term, β, captures the differential impact of the protests on the likelihood and magnitude of damage to the assets of politically connected firms when these assets are located in a province where at least one protester death was reported. The coefficient estimates in both columns 3 and 6 are statistically significant. Column 3 shows that, among firms of similar size and operating within the same industry, the likelihood of damage to politically connected firms' assets during the protests is 0.75 percentage

[28] See Table 17

[29] https://www.amnesty.org/en/wp-content/uploads/2022/07/MDE1323082020ENGLISH.pdf

points higher if the asset is located in a province where at least one protester was killed, compared to provinces where no protester deaths occurred. Similarly, the coefficient estimate in Column 6 is statistically significant, indicating that damages to connected firms' assets destroyed 2.2 percent more of the insured asset value compared to damages to similar assets of unconnected firms within the same municipal district.

Panel B of Table 9 measures the intensity of the protests using the political orientation of provinces. Data from five presidential elections held between 1997 and 2009 was used to estimate the political orientation of each province. This data is presented in the last column of Table 17, with its geographic distribution illustrated in Figure 2c. The political orientation measure ranges from 1 to 4, with higher values indicating a more conservative populace. Protest intensity is proxied by Reformist_p, an indicator set to one if the political orientation score of province p is 1 or 2.[30]

In Panel B of Table 9, the coefficient of the triple interaction term, β, examines whether the likelihood and magnitude of damage to assets of politically connected firms during social protests vary based on local political orientation. The coefficient estimates in the first three columns are statistically significant. Column 3, the most rigorous model, shows that, among firms of similar size and industry, damage to politically connected firms' assets is 0.35 percentage points more likely during protests if located in reformist provinces. The last three regression specifications shift the focus to the intensive margin. In Column 6, the coefficient estimate of the triple interaction term, β, is positive but not statistically significant. This suggests that damages to connected firms' assets were not more severe in reformist provinces compared to those incurred by connected firms in conservative provinces.

3.1.6 Firms Led by Former Military and Bureaucrat CEOs

As a robustness test, I examine whether corporate political affiliation with the government, through having a former member of the armed forces as CEO, is associated with a higher likelihood of asset damage during social protests. Analyzing firms led by former armed forces personnel is particularly important due to their role in controlling social protests. This role may make companies managed by former military personnel potential targets for protesters seeking retaliation. Moreover, in the context of developing countries, the authority of the armed forces often extends beyond their formal organizational scope.

[30] See Table 17

To conduct this analysis, I estimate regression Equation (1), where the dependent variable is $\mathbb{1}_{damage}$. Table 26 reports coefficient estimates across two panels. In Panel A, politically connected firms are defined as those led by CEOs who held political office at least once before the protests, with firms led by former military CEOs who have never been politicians excluded from the sample. In Panel B, politically connected firms are defined as those led by former military officials, excluding firms led by former politician CEOs who have never been military officials.

The coefficient estimate in Column 4 of Panel B of Table 26 indicates that, during the protests, the likelihood of damage to assets of firms led by a former military CEO was significantly higher, about 0.46 percentage points higher, compared to similar assets of unconnected firms with comparable value located in the same municipal district. This increase in the likelihood of damage for these firms is also economically significant when compared to the unconditional average likelihood of damage during the protests.

On the intensive margin, I reestimate regression Equation (1), where the dependent variable is damage/asset value. Table 27 presents coefficient estimates. Column 4 of Panel B shows that, conditional on sustaining damage, damages to assets of firms led by former military officials were marginally more severe than those of unconnected firms during the protests.

As another robustness analysis, I examine whether assets owned by firms led by managers who held exclusively non-managerial roles in the public sector were also more likely to incur damage during the protests. To do so, I estimate regression Equation (1), where the dependent variable is $\mathbb{1}_{damage}$. In this analysis, firms led by former military or politician CEOs are excluded from the sample. Table 28 reports coefficient estimates. As expected, tangible assets owned by firms led by former rank-and-file government employees were not more likely to incur damage during the protests.

Lastly, I investigate whether, conditional on sustaining damage during social protests, the severity of damages to assets owned by firms led by former rank-and-file government employees was higher. As in Table 5, the extent of damage is measured in both absolute and relative terms. The coefficient estimates are presented in Table 29. The coefficient estimate in Column 4 across both Panels A and B is statistically insignificant. This indicates that not only was the likelihood of damage to assets of such connected firms during the protests not higher, but also, conditional on sustaining damage, damages to assets of these connected firms did not differ significantly from the extent of damage incurred by similar assets of unconnected firms with

comparable value located in the same municipal district.

3.2 Politically Connected Firms' Response to Protests

3.2.1 Insuring Additional Assets Following Protests

In this section, I examine whether politically connected firms insure additional assets in the aftermath of the protests. To do this, I test whether the likelihood that a newly insured corporate asset is owned by a politically connected firm is higher in the quarters following the protests compared to the quarters prior. Since politically connected firms tend to be larger and have easier access to credit, it is plausible that they are better able to withstand the financial difficulties caused by social protests and, as a result, insure more assets after the protests.

To address this endogeneity concern, I compare firms of similar size, operating in the same industry, and located within the same province. The most rigorous regression specification I estimate is

$$\begin{aligned}(\text{Newly Insured})_{ait} = \alpha\, \text{Connected}_i + \mu\, \text{Connected}_i \times \text{Following-Protest}_t \\ + \text{Firm Size} \times \text{Industry} \times \text{Province} \times \text{Y-Quarter FE} + \varepsilon_{ait}\end{aligned} \tag{5}$$

where a represents assets, i indexes firms, and t denotes time. The term ε_{ait} captures the error. The observations are at the asset level on a quarterly basis.

The dependent variable is an indicator set to one if asset a was insured by firm i for the first time at time t, meaning the dataset contains no prior policy covering asset a by firm i before t. The independent variable, Connected_i, is defined as in regression Equation (1). Province, indicates the province where the headquarters of the firms are located, unless stated otherwise. $\text{Following-Protest}_t$ is an indicator set to one for all quarters after the 2019 social protests, and zero otherwise. The sample includes data for eight quarters following the protests.

The coefficient of interest is μ. In regression Equation (7), this coefficient captures whether, following the protests, newly insured corporate assets are more likely to be owned by politically connected firms, controlling for firms of similar size operating in the same industry and located within the same province. The coefficient estimates are presented in Table 10.

The regression specification in Column 1 of Table 10 presents the standard difference-in-differences estimator. In Column 2, the specification adds Province × Y-Quarter FE to control for location-specific, time-varying heterogeneity. Column 3 incorporates Firm Size × Y-Quarter FE,

while Column 4 includes Industry × Y-Quarter FE to account for industry-specific, time-varying heterogeneity. Finally, Column 5 adds Firm Size × Industry × Province × Y-Quarter FE, enabling comparisons between firms of similar size, located in the same province, operating in the same industry, and during the same quarter.

In Table 10, the coefficient of interest is positive and statistically significant across all five regression specifications. This finding suggests that, following the protests, politically connected firms were more likely to insure new assets compared to unconnected firms of similar size, operating in the same industry, and located within the same province. In the most rigorous regression specification, the coefficient estimate indicates that a newly insured corporate asset was 1.5 percentage points more likely to be owned by politically connected firms after the protests. This effect represents an increase of over 20 percent relative to the average likelihood of a newly insured asset belonging to connected firms post-protests.

Next, I examine whether the intensity of social protests in the province where firms are located is correlated with the post-protest increase in the likelihood that politically connected firms insure additional assets. The most rigorous regression specification I estimate is

$$\begin{aligned}(\text{Newly Insured})_{ait} = {} & \alpha_1 \,\text{Connected}_i + \alpha_2 \,\text{Connected}_i \times \text{Following-Protest}_t + \alpha_3 \,\text{Connected}_i \times \text{Intensity}_p \\ & + \mu \,\text{Connected}_i \times \text{Following-Protest}_t \times \text{Intensity}_p \\ & + \text{Firm Size} \times \text{Industry} \times \text{Province} \times \text{Y-Quarter FE} + \varepsilon_{ait}\end{aligned} \tag{6}$$

where Intensity_p is defined as in regression Equation (9), and all other variables are defined as in regression Equation (5).

The coefficient estimates are presented in Table 11. In Panel A, the coefficient estimate in Column 5 reveals that, following the protests, newly insured corporate assets were 1.6 percentage points more likely to be owned by politically connected firms in provinces where at least one protester was killed compared to those in provinces where no protester deaths occurred.

In Panel B, the intensity of protests is proxied by the political orientation of provinces. The coefficient estimates are presented in Panel B of Table 11. The triple interaction term is statistically significant across all regression specifications. In the most rigorous specification, the coefficient estimate indicates that, in the aftermath of the protests, newly insured corporate assets were 1.1 percentage points more likely to be owned by politically connected firms in reformist provinces compared to conservative provinces.

Overall, the findings from Tables 10 and 9 suggest that politically connected firms were more likely to insure additional assets after the protests, with the likelihood significantly higher in provinces where the protests were more intense.

3.2.2 Expanding Insurance Coverage Following Protests

In this section, I investigate whether politically connected firms increased their asset insurance more than unconnected firms in the aftermath of the protests. The analysis focuses on determining whether the aggregate liability limit on all insurance policies held by politically connected firms expanded significantly following the protests. The liability limit refers to the maximum amount an insurance company is obligated to pay for a loss or damage to an insured asset.

As previously mentioned, the unit of observation in the corporate insurance dataset is an individual insurance policy, each covering a specific asset. To conduct the analysis, I calculate the total sum of liability limits across all active insurance policies for each firm on a quarterly basis. The most rigorous regression specification I estimate is

$$\begin{aligned}\text{Ln}(\sum_{\text{assets}} \text{Liability Limit})_{it} = \alpha\, \text{Connected}_i + \mu\, \text{Connected}_i \times \text{Following-Protest}_t \\ + \text{Firm Size} \times \text{Industry} \times \text{Province} \times \text{Y-Quarter FE} + \varepsilon_{it}\end{aligned} \tag{7}$$

where i indexes firms and t represents time, ε_{it} denotes the error term. The observations are at the firm-quarter level. The dependent variable is the logarithm of the total liability limit across all insured assets of firm i at time t. The independent variable, Connected_i, is defined as in regression Equation (1).

The most rigorous specification, shown in regression Equation (7), includes Firm Size × Industry × Province × Y-Quarter FE, allowing for comparisons between observationally similar firms, those of similar size, located within the same province, operating in the same industry during the same quarter. The coefficient of interest, μ, captures whether the social protests prompted politically connected firms to increase their total liability limit more than similar unconnected firms.

The coefficient estimates are presented in Table 12, with regression specifications mirroring those in Table 10. Across all five specifications, the coefficient of interest is positive and statistically significant, indicating that politically connected firms significantly increased their total liability limit following the protests. In the most rigorous specification, the coefficient estimate

implies that, in the aftermath of the protests, politically connected firms increased their total liability limit by 9.6 percent more than unconnected firms of similar size, located in the same province, and operating in the same industry during the same quarter.

It is plausible that politically connected firms may have acquired and insured new assets following the protest period, which could naturally contribute to an increase in their total liability limit. To address this possibility, I estimate a modified version of regression Equation (7), restricting the sample to include only corporate assets that were continuously insured prior to, during, and after the protests. This approach ensures the analysis focuses exclusively on changes in the liability limits of consistently insured assets, eliminating the potential confounding effect of newly acquired and insured assets. The most rigorous regression specification I estimate is

$$\begin{aligned}\text{Ln(Liability Limit)}_{ait} = {} & \alpha\,\text{Connected}_i + \mu\,\text{Connected}_i \times \text{Following-Protest}_t \\ & + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District FE} \times \text{Y-Quarter FE} \\ & + \text{Firm Size} \times \text{Industry} \times \text{Y-Quarter FE} + \varepsilon_{ait}\end{aligned} \tag{8}$$

where a denotes corporate assets, i indexes firms, and t represents time, ε_{ait} represents the error term. The observations are at the asset level on a quarterly basis.

The coefficient estimates are presented in Panel A of Table 13. The coefficient of interest, μ, remains statistically significant across all four regression specifications. In the most rigorous specification, shown in Column 4, the coefficient estimate is 0.0163. This indicates that, in the aftermath of the protests, the liability limit of policies covering assets of politically connected firms increased by 1.6 percent more than that of policies covering similar assets owned by unconnected firms, located within the same municipal district during the same quarter.

The increase in the liability limit of policies covering assets of politically connected firms following the protests is likely more pronounced if the connected firm itself incurred at least one instance of asset damage during the protests. To test this hypothesis, I estimate the following

regression specification:

$$\begin{aligned}\text{Ln(Liability Limit)}_{ait} = {} & \alpha_1 \,\text{Connected}_i + \alpha_2 \,\text{Damaged}_i + \alpha_3 \,\text{Connected}_i \times \text{Damaged}_i \\ & + \alpha_4 \,\text{Connected}_i \times \text{Following-Protest}_t + \alpha_5 \,\text{Damaged}_i \times \text{Following-Protest}_t \\ & + \mu \,\text{Connected}_i \times \text{Damaged}_i \times \text{Following-Protest}_t \\ & + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District FE} \times \text{Y-Quarter FE} \\ & + \text{Firm Size} \times \text{Industry} \times \text{Y-Quarter FE} + \varepsilon_{ait}\end{aligned} \tag{9}$$

where i indexes firms and t represents time. The independent variable, Damaged_i, is an indicator set to one for firm i if it incurred at least one instance of damage to its assets during the protests.

The coefficient estimates are presented in Panel B of Table 13. The estimate of the coefficient of interest, μ, is statistically significant and positive across all regression specifications. This result indicates that the liability limit of policies covering assets of politically connected firms that incurred damage during the protests increased significantly more than those covering assets of politically connected firms that remained undamaged. In the most rigorous specification, the coefficient estimate is 0.1250, statistically significant at the 1 percent level. This implies that, in the aftermath of the protests, the liability limit of policies covering assets of damaged politically connected firms increased by 13.3 percent more than that of policies covering assets of politically connected firms that remained undamaged during the protests.

Next, I investigate whether the intensity of social protests in the province where the headquarters of a connected firm is located is associated with the post-protest increase in the liability limit of policies covering assets of that firm. To test this hypothesis, I estimate regression Equation (4), where the dependent variable is $\text{Ln(Liability Limit)}_{ait}$.

The coefficient estimates are presented in Table 14 across two panels. In Panel A, the coefficient estimate in Column 4 is not statistically significant, suggesting that, following the protests, the liability limit of policies covering the assets of politically connected firms did not increase more if the headquarters of such firms were located in provinces where at least one protester was killed.

In Panel B, the estimate of the triple interaction term is statistically significant across all four regression specifications. In the most rigorous specification, the coefficient estimate is 0.0143, statistically significant at conventional levels. This result indicates that, in the aftermath of the protests, the liability limit of policies covering the assets of politically connected firms increased

by 1.4 percent more if the headquarters of such firms were located in reformist provinces.

Overall, the findings from Tables 12, 13, and 14 reveal that, following the protests, the liability limits of policies covering the assets of politically connected firms increased significantly more than those covering similar assets of unconnected firms. Furthermore, this increase was more pronounced if the politically connected firm incurred damage during the protests or if its headquarters were located in provinces where the protests were more intense.

3.2.3 Pre-Protest Trends in Corporate Insurance Policies

I employ an event study approach to illustrate the dynamics of the effect of the protests on the liability limits of policies covering the assets of politically connected firms over the sample period. The regression equation I estimate is

$$\begin{aligned}\text{Ln(Liability Limit)}_{ait} = {} & \beta_{con}\,\text{Connected}_i + \beta_{pre}\,\text{Connected}_i \times \text{Pre}_t + \sum_{\substack{q=-5 \\ q\neq -1}}^{+3} \beta_q\,\text{Connected}_i \times D_t^q \\ & + \beta_{post}\,\text{Connected}_i \times \text{Post}_t + \beta'_{pre}\,\text{Pre}_t + \sum_{\substack{q=-5 \\ q\neq -1}}^{+3} \beta'_q\,D_t^q + \beta'_{post}\,\text{Post}_t \\ & + \text{Asset Value} \times \text{Asset Class} \times \text{Municipal District FE} + \text{Firm Size} \times \text{Industry} \\ & + \varepsilon_{ait}\end{aligned} \tag{10}$$

where D_t^q are indicator variables set to one for observations in q quarters after (or before, if negative) the first quarter following the end of the protests. Thus, D_0^q captures observations occurring in the first quarter following the end of the protests, which is 2020 Q1. All other variables are defined as in regression Equation (1). The observations are at the granularity of asset on a quarterly basis. Observations occurring at least 5 quarters after the end of the protests are denoted by Post_t, while those occurring at least 5 quarters prior to the end of the protests are captured by Pre_t. Observations from the quarter in which the social protests occurred, which is 2019 Q3, denoted as D_t^{-1}, are excluded to serve as the reference point.

For a given asset, the lags and leads indicate the differential size of the liability limit of the policy covering the asset if the firm is politically connected. The differences between the liability limits for assets of politically connected firms and those owned by unconnected firms during the protest quarter, 2019 Q3, are anchored at 0 in the omitted base period (i.e., the first lead in regression Equation (10)). Therefore, the lags and leads capture the difference between

the treated and control groups relative to the prevailing difference in the omitted base period.

Figure 5a visualizes the estimated coefficients from regression Equation (10). The coefficients on the leads are close to zero, supporting the absence of a pre-existing trend in the difference in liability limits covering assets of connected firms compared to those of unconnected firms. However, starting from the first quarter after the end of the protests, there is a notable increase in the liability limits of policies covering assets of politically connected firms, with this increase appearing to persist over time. This suggests that social protests may lead connected firms to recognize their assets as more susceptible to damage during protests, prompting them to expand their insurance coverage in the future.

3.2.4 Severing Political Connections Following Protests

A body of economic theories suggests that mass political actions act as mechanisms for signaling private information to others (Lohmann, 1994b,a, 1993). These often costly political actions are especially impactful in less open societies, where individuals opposing the status quo may be reluctant to openly express their desire for change (Kuran, 1989, 1991, 1995, 1998). Beyond signaling existing political preferences, social protests can shape political opinions, build movements, and help citizens overcome collective action problems, thus increasing the likelihood of shifts in the future distribution of de jure political power (Acemoglu and Robinson, 2008; Madestam et al., 2013; Aidt and Franck, 2015). This concept is integral to many economic models, where de facto political power drives changes in political institutions and influences the future distribution of de jure political power (Acemoglu and Robinson, 2000, 2001, 2006).

Building on these economic theories, I hypothesize that mass political actions, such as social protests, can prompt politically connected firms to reassess the expected value of their political connections. This reassessment may cause a fraction of firms that were politically connected before the protests to sever their political ties afterward by dismissing their former politician managers. To investigate whether politically connected firms are more likely to sever these connections following the 2019 protests, I analyze a dataset of resumes to determine if former politician corporate officers are more likely to be involuntarily dismissed in the year following the protests compared to their non-former politician counterparts. To test this hypothesis, I

estimate the following regression equation within the subsample of corporate officers:

$$\begin{aligned}\mathbb{1}\text{turnover}_{jit}(t, t+4) = \nu\, \text{FP}_j \times \text{Protest}_t + \text{Gender} \times \text{College} \times \text{Province} \times \text{Y-Quarter FE} \\ + \text{CEO} \times \text{Y-Quarter FE} + \varepsilon_{jit}\end{aligned} \tag{11}$$

where j indexes corporate officers, i denotes firms, and t represents time in quarters. The dependent variable, $\mathbb{1}\text{turnover}_{jit}(t, t{+}4)$, is an indicator set to one if worker j at firm i experiences turnover within four quarters following time t, including time t itself. The ε_{jit} is the error term.

The independent variable, FP_j, is an indicator set to one if corporate officer j was a former politician as of the reference date. The variable CEO is an indicator set to one if the resume holder was employed as the CEO on the reference date. The categorical variables Gender, College, and Province represent the corporate officer's gender, whether they hold a college degree, and their province of residence, respectively.

I estimate regression Equation (11) within the subsample of individuals who, based on their resumes, held corporate officer positions as of the reference date. In regression Equation (11), the comparison group for a given former-politician corporate officer consists of non-former-politician corporate officers who share the same gender, have comparable educational attainment (whether they hold a college degree or not), and reside in the same province during the same quarter.

In Table 15, the coefficient estimates across all five specifications are statistically significant. According to the most rigorous specification in Column 5, former-politician corporate officers are 3.0 percentage points more likely to experience turnover in the year following the protests compared to non-former-politician corporate officers with the same gender, similar educational attainment, and residing in the same province during the same quarter. This represents approximately a 20 percent increase relative to the unconditional probability of turnover.

The likelihood of severing corporate political connections likely increases with the extent to which a connected firm revises its beliefs about the potential ex-post costs of being affiliated with the government. Consequently, I hypothesize that the likelihood of severing corporate political connections will be higher for connected firms that experienced at least one instance of asset damage during the protests. To test this hypothesis, I re-estimate regression Equation (11), focusing on former-politician corporate officers at connected firms that incurred asset damage during the protests.

The coefficient estimates are presented in Table 16, with the regression specifications mirroring those in Table 15. In Panel A, the coefficient estimates across all five specifications are

statistically significant. In the most rigorous specification, shown in Column 5, the results indicate that former-politician corporate officers at firms that incurred damage during the protests were 17.1 percentage points more likely to experience turnover within a year of the protests compared to non-former-politician corporate officers with the same gender, similar educational attainment, and residing in the same province during the same quarter.

A similar analysis is conducted for corporate officers working at connected firms that did not incur damage during the protests. The coefficient estimates are presented in Panel B of Table 16. In the most rigorous specification, the results show that former-politician corporate officers at firms unaffected by protest-related damage were 2.7 percentage points more likely to experience turnover within a year of the protests. This represents a 17.7 percent increase in the likelihood of turnover relative to the unconditional probability of turnover in this subsample.

Overall, the findings in Tables 16 indicate that former-politician corporate officers are significantly more likely to experience turnover within a year of the protests, regardless of whether their firm sustained damage. However, the extent of this increased likelihood of turnover varies based on whether the employer was directly affected by the protests, with a notably larger effect observed for firms that experienced protest-related damage.

3.2.5 Pre-Protest Trends in Turnover

To test the identification assumption of no pre-event trends and to explore the post-event dynamics of how social protests affect the likelihood of turnover for former politician corporate officers, I estimate the following regression equation:

$$\begin{aligned}\text{Turnover}_{jit} = \nu_{FP}\,\text{FP}_j + \nu_{pre}\,\text{FP}_j \times \text{Pre}_t + \sum_{\substack{q=-4\\q\neq-1}}^{+4} \nu_q\,\text{FP}_j \times D_t^q + \nu_{post}\,\text{FP}_j \times \text{Post}_t \\ + \nu'_{pre}\,\text{Pre}_t + \sum_{\substack{q=-4\\q\neq-1}}^{+4} \nu'_q\,D_t^q + \nu'_{post}\,\text{Post}_t + \text{Gender} \times \text{College} \times \text{Province FE} + \varepsilon_{jit}\end{aligned} \tag{12}$$

where D_t^q represents indicator variables set to one for observations occurring q quarters after (or before, if negative) the protests. All other variables are defined as in regression Equation (11). The observations from the quarter immediately preceding the protests, denoted as D_t^{-1}, are excluded to serve as the reference point.

The lags and leads capture the differential likelihood of turnover for former politician corpo-

rate officers working in the private sector, compared to non-former politician corporate officers of the same gender, with similar educational attainment, and residing in the same province during the same quarter. This comparison is relative to the differential likelihood between the two groups in the omitted base period, which is one quarter prior to the protests. Unbiased estimation of the protests' effect on turnover for former politician corporate officers in the subsequent year relies on the parallel trends assumption. This assumption suggests that, in the absence of the protests, former politician corporate officers would have exhibited similar differences in their likelihood of experiencing turnover relative to comparable non-former politician corporate officers.

Figure 6 presents the estimates and statistical significance of the event-study coefficients from regression Equation (12). The coefficients for the lead periods are centered around zero, indicating no significant pre-event differences in turnover likelihood between former politician corporate officers and their non-former politician counterparts. However, one year after the protests, there is a significant increase in the likelihood of turnover for former politician corporate officers compared to observationally similar non-former politician corporate officers.

4 Conclusion

I study about one million corporate assets to investigate whether maintaining close ties with politicians imposes costs on firms when government disapproval escalates, such as during social protests. My analysis reveals that assets of politically connected firms are significantly more likely to incur damage during protests. Additionally, the damages to these firms are more severe, eroding a larger portion of the underlying asset value. I also provide empirical evidence on how protesters identified assets owned by connected firms. The internet, likely through facilitating information sharing and coordination, emerges as the key driver behind the heightened vulnerability of connected firms to asset damage.

The second part of the paper examines how politically connected firms respond to social protests in subsequent years. Politically connected firms, even those that remain undamaged during protests, insure additional assets and expand coverage on existing policies in the years following the protests. The response of politically connected firms goes beyond merely increasing insurance coverage. I document a significant decline in job opportunities for former politicians in managerial roles after the protests. This provides the first direct empirical evidence that social

protests can reduce firms' incentives to form or maintain political ties. From a macroeconomic perspective, this finding is important, as political connections often distort resource allocation within and across firms, potentially stifling economic growth.

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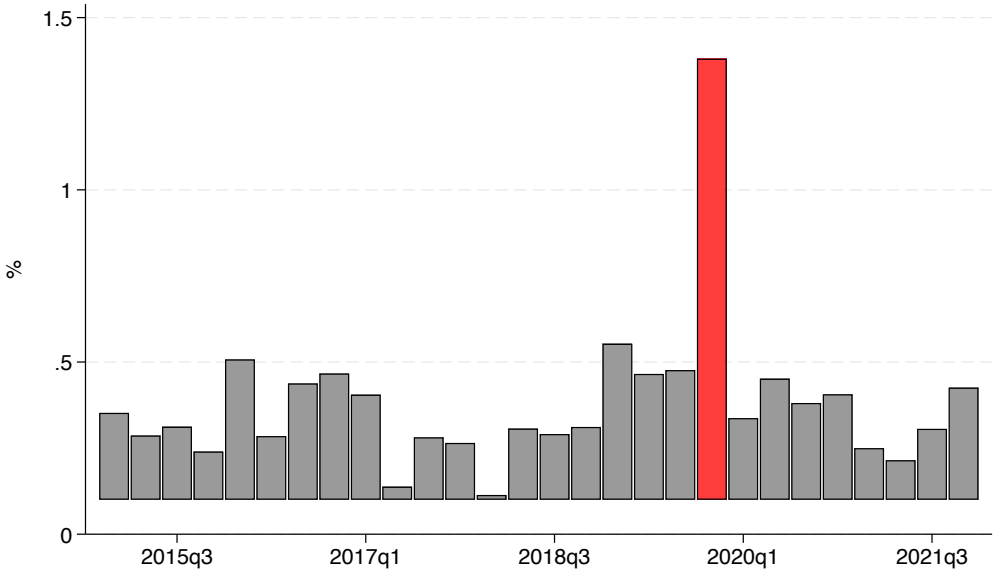
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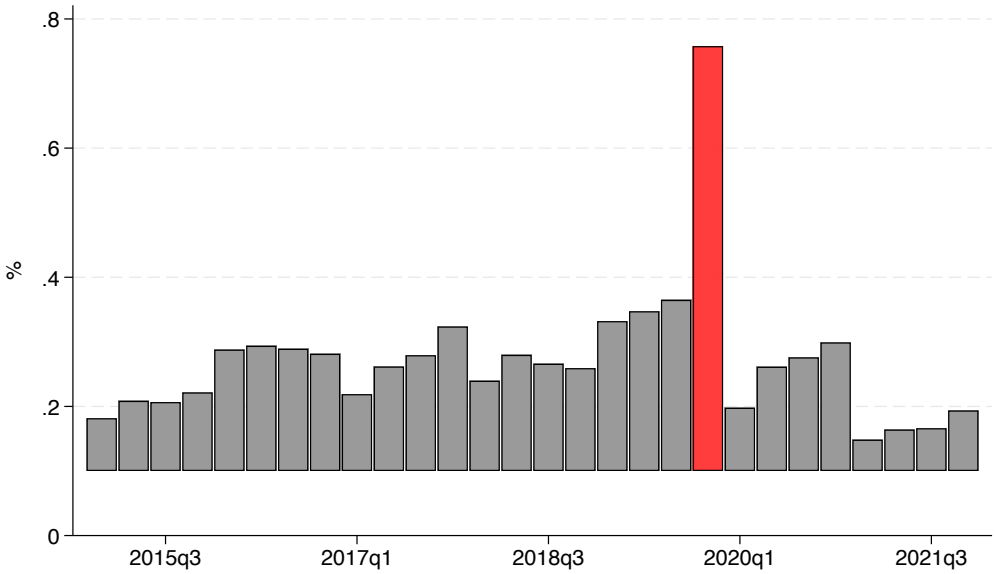
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5 Figures

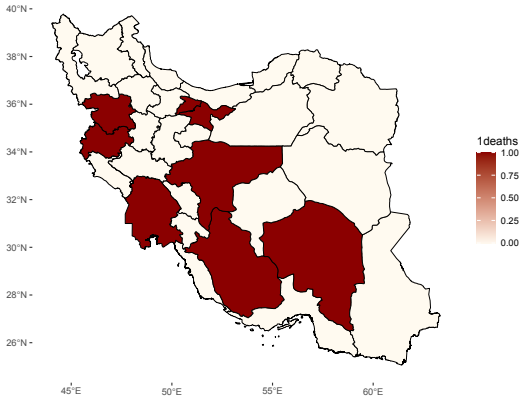


(a) Likelihood of Damage to Connected Firms

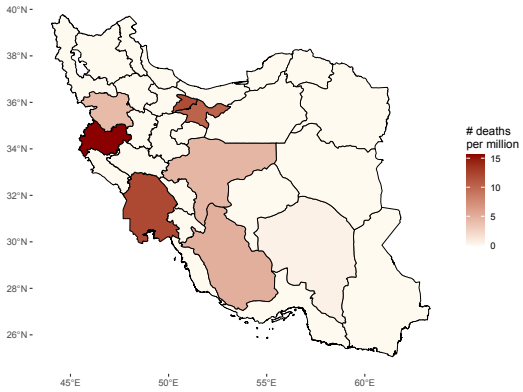


(b) Likelihood of Damage to Unconnected Firms

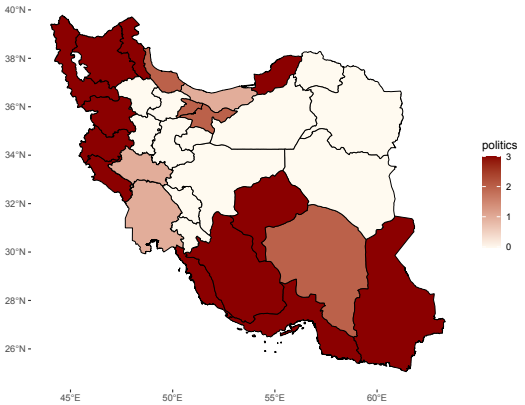
Figure 1: The figure displays the time series of the average likelihood of an insurance event on a quarterly basis from 2015 Q1 to 2021 Q4. The red bars indicate the 2019 Q4 social protests. Panel (a) shows the likelihood of insurance claims by politically connected firms, led by former politicians or military CEOs. Panel (b) shows the likelihood for politically unconnected firms.



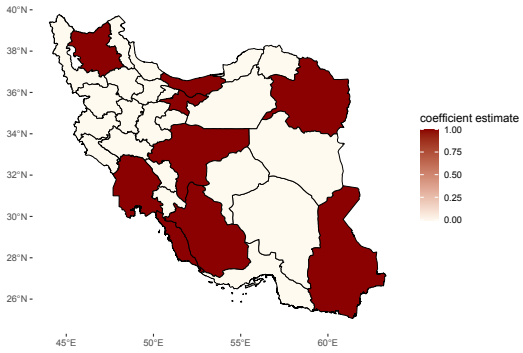
(a) Any Deaths



(b) Deaths Per Million

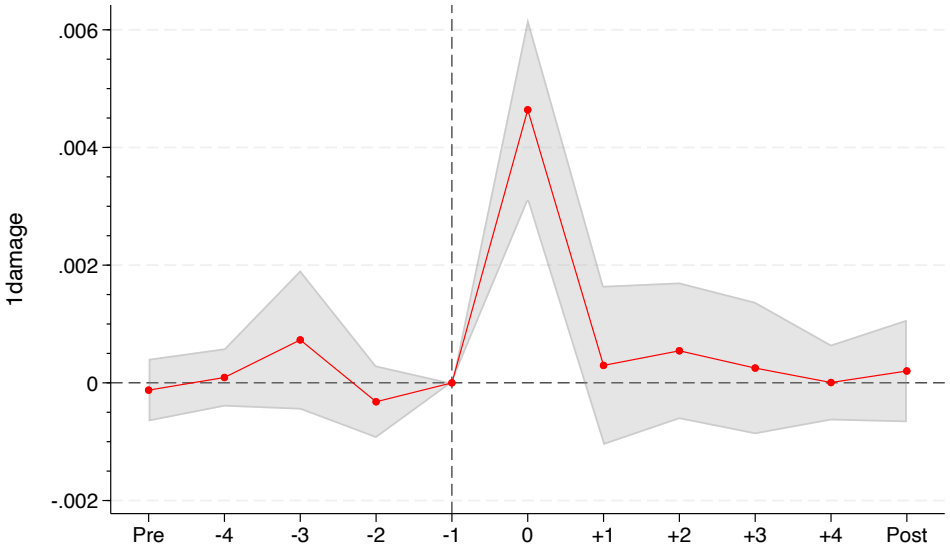


(c) Political orientation

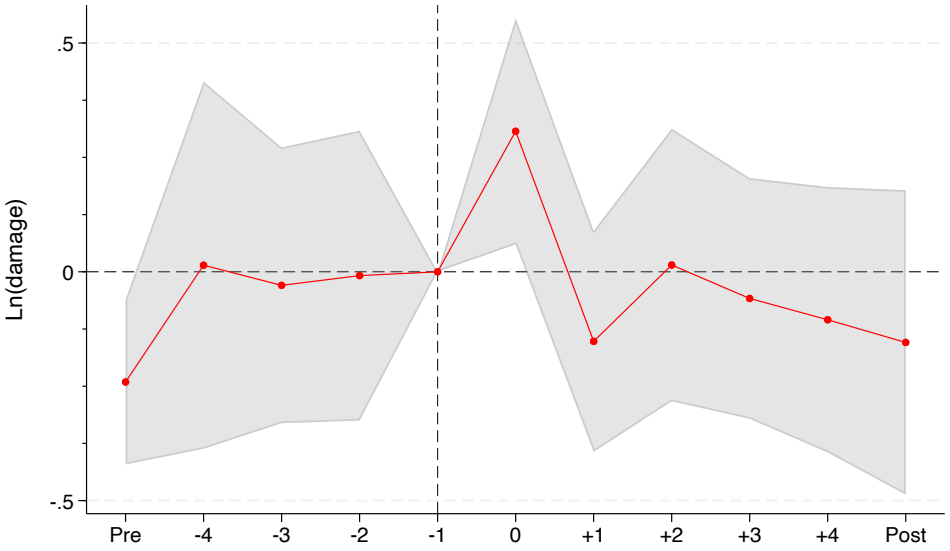


(d) Likelihood of Damage to Connected Firms

Figure 2: The figure presents the geographic distribution of the 2019 social protests and their impact on connected firms across provinces. Panel (a) highlights whether at least one protest-related death occurred in each province, while Panel (b) displays the number of deaths per million residents during the protests, based on Amnesty International data. Panel (c) depicts the political orientation of each province, derived from the outcomes of five presidential elections held between 1997 and 2009. Panel (d) illustrates the provinces where non-industrial properties of connected firms faced a higher likelihood of damage, compared to unconnected firms' similar properties of comparable value within the same municipal district. In provinces colored red, the estimate of β in Equation (1), where the fixed effects are Asset Value $\times$ Y-Quarter FE, is positive and statistically significant at the 5 percent level.



(a) Extensive Margin



(b) Intensive Margin

Figure 3: The figure presents coefficient estimates from regression Equation (2), with the dependent variables being $\mathbb{1}$claim in Panel (a) and Ln(damage) in Panel (b). Panel (a) shows the quarterly differential likelihood of damage to the assets of politically connected firms compared to similar assets of unconnected firms within the same municipal district. Panel (b) illustrates the quarterly differential in the size of damage sustained by the assets of connected firms relative to the size of damages to unconnected firms' assets, also within the same municipal district. The x-axis represents quarters relative to the 2019 social protests, with the quarter immediately preceding the protests omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.

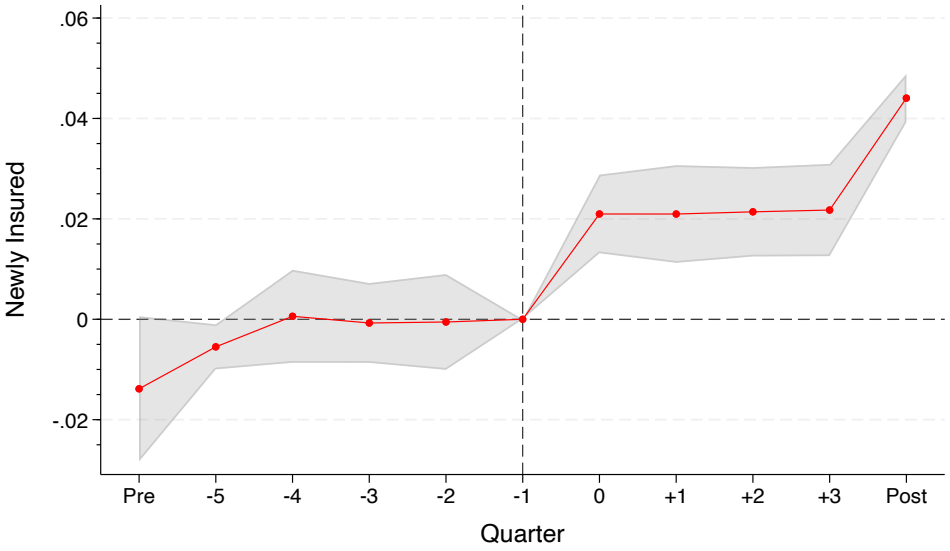
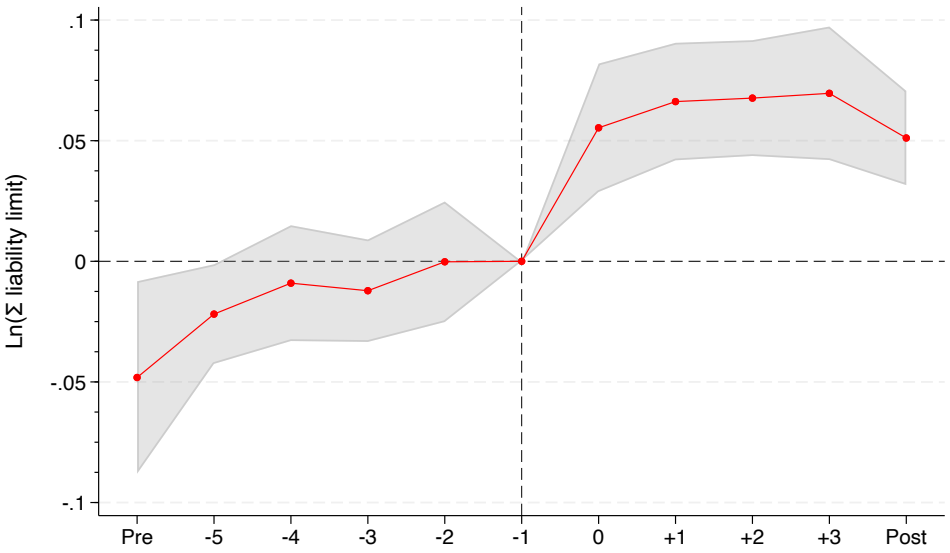
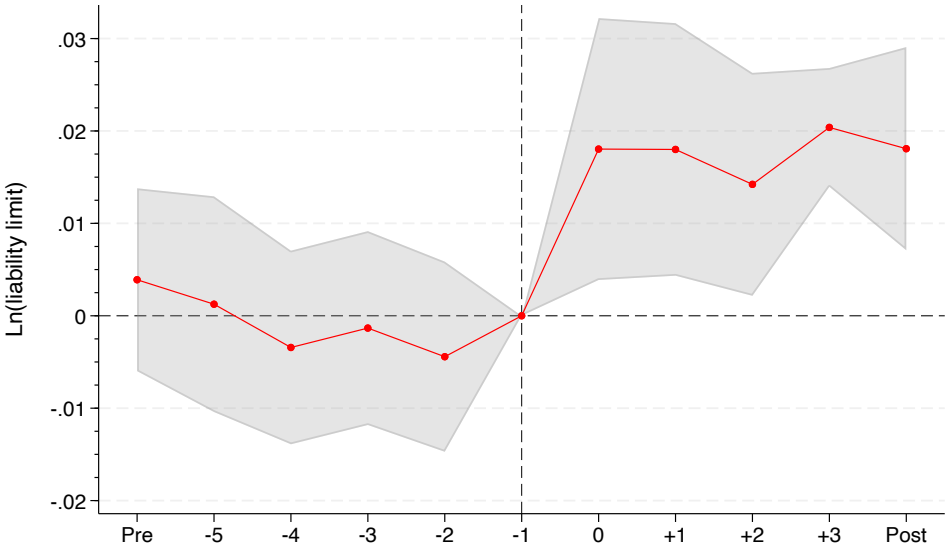


Figure 4: The figure presents coefficient estimates from regression Equation (10), where the dependent variable is an indicator, $\mathbb{1}$(Newly Insured), equal to one if an asset was insured by firm i for the first time at time t. The x-axis represents the quarters relative to the end of the 2019 social protests, with the protest quarter omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.



(a) Aggregate Liability Limit of Connected vs. Unconnected Firms



(b) Liability Limit of Connected vs. Unconnected Firms' Assets

Figure 5: The figure presents coefficient estimates from regression Equation (10). In Panel A, the dependent variable is the logarithm of the total liability limit for each firm across all their assets. In Panel B, the dependent variable is the logarithm of the liability limit for each individual asset. The x-axis represents the quarters relative to the end of the 2019 social protests, with the protest quarter omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.

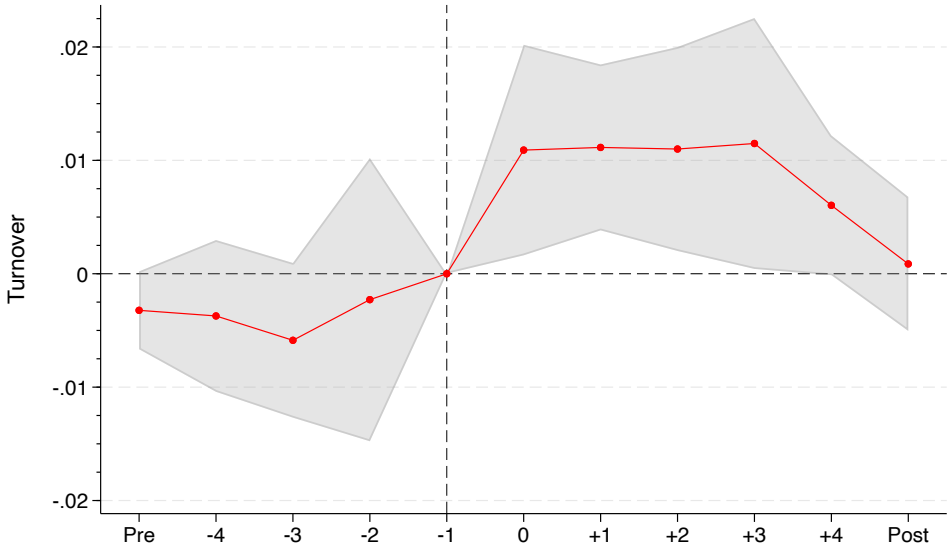


Figure 6: The figure presents coefficient estimates from regression Equation (12), where the dependent variable is an indicator, $\mathbb{1}(\text{Turnover}_{jit})$, equal to one if corporate officer j at firm i experiences turnover at time t. The regression is estimated on a subsample of corporate officers. The figure displays the quarterly difference in the likelihood of turnover between former politician corporate officers and their observationally similar non-former politician counterparts. The x-axis represents the quarters relative to the protests, with the quarter immediately preceding the protests omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.

6 Tables

Table 1: Descriptive Statistics: Politically Connected Vs. Unconnected Firms

	Count	Mean	S.D.	P25	Median	P75
Panel A: Politically Connected Firms						
Firm Size Category	7,448	2.449	1.317	1.000	2.000	3.000
Firm Total Insured Assets Value (in Thousand USD)	7,448	1,029.848	2,710.091	183.054	429.906	907.347
Firm Total Number of Insured Assets	7,448	1.087	0.311	1.000	1.000	1.000
Insured Asset Value (in Thousand USD)	7,448	918.209	2,285.693	170.962	394.880	826.036
Industrial Property	7,448	0.071	0.257	0.000	0.000	0.000
Local Politics at Headquarters Province	7,448	2.307	1.022	2.000	2.000	3.000
Population at Headquarters Province (in Millions)	7,448	7.506	5.081	2.712	5.121	13.268
Urban Household Income at Headquarters Province (in Million IRR)	7,448	612.944	176.856	468.326	520.580	813.170
Rural Household Income at Headquarters Province (in Million IRR)	7,448	359.487	75.728	312.645	400.174	421.664
Unemployment Rate at Headquarters Province	7,448	0.105	0.020	0.091	0.107	0.107
Panel B: Politically Unconnected Firms						
Firm Size Category	122,806	2.022	1.113	1.000	2.000	2.000
Firm Total Insured Assets Value (in Thousand USD)	122,806	691.736	891.298	177.633	409.474	802.268
Firm Total Number of Insured Assets	122,806	1.041	0.213	1.000	1.000	1.000
Insured Asset Value (in Thousand USD)	122,806	663.268	851.651	170.962	392.795	771.412
Industrial Property	122,806	0.061	0.239	0.000	0.000	0.000
Local Politics at Headquarters Province	122,806	2.283	1.019	2.000	2.000	3.000
Population at Headquarters Province (in Millions)	122,806	7.457	5.093	2.712	5.121	13.268
Urban Household Income at Headquarters Province (in Million IRR)	122,806	611.483	177.191	468.326	503.174	813.170
Rural Household Income at Headquarters Province (in Million IRR)	122,806	358.921	75.983	312.645	361.765	421.664
Unemployment Rate at Headquarters Province	122,806	0.105	0.020	0.091	0.107	0.107

The table summarizes descriptive statistics comparing politically connected and unconnected firms based on firm characteristics and regional attributes of their headquarters. In this table, a firm is classified as politically connected if it was led by a former politician or former military official as of 2019 Q3.

Table 2: Descriptive Statistics: Yearly Insurance Policies Across Asset Classes

	Count	Mean	S.D.	P25	Median	P75
Panel A: Non-Industrial Properties						
Value of insured asset (in Billion IRR)	765,225	83.925	141.984	19.300	43.700	91.800
Value of insured asset (in Thousand USD)	765,225	910.728	1,473.417	205.216	469.542	1,014.114
Former politician CEO	765,225	0.055	0.228	0.000	0.000	0.000
Former politician or military CEO	765,225	0.058	0.233	0.000	0.000	0.000
Claim amount (in Million IRR)	7,567	199.962	646.907	33.000	66.000	158.000
Claim amount (in Thousand USD)	7,567	1.974	5.531	0.350	0.724	1.638
Claim amount/Value of insured asset	7,567	0.012	0.067	0.001	0.002	0.006
Panel B: Industrial Properties						
Value of insured asset (in Billion IRR)	58,681	137.301	296.355	24.500	62.800	158.200
Value of insured asset (in Thousand USD)	58,681	1,527.545	2,856.221	258.107	694.904	1,765.537
Former politician CEO	58,681	0.070	0.256	0.000	0.000	0.000
Former politician or military CEO	58,681	0.074	0.262	0.000	0.000	0.000
Claim amount (in Million IRR)	1,294	350.273	3,827.275	31.000	69.000	153.000
Claim amount (in Thousand USD)	1,294	2.479	15.383	0.341	0.714	1.776
Claim amount/Value of insured asset	1,294	0.012	0.138	0.000	0.001	0.004

The table presents summary statistics for 823,906 yearly insurance policies, categorized by the class of the underlying insured asset. Panels A and B display the summary statistics for insurance policies covering non-industrial and industrial properties, respectively. The dataset spans a seven-year period from 2015 to 2021.

Table 3: Descriptive Statistics: Prevalence of Political Connections Across Industries

NAICS	Industry	Count	Percent	%Former Politician CEO	% Former Politician or Former Military CEO
11	Agriculture, Forestry, Fishing and Hunting	5,311	4.1	6.2	10.6
21	Mining, Quarrying, and Oil and Gas Extraction	1,606	1.2	14.4	25.5
22	Utilities	784	0.6	2.0	4.2
23	Construction	16,715	12.8	3.8	6.6
31-33	Manufacturing	11,683	9.0	4.6	8.0
42	Wholesale Trade	3,535	2.7	1.0	2.1
44-45	Retail Trade	10,775	8.3	1.2	2.2
48-49	Transportation and Warehousing	3,656	2.8	3.1	5.6
51	Information	5,586	4.3	3.5	6.0
52	Finance and Insurance	7,622	5.9	6.7	11.1
53	Real Estate and Rental and Leasing	6,473	5.0	2.7	4.5
54	Professional, Scientific, and Technical Services	18,052	13.9	2.4	4.3
55	Management of Companies and Enterprises	488	0.4	2.3	4.3
56	Administrative and Support and Waste Management and Remediation Services	1,074	0.8	5.2	9.0
61	Educational Services	3,647	2.8	1.0	2.1
62	Health Care and Social Assistance	10,427	8.0	3.0	5.2
71	Arts, Entertainment, and Recreation	1,375	1.1	0.6	0.9
72	Accommodation and Food Services	10,892	8.4	1.6	2.9
81	Other Services	10,553	8.1	3.0	5.2
—	All	130,254	100.0	3.3	5.7

The table shows the distribution of economic activity among firms with active insurance policies as of the reference date. Column 2 lists the 2-digit NAICS codes, while Column 3 shows the percentage of policyholders in each sector relative to the total sample. Columns 4 and 5 respectively indicate the percentage of firms led by a former politician as CEO, and the percentage of firms led by either a former politician CEO or a former military CEO. The Mining, Quarrying, and Oil and Gas Extraction sector exhibits the highest prevalence of corporate political connections, with approximately 25.5 percent of firms led by either a former politician CEO or a former military CEO. In contrast, the Arts, Entertainment, and Recreation sector has the lowest incidence, with only about 0.9 percent of firms having a former politician or former military CEO.

Table 4: Likelihood of Damage to Assets of Connected Firms During the Protests

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0046***	0.0044***	0.0044***	0.0045***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Protest	0.0051***			
	(0.0002)			
Connected	0.0007***	0.0006***	0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	3,106,853	3,106,853	3,100,944	3,100,944
R2	0.000	0.003	0.016	0.017

The table presents coefficient estimates from regression Equation (1), where the dependent variable is $\mathbb{1}$damage. The table investigates whether the assets of politically connected firms were more likely to incur damage during the protests compared to similar assets of unconnected firms. Politically connected firms are defined as those led by former politician CEOs. Standard errors are two-way clustered at the municipality district and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Magnitude of Damage to Assets of Connected Firms During the Protests

	damage			
	(1)	(2)	(3)	(4)
Panel A: Absolute Magnitude				
Connected×Protest	0.3953***	0.3935***	0.4475***	0.3232**
	(0.0536)	(0.0528)	(0.0882)	(0.1181)
Protest	-0.5823***			
	(0.1228)			
Connected	0.0517	0.0154	0.0426	0.2258**
	(0.0457)	(0.0466)	(0.0547)	(0.1045)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	6.711	6.675	6.635	6.542
N	8,861	7,379	4,313	3,461
R2	0.025	0.423	0.487	0.635
	damage/asset value			
	(1)	(2)	(3)	(4)
Panel B: Relative Magnitude				
Connected×Protest	0.0073***	0.0101**	0.0062***	0.0070*
	(0.0015)	(0.0043)	(0.0021)	(0.0034)
Protest	-0.0063***			
	(0.0017)			
Connected	-0.0026**	-0.0054	-0.0003	0.0001
	(0.0013)	(0.0044)	(0.0015)	(0.0034)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.012	0.011	0.010	0.011
N	8,861	7,379	4,313	3,461
R2	0.001	0.301	0.293	0.604

The table presents coefficient estimates from regression Equation (1), where the dependent variable is Ln(damage) in Panel A and damage/asset value in Panel B. The table examines whether, conditional on sustaining damage during social protests, the assets of politically connected firms experienced more severe damage. In Panel A, damage severity is measured in absolute terms using the natural logarithm of the monetary amount of insurance claims. In Panel B, severity is measured in relative terms, with respect to the monetary value of the underlying assets. In both panels, standard errors are two-way clustered at the municipality district and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Protest Days in the Absence of Internet Access

	$\mathbb{1}$damage				
	(1)	(2)	(3)	(4)	(5)
Connected × Internet Shutdown	-0.00041**	-0.00040**	-0.00041**	-0.00042**	-0.00043**
	(0.00018)	(0.00018)	(0.00018)	(0.00018)	(0.00017)
Internet Shutdown	0.00009				
	(0.00005)				
Connected	0.00050***	0.00050***	0.00049***	0.00049***	0.00049***
	(0.00014)	(0.00014)	(0.00014)	(0.00014)	(0.00013)
Asset Class×Y-Day FE	-	Yes	Yes	Yes	-
Asset Value×Y-Day FE	-	-	Yes	Yes	-
Municipal District×Y-Day FE	-	-	-	Yes	-
Asset Class×Asset Value×Municipal District×Y-Day FE	-	-	-	-	Yes
Avg (y)	0.0004	0.0004	0.0004	0.0004	0.0004
N	1,694,770	1,694,770	1,694,770	1,694,770	1,692,471
R2	0.0000	0.0000	0.0001	0.0014	0.0109

The table presents coefficient estimates from regression Equation (3), where the dependent variable is $\mathbb{1}$damage. The analysis investigates whether politically connected firms were less likely to experience asset damage during the protests when the internet was shut down. Standard errors are two-way clustered at the municipality district and year-day levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Likelihood of Damage to Connected Firms During the Protests Across Asset Classes

	$\mathbb{1}$damage			
	Non-Industrial		Industrial	
	(1)	(2)	(3)	(4)
Connected×Protest	0.0048***	0.0049***	0.0011	-0.0020
	(0.0003)	(0.0002)	(0.0027)	(0.0024)
Connected	0.0006***	0.0007***	0.0003	0.0004
	(0.0002)	(0.0002)	(0.0008)	(0.0009)
Asset Value×Y-Quarter FE	Yes	Yes	Yes	Yes
Municipal District×Y-Quarter FE	-	Yes	-	Yes
Firm size×Industry×Y-Quarter FE	-	Yes	-	Yes
Avg (y)	0.003	0.003	0.006	0.006
N	2,885,436	2,885,436	221,417	220,820
R2	0.001	0.004	0.002	0.039

The table presents coefficient estimates from regression Equation (1), where the dependent variable is $\mathbb{1}$damage. The table explores which asset classes owned by politically connected firms were more likely to incur damage during the protests. Standard errors are two-way clustered at the municipality district and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Magnitude of Damage to Connected Firms During the Protests Across Asset Classes

	damage			
	Non-Industrial		Industrial	
	(1)	(2)	(3)	(4)
Panel A: Absolute Magnitude				
Connected×Protest	0.4715***	0.4766***	-0.0461	-0.3621
	(0.0606)	(0.0836)	(0.3709)	(0.2906)
Connected	0.0543	0.0500	-0.2009	0.0307
	(0.0343)	(0.0503)	(0.2017)	(0.1779)
Asset Value×Y-Quarter FE	Yes	Yes	Yes	Yes
Municipal District×Y-Quarter FE	-	Yes	-	Yes
Avg (y)	6.709	6.667	6.724	6.641
N	7,567	6,065	1,292	877
R2	0.258	0.443	0.294	0.461
	damage/asset value			
	Non-Industrial		Industrial	
	(1)	(2)	(3)	(4)
Panel B: Relative Magnitude				
Connected×Protest	0.0099***	0.0072***	0.0262	-0.0047
	(0.0017)	(0.0017)	(0.0256)	(0.0030)
Connected	-0.0034**	-0.0016	-0.0282	0.0024
	(0.0016)	(0.0013)	(0.0254)	(0.0030)
Asset Value×Y-Quarter FE	Yes	Yes	Yes	Yes
Municipal District×Y-Quarter FE	-	Yes	-	Yes
Avg (y)	0.012	0.011	0.012	0.007
N	7,567	6,065	1,292	877
R2	0.071	0.278	0.286	0.445

The table presents coefficient estimates from regression Equation (1), where the dependent variable is Ln(damage) in Panel A and damage/asset value in Panel B. The analysis investigates, conditional on sustaining damage during social protests, which asset classes owned by politically connected firms experienced more severe damage. In Panel A, damage severity is measured in absolute terms using the natural logarithm of the monetary amount of insurance claims. In Panel B, severity is measured in relative terms as a fraction of the monetary value of the underlying assets. In both panels, standard errors are two-way clustered at the municipality district and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Damage to Assets of Connected Firms During the Protests in Provinces with Higher Protest Intensity

	𝟙damage			damage/asset value		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Connected×Protest×Death	0.0086***	0.0082***	0.0081***	0.0028	0.0017	0.0051
	(0.0006)	(0.0006)	(0.0006)	(0.0053)	(0.0027)	(0.0123)
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	Yes	Yes	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	Yes	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.012	0.010	0.011
N	3,106,853	3,100,944	3,100,944	8,861	4,313	3,461
R2	0.001	0.016	0.017	0.001	0.293	0.604
Panel B						
Connected×Protest×Reformist	0.0036***	0.0035***	0.0034***	0.0070*	0.0046*	0.0011
	(0.0004)	(0.0002)	(0.0002)	(0.0036)	(0.0026)	(0.0099)
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	Yes	Yes	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	Yes	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.012	0.010	0.011
N	3,106,853	3,100,944	3,100,944	8,861	4,313	3,461
R2	0.000	0.016	0.017	0.001	0.293	0.604

The table presents coefficient estimates from regression Equation (4), which explores whether the likelihood and severity of damage to politically connected firms' assets during the protests were greater in provinces where the protests were more intense. In Panel A, protest intensity is measured by 𝟙death, an indicator set to one if at least one protester death was reported in the province. In Panel B, intensity is measured by 𝟙reformist, an indicator set to one for provinces where the majority of residents typically vote for reformist politicians, as opposed to conservative provinces. The first three regression specifications assess whether damage was more likely, while the subsequent three specifications examine the severity of the damage. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Insuring New Assets Following the Protests

	𝟙(Newly Insured)				
	(1)	(2)	(3)	(4)	(5)
Connected×Following Protest	0.0151***	0.0146***	0.0143***	0.0146***	0.0149***
	(0.0021)	(0.0029)	(0.0030)	(0.0032)	(0.0031)
Following Protest	-0.0644***				
	(0.0190)				
Connected	-0.0003	0.0000	0.0006	0.0005	0.0004
	(0.0003)	(0.0009)	(0.0010)	(0.0010)	(0.0009)
Province×Y-Quarter FE	-	Yes	Yes	Yes	-
Firm Size×Y-Quarter FE	-	-	Yes	Yes	-
Industry×Y-Quarter FE	-	-	-	Yes	-
Province×Firm Size×Industry×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.078	0.078	0.078	0.078	0.078
N	4,598,889	4,598,889	4,598,889	4,598,889	4,593,005
R2	0.013	0.172	0.172	0.172	0.184

The table presents coefficient estimates from the regression Equation (5), where the dependent variable, 𝟙(Newly Insured), is an indicator set to one if an asset was insured by firm i for the first time at time t, meaning the dataset contains no prior policy covering that asset by firm i before t. The analysis examines whether, in the aftermath of the protests, politically connected firms are more likely than comparable politically unconnected firms to insure new corporate assets. Standard errors are two-way clustered at the province and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Insuring New Assets Following the Protests in Provinces with Higher Protest Intensity

	𝟙(Newly Insured)				
	(1)	(2)	(3)	(4)	(5)
Panel A					
Connected×Following Protest×Death	0.0146***	0.0140***	0.0140***	0.0140***	0.0156***
	(0.0026)	(0.0032)	(0.0032)	(0.0032)	(0.0037)
Province×Y-Quarter FE	-	Yes	Yes	Yes	-
Firm Size×Y-Quarter FE	-	-	Yes	Yes	-
Industry×Y-Quarter FE	-	-	-	Yes	-
Province×Firm Size×Industry×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.078	0.078	0.078	0.078	0.078
N	4,598,889	4,598,889	4,598,889	4,598,889	4,593,005
R2	0.013	0.172	0.172	0.172	0.184
Panel B					
Connected×Following Protest×Reformist	0.0084*	0.0105**	0.0105**	0.0105**	0.0113**
	(0.0043)	(0.0050)	(0.0050)	(0.0050)	(0.0053)
Province×Y-Quarter FE	-	Yes	Yes	Yes	-
Firm Size×Y-Quarter FE	-	-	Yes	Yes	-
Industry×Y-Quarter FE	-	-	-	Yes	-
Province×Firm Size×Industry×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.078	0.078	0.078	0.078	0.078
N	4,598,889	4,598,889	4,598,889	4,598,889	4,593,005
R2	0.013	0.172	0.172	0.172	0.184

The table presents coefficient estimates from the regression Equation (6), where the dependent variable is 𝟙(Newly Insured). The analysis investigates whether the intensity of social protests in the province where firms are located is correlated with the post-protest increase in the likelihood that politically connected firms insure additional assets. In Panel A, protest intensity is measured by 𝟙death, an indicator set to one if at least one protester death was reported in the province. In Panel B, intensity is measured by 𝟙reformist, an indicator set to one for provinces where the majority of residents typically vote for reformist politicians, as opposed to conservative provinces. In both panels, standard errors are two-way clustered at the province and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Aggregate Liability Limit of Connected Firms' Insurance Policies Following the Protests

	Ln($\sum$ liability limit)				
	(1)	(2)	(3)	(4)	(5)
Connected×Following Protest	0.0940***	0.0949***	0.0934***	0.0923***	0.0921***
	(0.0081)	(0.0074)	(0.0048)	(0.0040)	(0.0048)
Following Protest	0.7163***				
	(0.0898)				
Connected	0.1372***	0.1329***	-0.0485	-0.0515	-0.0532
	(0.0361)	(0.0370)	(0.0374)	(0.0373)	(0.0385)
Province×Y-Quarter FE	-	Yes	Yes	Yes	-
Firm Size×Y-Quarter FE	-	-	Yes	Yes	-
Industry×Y-Quarter FE	-	-	-	Yes	-
Province×Firm Size×Industry×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	3.791	3.791	3.791	3.791	3.790
N	3,106,853	3,106,853	3,106,853	3,106,853	3,100,185
R2	0.065	0.090	0.200	0.200	0.216

The table presents coefficient estimates from regression Equation (7), where the dependent variable, Ln($\sum$ liability limit), represents the natural logarithm of the total liability limits across all insured assets of firm i at time t. The analysis examines whether the aggregate liability limit across all insurance policies held by politically connected firms significantly increased following the protests. Standard errors, shown in parentheses, are two-way clustered at the province and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Liability Limit of Policies Covering Assets of Connected Firms Following the Protests

	Ln(liability limit)			
	(1)	(2)	(3)	(4)
Panel A				
Connected×Following Protest	0.1170***	0.0111***	0.0128***	0.0163***
	(0.0036)	(0.0003)	(0.0003)	(0.0022)
Following Protest	0.7006***			
	(0.0903)			
Connected	0.0568**	0.0455***	0.0437***	0.0162
	(0.0275)	(0.0122)	(0.0123)	(0.0114)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	3.678	3.678	3.678	3.678
N	923,431	923,431	918,636	918,631
R2	0.060	0.835	0.840	0.842
Panel B				
Connected×Following Protest×Damaged	0.0382*	0.1180***	0.1282***	0.1250***
	(0.0198)	(0.0082)	(0.0051)	(0.0042)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	3.678	3.678	3.678	3.678
N	923,431	923,431	918,636	918,631
R2	0.060	0.835	0.840	0.842

Panel A presents coefficient estimates from regression Equation (8), where the dependent variable is Ln(liability limit). The analysis focuses on the subsample of corporate assets that were insured before, during, and after the protests. Panel B presents coefficient estimates from regression Equation (9), which investigates whether the liability limits on policies covering politically connected firms' assets that sustained damage during the protests increased more than those for similar assets of politically connected firms that were not damaged. In both panels, standard errors are two-way clustered at the municipality district and year-quarter levels, with values reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14: Liability Limit of Policies Covering Assets of Connected Firms Following the Protests in Provinces with Higher Protest Intensity

	Ln(liability limit)			
	(1)	(2)	(3)	(4)
Panel A				
Connected×Following Protest×Death	0.0054	0.0053***	0.0033*	0.0030
	(0.0092)	(0.0011)	(0.0018)	(0.0025)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	3.678	3.678	3.678	3.678
N	923,431	923,431	918,636	918,631
R2	0.060	0.835	0.840	0.842
Panel B				
Connected×Following Protest×Reformist	0.0069*	0.0133***	0.0155***	0.0143***
	(0.0038)	(0.0007)	(0.0008)	(0.0015)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	3.678	3.678	3.678	3.678
N	923,431	923,431	918,636	918,631
R2	0.060	0.835	0.840	0.842

The table presents coefficient estimates from regression Equation (4), where the dependent variable is Ln(Liability Limit)$_{ait}$. The analysis investigates whether the intensity of social protests in the province where the headquarters of a connected firm is located is associated with the post-protest increase in the liability limit of policies covering assets of that firm. In Panel A, protest intensity is measured by $\mathbb{1}$death, an indicator set to one if at least one protester death was reported in the province. In Panel B, intensity is measured by $\mathbb{1}$reformist, an indicator set to one for provinces where the majority of residents typically vote for reformist politicians, as opposed to conservative provinces. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Turnover for Former Politician Corporate Officers Following the Protests

	$\mathbb{1}\text{turnover}_{jit}(t, t+4)$				
	(1)	(2)	(3)	(4)	(5)
Former Politician×Protest	0.032***	0.032***	0.031***	0.031***	0.030***
	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)
Protest	0.010***				
	(0.002)				
Former politician	0.022***	0.016***	0.016***	0.016***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Gender×Y-Quarter FE	-	Yes	-	-	-
College Degree×Y-Quarter FE	-	-	Yes	-	-
Province×Y-Quarter FE	-	-	-	Yes	-
Gender×College Degree×Province×Y-Quarter FE	-	-	-	-	Yes
CEO Rank×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.141	0.141	0.141	0.141	0.141
N	427,056	427,056	427,056	427,056	427,056
R2	0.000	0.003	0.004	0.005	0.011

The table presents coefficient estimates from regression Equation (11), where the dependent variable, $\mathbb{1}\text{turnover}_{jit}(t, t+4)$, is an indicator equal to one if corporate officer j at firm i experiences turnover within four quarters following time t, including time t. The analysis investigates whether corporate officers who are former politicians are more likely to experience turnover in the aftermath of the 2019 protests. Standard errors, reported in parentheses, are two-way clustered at the province and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 16: Turnover for Former Politician Corporate Officers Following the Protests

	$\mathbb{1}\text{turnover}_{jit}(t, t+4)$				
	(1)	(2)	(3)	(4)	(5)
Panel A: Damaged Connected Firms					
Former Politician×Protest	0.174***	0.173***	0.172***	0.171***	0.171***
	(0.035)	(0.027)	(0.026)	(0.021)	(0.021)
Protest	0.010***				
	(0.002)				
Former politician	0.038	0.035	0.037	0.036	0.041
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Gender×Y-Quarter FE	-	Yes	-	-	-
College Degree×Y-Quarter FE	-	-	Yes	-	-
Province×Y-Quarter FE	-	-	-	Yes	-
Gender×College Degree×Province×Y-Quarter FE	-	-	-	-	Yes
CEO Rank×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.139	0.139	0.139	0.139	0.139
N	383,397	383,397	383,397	383,397	383,397
R2	0.000	0.003	0.003	0.005	0.012
Panel B: Undamaged Connected Firms					
Former Politician×Protest	0.030***	0.030***	0.029***	0.029***	0.027***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)
Protest	0.010***				
	(0.002)				
Former politician	0.022***	0.015***	0.016***	0.016***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Gender×Y-Quarter FE	-	Yes	-	-	-
College Degree×Y-Quarter FE	-	-	Yes	-	-
Province×Y-Quarter FE	-	-	-	Yes	-
Gender×College Degree×Province×Y-Quarter FE	-	-	-	-	Yes
CEO Rank×Y-Quarter FE	-	-	-	-	Yes
Avg (y)	0.141	0.141	0.141	0.141	0.141
N	426,489	426,489	426,489	426,489	426,489
R2	0.000	0.003	0.004	0.005	0.011

The table reports coefficient estimates from regression Equation (11), where the dependent variable, $\mathbb{1}\text{turnover}_{jit}(t, t+4)$, is an indicator equal to one if corporate officer j at firm i experiences turnover within four quarters following time t, including time t. Panel A evaluates whether the likelihood of turnover for former politician corporate officers is higher if their firm incurred damage during the protests. Panel B, on the other hand, investigates whether turnover likelihood increased for those employed by connected firms that did not suffer any damage during the protests. Standard errors, reported in parentheses, are two-way clustered at the province and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

7 Appendix



مشخصات بیمه‌نامه
شماره‌بیمه‌نامه: [redacted] کدیکتابیمه‌مرکزی: [redacted] نمایندگی: [redacted]
عنوان‌قرارداد: تاریخ‌صدور: [redacted] کدنمایندگی: [redacted]
شماره‌بیمه‌نامه‌سال‌قبل: [redacted] کدرایانه‌بیمه‌نامه‌سال‌قبل: [redacted] کدرایانه‌بیمه‌نامه: [redacted]

مشخصات بیمه‌گذار
نام: [redacted] کدملی/شماره‌اقتصادی: [redacted] تلفن: [redacted]
نشانی: استان تهران،شهر تهران-خیابان آزادی خیابان خوش شمالی [redacted] کدپستی: [redacted] شماره‌همراه: [redacted]

ذینفع بیمه‌نامه
ذینفع:

مشخصات موردبیمه
نوع‌کاربری: آتش سوزی - غیر صنعتی موضوع‌فعالیت: ساختمان های اداری
نام‌استان: تهران نام‌شهر: تهران
نشانی‌محل‌موردبیمه: خیابان خوش شمالی [redacted] کدپستی: [redacted]

خطرات موردتعهد
خطرات زیر طبق شرایط پیوست تحت پوشش این بیمه نامه می باشد:
تش سوزی، صاعقه، انفجار: شامل تمام موارد (۰/۲۵) ، پوشش ترکیدگی لوله های آب: شامل تمام موارد (۰/۱) ، پوشش زلزله و آتشفشان: شامل تمام موارد (۰/۱۵)

مدت بیمه
این‌بیمه‌نامه‌ازساعت۲۴مورخ [redacted] تاساعت۲۴مورخ [redacted] بمدت ۳۶۵ روزمعتبرمی‌باشد.

	شرح‌وارزش‌موردبیمه	ارزش‌موردبیمه(ریال)	نرخ‌درهزار	حق‌بیمه(ریال)
	مواردبیمه‌عبارت‌است‌از:			
۱	اثاثیه‌ثابت‌اداری‌جمعابه‌مبلغ:	۵,۰۰۰,۰۰۰,۰۰۰	۰.۲۵	۱,۲۵۰,۰۰۰
۲	دستگاههای‌نوبت‌دهی‌بیمارستانها‌وکارت‌خوانهاوپرینترجمعابه‌مبلغ:	۳,۰۰۰,۰۰۰,۰۰۰	۰.۲۵	۷۵۰,۰۰۰
۳	تجهیزات‌اداری‌واقع‌درمحل‌موردبیمه‌جمعابه‌مبلغ:	۷,۰۰۰,۰۰۰,۰۰۰	۰.۲۵	۱,۷۵۰,۰۰۰
	جمع‌ارزش‌موردبیمه:	۱۵,۰۰۰,۰۰۰,۰۰۰ریال	حق‌بیمه‌موارد	۳,۷۵۰,۰۰۰ریال
			حق‌بیمه‌خطرات‌اضافی	۳,۷۵۰,۰۰۰ریال
			حق‌بیمه‌کل‌آتش‌سوزی	۷,۵۰۰,۰۰۰ریال

شرایط خصوصی
شرایط‌خصوصی‌طبق‌پیوست

حق بیمه
حق‌بیمه‌بدون‌مالیات: ۷,۵۰۰,۰۰۰ ریال تخفیف:
جمع‌حق‌بیمه‌قابل‌پرداخت(به‌عدد): ۸,۱۷۵,۰۰۰ ریال مالیات‌برارزش‌افزوده: ۶۷۵,۰۰۰ ریال
جمع‌حق‌بیمه‌قابل‌پرداخت(به‌حروف): هشت میلیون و یکصد و هفتاد و پنج هزار ریال

Figure 7: The figure shows a corporate insurance policy in which the identifying information of both the insurer and the firm has been obscured for privacy. These policies typically consist of eight sections. The first section includes policy declarations, which includes information such as the policy number and details of the insurance company's issuing branch. This is followed by sections on policyholder information, covered property, covered perils, policy period, a breakdown of covered assets and premium, policy conditions, and the payment schedule.

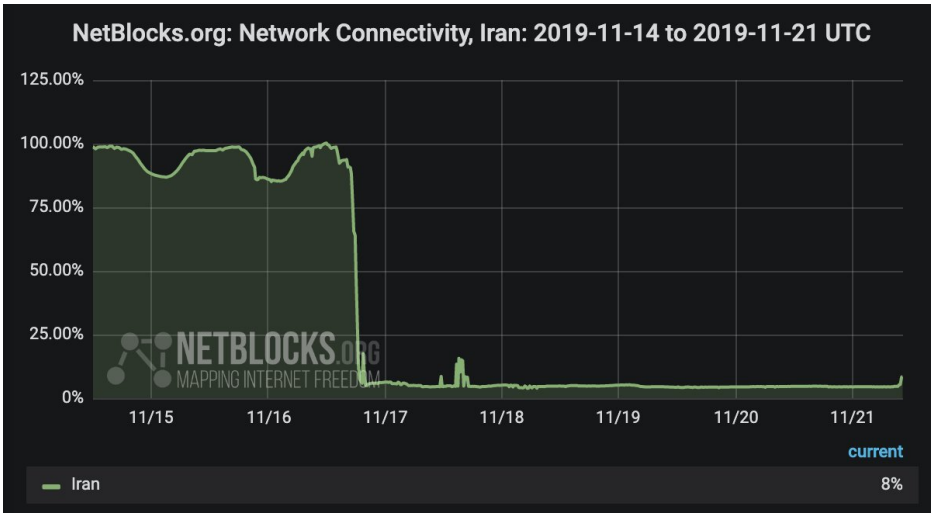


(a) Abbas Nasiri

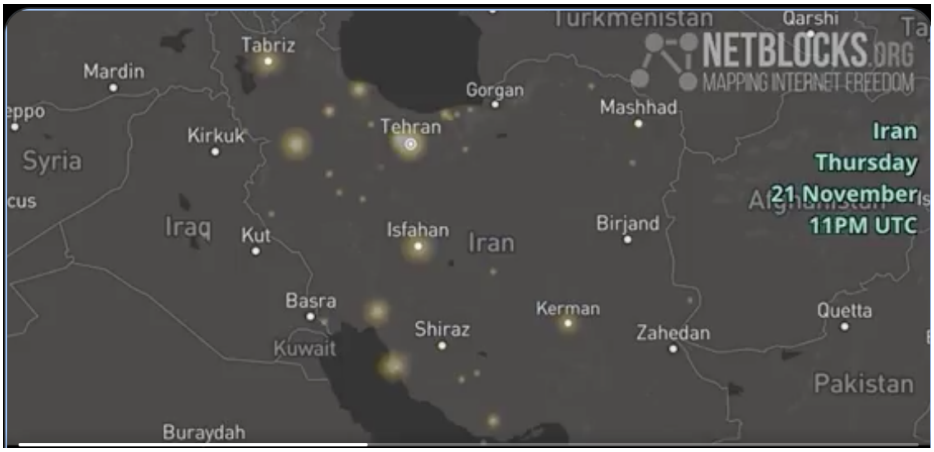


(b) Colonel Hussein Goudarzi

Figure 8: Although many of the social media doxing campaigns during the protests were either suspended by the platforms or later removed by account owners, the figure provides two examples of such posts. Each post identifies an individual allegedly linked to the government or armed forces, typically disclosing their employment history in these sectors along with current identifying details such as name, photo, phone number, and the addresses of their homes and businesses. For instance, the text in Panel (a), translated by Google, reads: "Abbas Nasiri, Head of Sepah Bank in Malayer. This mercenary is an employee of the Ministry of Intelligence who played a significant role in suppressing the protests. He was responsible for interrogating and obtaining confessions from young fighters arrested by the Intelligence Department. In Malayer, he has been appointed as the head of Sepah Bank as a cover ..."

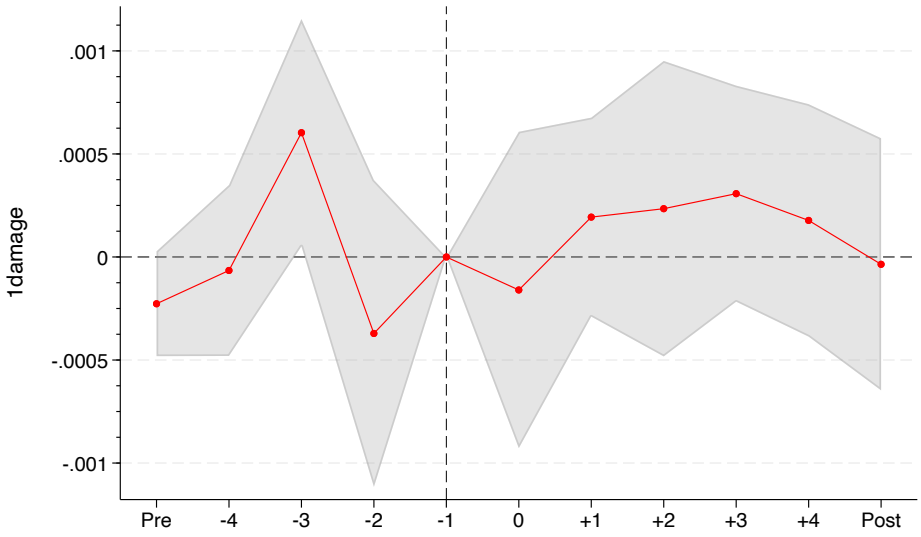


(a) Internet Connectivity from November 14 to 21

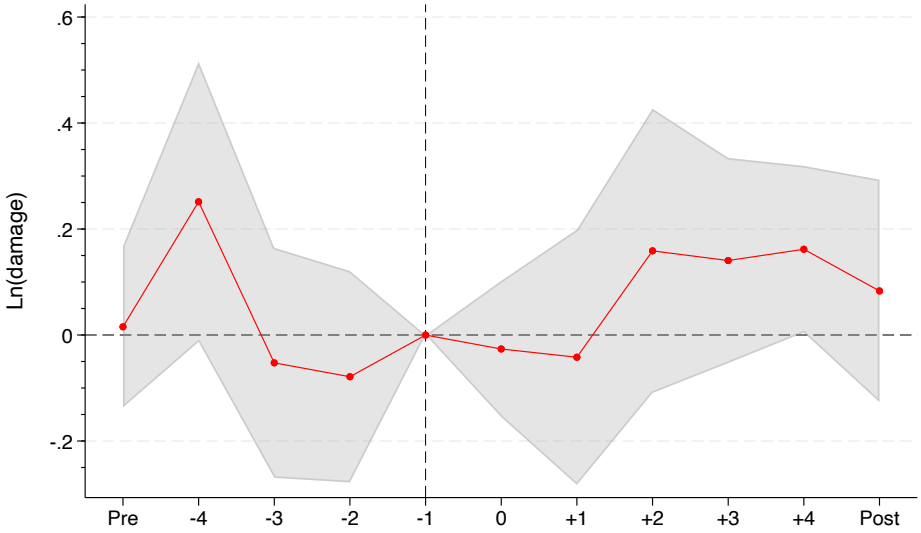


(b) Internet Connectivity on November 21 at 11 PM UTC

Figure 9: The figure presents the time series of internet connectivity in Iran from November 14 to 21, as reported by the NetBlocks internet observatory. A near-total national internet shutdown commenced on the evening of November 16 and continued until November 21, when connectivity gradually began to be restored, as shown in Panel (b).

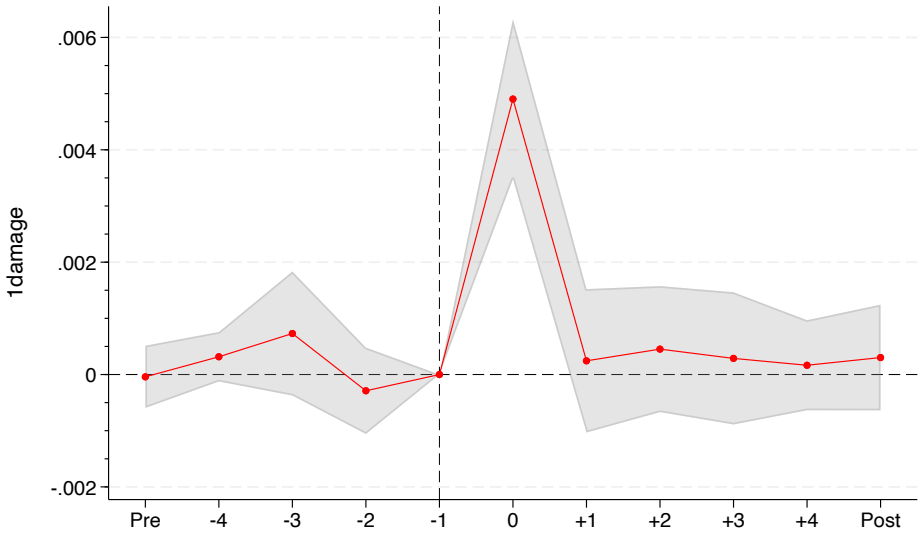


(a) Extensive Margin

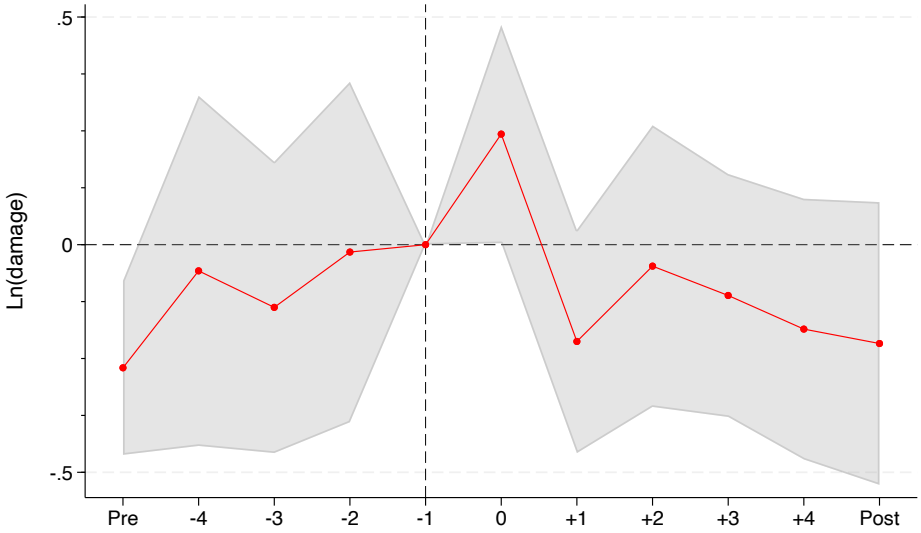


(b) Intensive Margin

Figure 10: The figure presents coefficient estimates from regression Equation (2), where the dependent variables are 1claim in Panel (a) and Ln(damage) in Panel (b). Panel (a) displays the quarterly differential likelihood of damage to the assets of firms led by CEOs who are non-politician, non-military former bureaucrats compared to similar assets of unconnected firms within the same municipal district. Panel (b) illustrates the quarterly differential in the size of damage sustained by these firms' assets relative to the size of damages to unconnected firms' similar assets within the same municipal district. The x-axis represents the quarters relative to the 2019 social protests, with the quarter immediately preceding the protests omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.



(a) Extensive Margin



(b) Intensive Margin

Figure 11: The figure presents coefficient estimates from regression Equation (2), where the dependent variables are $\mathbb{1}$claim in Panel (a) and Ln(damage) in Panel (b). Panel (a) shows the quarterly differential likelihood of damage to the assets of firms led by former military CEOs compared to similar assets of unconnected firms within the same municipal district. Panel (b) illustrates the quarterly differential in the size of damage sustained by these firms' assets relative to the size of damages to unconnected firms' similar assets within the same municipal district. The x-axis represents the quarters relative to the 2019 social protests, with the quarter immediately preceding the protests omitted as the benchmark. Standard errors are two-way clustered at the province and year-quarter levels.

Table 17: Descriptive Statistics: Measuring the Intensity of the Protests

Province	Ethnicity	Deaths	Population (m)	Deaths (per capita)	Politics
Alborz	Persian	34	2.865	11.87	2
Ardabil	Turk	0	1.297	0	1
Bushehr	Persian	0	1.23	0	1
Chaharmahal & Bakhtiari	Mixed	0	.979	0	4
East Azerbaijan	Turk	0	4.018	0	1
Fars	Persian	25	5.006	4.99	1
Gilan	Gilak	0	2.562	0	2
Golestan	Mixed	0	1.951	0	1
Hamadan	Persian	0	1.771	0	4
Hormozgan	Persian	0	1.902	0	1
Ilam	Mixed	0	.597	0	1
Isfahan	Persian	24	5.292	4.54	4
Kerman	Persian	2	3.299	0.61	2
Kermanshah	Kurd	31	1.989	15.59	1
Khuzestan	Mixed	56	4.885	11.46	3
Kohgiluyeh & Boyer-Ahmad	Lur	0	.744	0	4
Kurdistan	Kurd	7	1.658	4.22	1
Lorestan	Lur	0	1.793	0	3
Markazi	Persian	0	1.467	0	4
Mazandaran	Mazani	0	3.365	0	3
North Khorasan	Persian	0	.892	0	4
Qazvin	Turk	0	1.322	0	4
Qom	Persian	0	1.373	0	4
Razavi Khorasan	Persian	0	6.768	0	4
Semnan	Persian	0	.750	0	4
Sistan & Baluchestan	Baluch	0	2.978	0	1
South Khorasan	Persian	0	.809	0	4
Tehran	Persian	142	13.807	10.28	2
West Azerbaijan	Turk	0	3.398	0	1
Yazd	Persian	0	1.213	0	1
Zanjan	Turk	0	1.095	0	4

The table displays two measures of the intensity of the 2019 social protests at the provincial level: the number of protester deaths per capita and the political orientation of each province. Column 2 presents the predominant ethnicity in each province. Column 3 lists the total number of protester deaths during the 2019 social protests in each province, as reported by Amnesty International. Column 4 provides the population of each province for the period from March 21, 2019, to March 19, 2020, sourced from the Statistical Centre of Iran (SCI). Column 5 calculates the number of protester deaths per capita in each province. Column 6 indicates the political orientation of each province, based on the results of the five presidential elections held from 1997 to 2009, with orientation rated on a 1-4 scale, where higher numbers indicate a more conservative stance. Figure 2 illustrates the geographic distribution of protester deaths per million and the political orientation at the provincial level.

Table 18: Descriptive Statistics: Distribution of Public Sector Jobs Held by Former Politician CEOs

	Count	Percent
Panel A: Highest Leadership Positions	803	18.8
Parliament Member	372	46.3
Minister	60	7.5
Governor	39	4.9
Mayor	23	2.9
District Mayor	165	20.5
Misc.	144	17.9
Panel B: Second-Highest Leadership Positions	3,462	81.2
Vice Governor	72	2.1
Vice Minister	109	3.1
Vice Mayor	89	2.6
District Vice Mayor	303	8.8
VP in Cultural Affairs	121	3.5
VP in Environment	157	4.5
VP in Financial Affairs	452	13.1
VP in Health	106	3.1
VP in Human Resources	261	7.5
VP in Informatics	237	6.8
VP in Legal Affairs	135	3.9
VP in Operations	383	11.1
VP in Parliamentary Affairs	385	11.1
VP in Public Relations	223	6.4
Misc.	429	12.4

The table displays the distribution of positions held by non-military former politician CEOs during their tenure in the government, as reported on their resumes.

Table 19: Descriptive Statistics: Prevalence of Political Connections Across Different Firm Sizes

Employees	Count	Percent	% Former Politician CEO	% Former Politician or Former Military CEO
1-9	50,842	39.0	2.5	4.6
10-49	46,339	35.6	2.4	4.3
50-99	15,026	11.5	5.1	8.6
100-499	12,331	9.5	5.7	9.4
500+	5,716	4.4	7.2	12.0
All	130,254	100.0	3.3	5.7

The table outlines the distribution of firm size based on the total number of employees across firms. Column 2 provides the total number of firms in each size category. For each size category, Columns 3 and 4 respectively indicate the percentage of firms led by a former politician as CEO, and the percentage of firms led by either a former politician CEO or a former military CEO.

Table 20: Descriptive Statistics: Corporate Officers in the Private Sector

	Count	Mean	S.D.	P25	Median	P75
Panel A: Corporate Officers						
Gender (female=1)	20,336	0.266	0.442	0.000	0.000	1.000
Employed	20,336	1.000	0.000	1.000	1.000	1.000
Former politician	20,336	0.074	0.262	0.000	0.000	0.000
Former politician or military	20,336	0.130	0.336	0.000	0.000	0.000
Years of tenure in the public sector	20,336	8.750	3.830	6.000	9.000	11.000
Panel B: Other Resumes, Excluding Incomplete Ones						
Gender (female=1)	406,625	0.363	0.481	0.000	0.000	1.000
Employed	406,625	0.814	0.389	1.000	1.000	1.000
Former politician	406,625	0.015	0.122	0.000	0.000	0.000
Former politician or military	406,625	0.034	0.181	0.000	0.000	0.000
Years of tenure in the public sector	406,625	8.369	4.202	5.000	9.000	11.000

The table presents summary statistics for complete resumes in the database, where a resume is considered complete if it includes entries in the first name, surname, gender, and education sections. Panel A displays summary statistics for corporate officers, defined as individuals employed in the private sector with job titles containing the word "manager." Panel B provides summary statistics for all other individuals.

Table 21: Descriptive Statistics: Educational Levels of Corporate Officers in the Private Sector

	Count	Percent
Panel A: Corporate Officers	20,336	
High school diploma	1,600	7.9
Associate	3,592	17.7
Bachelor's	10,855	53.4
Master's	2,842	14.0
Doctorate	833	4.1
Others	614	3.0
Panel B: Other Resumes, Excluding Incomplete Ones	406,625	
High school diploma	72,538	17.8
Associate	63,858	15.7
Bachelor's	196,426	48.3
Master's	37,735	9.3
Doctorate	18,251	4.5
Others	17,817	4.4

The table displays the distribution of educational levels for complete resumes in the database, where a resume is considered complete if it includes entries in the first name, surname, gender, and education sections. Panel A outlines the educational attainment distribution for corporate officers, defined as individuals employed in the private sector with job titles containing the word "manager." Panel B shows the educational attainment distribution for all other individuals.

Table 22: Robustness Test: Likelihood of Damage to Assets of Connected Firms During the Protests, Excluding Municipal Districts with Major Government Buildings

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0032***	0.0030***	0.0030***	0.0032***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Protest	0.0047***			
	(0.0001)			
Connected	0.0006***	0.0005***	0.0005**	0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	2,086,612	2,086,612	2,080,907	2,080,907
R2	0.000	0.004	0.021	0.022

The table presents coefficient estimates from regression Equation (1), excluding municipal districts that contain at least one major government building from the sample. The statistical significance and magnitude of the coefficient estimates remain consistent with those reported in Panel A of Table 4. These results refute concerns that the findings may be driven by the proximity of connected firms to major government buildings, where protests are more likely to occur. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 23: Robustness Test: Likelihood of Damage to Assets of Connected Firms During the Protests, Excluding the Oil & Gas Industry

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0042***	0.0041***	0.0041***	0.0041***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Protest	0.0051***			
	(0.0002)			
Connected	0.0007***	0.0006***	0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	3,069,190	3,069,190	3,063,251	3,063,251
R2	0.000	0.003	0.016	0.017

The table presents coefficient estimates from regression Equation (1), excluding the Mining, Quarrying, and Oil and Gas Extraction sector (NAICS 21). The statistical significance and magnitude of the coefficient estimates remain consistent with those reported in Panel A of Table 4. These results indicate that the observed effects are robust and not driven solely by politically connected firms operating in the oil and gas industry. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 24: Robustness Test: Likelihood of Damage to Assets of Connected Firms During the Protests, Excluding the Quarter Immediately Preceding the Protests

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0046***	0.0044***	0.0044***	0.0045***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Protest	0.0051***			
	(0.0002)			
Connected	0.0007***	0.0006***	0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	2,970,951	2,970,951	2,965,254	2,965,254
R2	0.000	0.003	0.016	0.017

The table presents coefficient estimates from regression Equation (1), excluding the quarter immediately preceding the protests from the analysis. This robustness test follows Callaway and Sant'Anna (2021) to account for the possibility that firms may have anticipated the protests and altered their behavior, thus potentially violating the "no anticipation" identification assumption. The statistical significance and magnitude of the coefficient estimates remain consistent with those reported in Panel A of Table 4. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 25: Robustness Test: Likelihood of Damage to Assets of Connected Firms During the Protests, Excluding Large Firms

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0042***	0.0040***	0.0040***	0.0042***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Protest	0.0052***			
	(0.0002)			
Connected	0.0009***	0.0008***	0.0008***	0.0009***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	2,670,757	2,670,757	2,664,734	2,664,734
R2	0.000	0.003	0.018	0.019

The table displays coefficient estimates from regression Equation (1), excluding firms with 100 or more employees. The statistical significance and magnitude of the coefficient estimates remain consistent with those reported in Panel A of Table 4, indicating that the observed effects are robust and not limited to large politically connected firms. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 26: Robustness Test: Likelihood of Damage to Assets of Firms Led by Former Military CEOs During the Protests

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Panel A: Former Politician CEO				
Connected×Protest	0.0031***	0.0029***	0.0030***	0.0033***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Protest	0.0050***			
	(0.0002)			
Connected	0.0001	0.0001	0.0000	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	3,004,571	3,004,571	2,998,742	2,998,742
R2	0.000	0.003	0.016	0.017
Panel B: Former Military CEO				
Connected×Protest	0.0046***	0.0044***	0.0045***	0.0046***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Protest	0.0050***			
	(0.0002)			
Connected	0.0007***	0.0006***	0.0006***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	3,098,694	3,098,694	3,092,782	3,092,782
R2	0.000	0.003	0.016	0.017

The table presents coefficient estimates from regression Equation (1), assessing whether the assets of firms led by former military officials were more likely to incur damage during the protests compared to those of unconnected firms. In Panel A, politically connected firms are defined as those led by CEOs who had held political office at least once before the protests, excluding firms led by former military CEOs who never held political office. In Panel B, politically connected firms are defined as those led by former military officials, excluding firms led by former politician CEOs who have never been members of the armed forces. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 27: Robustness Test: Magnitude of Damage to Assets of Firms Led by Former Military CEOs During the Protests

	damage/asset value			
	(1)	(2)	(3)	(4)
Panel A: Former Politician CEO				
Connected×Protest	0.0093***	0.0098**	0.0060*	0.0024
	(0.0023)	(0.0039)	(0.0029)	(0.0053)
Protest	-0.0062***			
	(0.0017)			
Connected	-0.0042*	-0.0030	0.0029	0.0071
	(0.0021)	(0.0030)	(0.0027)	(0.0064)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.012	0.012	0.010	0.011
N	8,433	6,933	4,012	3,182
R2	0.001	0.339	0.291	0.608
Panel B: Former Military CEO				
Connected×Protest	0.0072***	0.0101**	0.0062***	0.0070*
	(0.0015)	(0.0043)	(0.0021)	(0.0034)
Protest	-0.0062***			
	(0.0017)			
Connected	-0.0026**	-0.0054	-0.0003	0.0001
	(0.0013)	(0.0044)	(0.0015)	(0.0034)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.012	0.011	0.010	0.011
N	8,832	7,351	4,295	3,443
R2	0.001	0.301	0.293	0.604

The table presents coefficient estimates from regression Equation (1), assessing whether, conditional on incurring damage, the damages to the assets of firms led by former military officials during the protests were greater than those sustained by unconnected firms. In Panel A, politically connected firms are defined as those led by CEOs who had held political office at least once prior to the protests, excluding firms led by former military CEOs who never held political office. In Panel B, politically connected firms are defined as those led by former military officials, excluding firms led by former politician CEOs who have never been members of the armed forces. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 28: Robustness Test: Likelihood of Damage to Assets of Firms Led by Former Bureaucrats During the Protests

	$\mathbb{1}$damage			
	(1)	(2)	(3)	(4)
Connected×Protest	0.0002**	0.0002***	-0.0001	-0.0001*
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Protest	0.0050***			
	(0.0002)			
Connected	-0.0002**	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.003	0.003	0.003	0.003
N	2,923,838	2,923,838	2,917,995	2,917,995
R2	0.000	0.003	0.017	0.018

The table presents coefficient estimates from regression Equation (1), which examines whether the assets of firms led by non-politician, non-military former bureaucrat CEOs were more likely to incur damage during the protests compared to similar assets of firms led by CEOs without a bureaucratic background. Firms led by former military or politician CEOs are excluded from this sample. Standard errors, reported in parentheses, are two-way clustered at the municipality district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 29: Robustness Test: Magnitude of Damage to Assets of Firms Led by Former Bureaucrats During the Protests

	damage			
	(1)	(2)	(3)	(4)
Panel A: Absolute Magnitude				
Connected×Protest	0.0413*	-0.0852***	0.0521**	0.0399
	(0.0219)	(0.0302)	(0.0220)	(0.0472)
Protest	-0.5894***			
	(0.1244)			
Connected	-0.0614*	0.0310	-0.0367	-0.0320
	(0.0347)	(0.0528)	(0.0480)	(0.0678)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	6.703	6.664	6.627	6.529
N	8,189	6,690	3,842	3,031
R2	0.027	0.431	0.499	0.658
	damage/asset value			
	(1)	(2)	(3)	(4)
Panel B: Relative Magnitude				
Connected×Protest	0.0013	0.0044***	0.0020	-0.0011
	(0.0045)	(0.0013)	(0.0021)	(0.0020)
Protest	-0.0064***			
	(0.0017)			
Connected	0.0002	-0.0037***	-0.0024	0.0003
	(0.0045)	(0.0012)	(0.0017)	(0.0019)
Asset Class×Y-Quarter FE	-	Yes	-	-
Asset Value×Y-Quarter FE	-	Yes	-	-
Municipal District×Y-Quarter FE	-	Yes	-	-
Asset Class×Asset Value×Municipal District×Y-Quarter FE	-	-	Yes	Yes
Firm size×Industry×Y-Quarter FE	-	-	-	Yes
Avg (y)	0.012	0.012	0.010	0.011
N	8,189	6,690	3,842	3,031
R2	0.001	0.341	0.290	0.610

The table presents coefficient estimates from regression Equation (1), which examines whether damages to assets of firms led by non-politician, non-military former bureaucrat CEOs were greater during the protests compared to damages to similar assets of firms led by CEOs without a bureaucratic background. In this analysis, firms led by former military or politician CEOs are excluded from the sample. Standard errors, reported in parentheses, are two-way clustered at the municipal district and year-quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.