Three Essays on Sustainability, Bank Solvency, and Stock Price Returns

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Abstract

Three Essays on Sustainability, Bank Solvency, and Stock Price Returns

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My dissertation consists of three essays in which I explore the effect of various types of news announcements (presidential tweets, natural disasters, and corporate innovations) on the stock price performance of firms and the solvency of banks.

Using event-study methodology and cross-sectional regression analysis, my first essay explores the effects of U.S. President Donald Trump's messages (tweets) on the stock prices of media and non-media companies. For media firms, we find that positive tweets have a pronounced positive stock price impact, whereas negative and neutral tweets have little or no effect. For non-media firms, we observe the opposite: negative tweets tend to be associated with significant stock price declines whereas neutral and positive tweets incur weekly positive stock price reactions. The paper provides important insights re. the ability of political figureheads to move stock prices on one hand and investors' ability to differentiate between presidential statements that are inconsequential for the affected firms or may have long-lasting implications on the other hand.

My second essay is based on a comprehensive dataset on natural catastrophes around the world and detailed financial statements for 9,928 banks that operate in 149 countries from 1990 to 2017. We use a variety of empirical analyses to explore (1) whether and how natural disasters affect bank solvency, (2) how accounting and regulatory measures of bank solvency reflect a bank's true affectedness, and (3) whether the effects differ across different types of banks. This study adds to the discussion of what type of capital and capital ratio best reflects a bank's sensitivity to risk. The main finding is that damages from disasters matter: they negatively affect capital ratios, and the severity of their impact depends on a bank's location, capitalization, and business model. In addition, the results show that accounting measures of solvency are more sensitive to disasters than are regulatory measures.

My third essay employs data on patents and trademarks collected from the United States Patent and Trademark Office (USPTO) and on disaster data collected from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) covering 12,897 publicly traded firms from 1990 to 2015. By using multiple measurements of innovation and estimating a variety of different models, we show that natural disasters have a negative impact on corporate innovations in general, with important differences among different industries. We also find several channels through which natural disasters can influence firms' innovation ability.

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Contribution of Authors

Part of this thesis is published work with Carl Ajjoub and Thomas Walker.

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The manuscript has been reformatted and reorganized according to the requirements set out in the guideline of the School of Graduate Studies

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1. Introduction

My first essay explores how the social media posts of one individual influence the stock market.

Social media platforms are frequently used for entertainment, networking and/or marketing purposes. However, their functionality and influence go far beyond. Many studies show that an increasing number of investors is turning to social media to share and access information about the market or specific firms in an attempt to improve their investment decisions. A 2019 survey by the Brunswick Group finds that in 2018, 88% of investors made decisions based on information from digital sources, up from 70% in the previous year. The study further documents that 49% of investors used digital media to learn what specific CEOs are saying and 74% employ them to follow market-moving news.[1] Similarly, a study by BMO Investorline finds that one third of investors use social media as a source for investment information and advice. The study also observes that, even though traditional media are preferred, social media sources are trusted by 24% of investors.[2] More recently, a study by Greenwich Associates on social media and investing finds that nearly all institutional investors (97%) use digital media sources for professional purposes, and a considerable proportion (79%) uses social media at work. The study also notes that approximately 40% of investors expect their use of social media to increase on a year-by-year basis.[3] Furthermore, the study reveals that the most common reason why institutional investors use social media is to access news updates, market updates, and manager commentaries. Finally, a 2019 survey of 277 institutional investors across North America, Europe, and Asia finds that investors are more likely to consult digital media (63%) than finance-specific trade publications (48%).[4] While the extant academic literature includes a number of studies examining the relationship between social media commentaries and stock prices and/or stock price volatility (see Section II for a detailed review of the related literature), there are, to the best of our knowledge, few studies that explore the relationship on a micro level; i.e., the impact of comments made by a single social media account or user on individual stocks. Despite the sparsity of formal research in this area, the topic is increasingly garnering interest among scholars and researchers as well as the mainstream media. An article on Investors.com reports that Amazon's stock plunged 5% following a negative Twitter message by President Donald Trump mentioning the company.[5] Similarly, the Independent reports that Toyota lost $1.2 billion in value after a negative tweet by President Trump

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[1] Brunswick Group, January 30, 2019. Suite execs need to up their game on social media if they want to keep investors close. Accessed on September 27, 2019. Retrieved from https://www.brunswickgroup.com/digital-investor-survey-c-suite-use-social-media-to-keep-investors-close-i9475

[2] BMO Investorline, August 23, 2013. Despite rise of social media, investors still rely on traditional media sources for information. Accessed on June 17, 2019. Retrieved from https://newsroom.bmo.com/2013-08-23-BMO-InvestorLine-Study-Despite-Rise-of-Social-Media-Investors-Still-Rely-on-Traditional-Media-Sources-for-Information

[3] Greenwich Associates, 2015. Institutional investing in the digital age: How social media informs and shapes the investing process. Accessed on June 17, 2019. Retrieved from https://www.greenwich.com/asset-management/institutional-investing-how-social-media-informs-and-shapes-investing-process

[4] Greenwich Associates, March 19, 2019. Investing in the Digital Age: How media influences the institutional investment journey. Accessed on September 24, 2019. Retrieved from https://business.linkedin.com/marketing-solutions/blog/marketing-for-financial-services/2019/-investing-in-the-digital-age--how-media-influences-the-institut

[5] Deagon, B./Investors.com, April 3, 2018. Trump hits Amazon again on taxes, using post office as 'delivery boy'. Accessed on August 3, 2019. Retrieved from https://www.investors.com/news/technology/trump-tweets-hurt-amazon-stock/

targeted the firm.[6] The Los Angeles Times reports that when Trump tweets, Wall Street begins trading instantly. They note how some traders use algorithms that instantly analyze the President's Twitter messages and then immediately buy or sell the affected stocks.[7] The phenomenon extends beyond stocks into the realm of foreign exchange. An article by Bloomberg explains why currency investors should follow President Trump's Twitter messages, stating that his tweets result in "jolts" of volatility in the foreign exchange markets.[8] Another article by Time Magazine reports that the U.S. dollar reached its lowest level in a month following a remark from the President saying the dollar is too strong.[9] These media reports are not just limited to Donald Trump. CNBC reports that the whole biotech sector took a "hit" after Hillary Clinton tweeted negatively about EpiPen pricing.[10] The aim of this study is to assess these anecdotal observations and empirically explore whether and how President Trump's Twitter activity influences stock returns. We have chosen to look at Trump's tweets because he has many social media followers and strong political power. Given the influence and authority he exerts as President of the United States, it is reasonable to assume that a large proportion of investors believe that his tweets foreshadow new policies. Additionally, many news articles have reported that the President's negative tweets towards certain companies caused their stock prices to decline. We examine the validity and generalizability of these reports using a series of rigorous statistical analyses that assess the effects of social media posts made by the President on market prices. In exploring this issue, we distinguish between media and non-media firms, and examine the influence of different tweet sentiments (positive, neutral, and negative) while controlling for various firm, market, and tweet characteristics.

It is important to examine whether social media as a popular new source of information has any impact on aggregate market perceptions, especially in the short term. A proper understanding of how social media affects the market is very important considering that numerous media reports in recent years have noted that social media is an unreliable source of information because it is riddled with fake news. Not surprisingly, according to a survey by Pew Research, around 42% of Americans believe that social media platforms should be held responsible for addressing the problem of fake news.[11] Some have even gone as far as accusing President Trump himself of disseminating fake news.[12,13] Thus, our

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[6] Revesz, R./The Independent, January 5, 2017. Toyota loses $1.2bn in value five minutes after Donald Trump's tweet. Accessed on June 17, 2019. Retrieved from https://www.independent.co.uk/news/world/americas/toyota-12bn-value-plummet-shares-stock-market-donald-trump-tweet-move-mexico-tax-a7512096.html?amp

[7] Peltz, F. J./The L.A. Times, January 16, 2017. When Trump tweets, Wall Street trades — Instantly. Accessed on June 21, 2019. Retrieved from http://www.latimes.com/business/la-fi-agenda-trump-tweets-stocks-20170116-story,amp.html

[8] Kawa, L./Bloomberg, May 2, 2017. Why currency traders should literally follow Trump tweets. Accessed on July 30, 2019. Retrieved from https://www.bloomberg.com/news/articles/2017-05-02/when-trump-tweets-move-the-greenback-play-follow-the-leader

[9] Abramson, A./Time.com, April 12, 2017. President Trump says the U.S. dollar is 'too strong'. Accessed on August 5, 2019. Retrieved from http://time.com/money/4737106/donald-trump-us-dollar-too-strong/

[10] Wang, C./CNBC, August 24, 2016. Biotech takes a hit after Clinton tweets about EpiPen pricing. Accessed on September 5, 2019. Retrieved from https://www.cnbc.com/2016/08/24/biotech-gains-amid-buyout-chatter-upbeat-clinical-trial-results.html

[11] Barthel, M./Pew Research Centre. December 15, 2016. Many Americans believe fake news is sowing confusion. Accessed on August 6, 2019. Retrieved from https://www.journalism.org/2016/12/15/many-americans-believe-fake-news-is-sowing-confusion/

[12] Leonhardt, D., Thompson, S.A./The New York Times. June 23, 2017. Trump's lies. Accessed on September 5, 2019. Retrieved from https://www.nytimes.com/interactive/2017/06/23/opinion/trumps-lies.html

study also addresses the question whether a source of news/information that is perceived to be unreliable can affect the markets.

This study contributes in many ways to the finance and political science literature. If social media posts by single influential people are found to affect markets, they may create trading opportunities for investors and financial managers and risk arbitrage opportunities for arbitrageurs. Financial institutions can create algorithms that can trade based on information gathered from social media platforms – a strategy that many investment houses have already implemented but that could be extended to other platforms, countries, and individuals. The results of the study will also address the fundamental assumption that markets are efficient, and that investors are rational. In the political science field, the findings of this research will provide valuable insights into how politicians can employ social media platforms to affect the public, and the differential influence of nominees and politicians in office. Finally, our study will give corporations that wish to back a certain campaign or a candidate in an election a better idea of the possible risks and benefits of their actions, considering that candidates or politicians could post negative messages on social media platforms targeting companies that backed their opponents.

This ecategorizes firms into non-media and media firms. We find that the effects of the President's tweets on each category is different. Specifically, we find that positive media tweets lead to positive abnormal returns and are more influential than negative and neutral tweets. Moreover, the influence of positive media tweets on stock prices became significantly stronger after Donald Trump's election in comparison to the tweets he made in the run-up to the election. For non-media firms, negative tweets lead to negative abnormal returns and are more significant on the first day than neutral and positive tweets, but this effect partially reverses on the following day.

There have been a number of theoretical and empirical studies that examine whether and how media reports can influence the financial markets (see, e.g.,Veldkamp (2006); Gentzkow (2006); Tetlock (2007); Dyck et al. (2008); Bhattacharya et al. (2009); Engelberg et al. (2011); Dougal et al. (2012); and Peress (2014)). Given our focus on social media, we consider here mainly those studies that examine aspects of the relationship between social media and the market. A key study by De Jong, Elfayoumy, and Schnusenberg (2017) explores whether there is a bidirectional intraday relationship between stock returns, stock price volatility, and tweets. The authors investigate three things: 1) if an increased mentioning of stocks affects their returns and whether the returns affect the number of tweets, 2) if an increased mentioning of stocks on Twitter increases the volatility of these stocks, and 3) if the increased volatility of these stocks increases the number of times they are mentioned on Twitter. The authors observe a unidirectional intraday relationship between tweets and stock returns. However, for volatility, the authors document a bidirectional relationship, with an effect of return volatility on tweets as well as an effect of tweets on return volatility, although the former is more significant than the latter. Similarly, Sul, Dennis, and Yuan (2017) find that tweets that are re-tweeted by users with many followers (more than the median of 171 followers) have an impact on future returns, and that a trading strategy based on these findings can produce meaningful economic gains that translate into 11% to 15% annualized returns.

Another strand of the literature focuses on roader social media sentiments and their effect on the overall market. Nofer and Hinz (2015), for example, document that a positive social mood, measured

[13] The Washington Post, November 19, 2019. The global reach of Trump's 'fake news' outrage. Accessed on November 20, 2019. Retrieved from https://www.washingtonpost.com/opinions/global-opinions/trump-is-spreading-his-fake-news-rhetoric-around-the-world-thats-dangerous/2019/11/19/a7b0a4c6-0af5-11ea-97ac-a7ccc8dd1ebc_story.html

by both a positive aggregate Twitter mood state and a high number of followers of positive tweets on a given day, tends to be followed by a rise in the German Stock Market Index (DAX) on the subsequent trading day. Similarly, Ho, Damien, Gu, and Konana (2017) demonstrate that the prediction errors of Fama-French or momentum models are significantly larger than those of a model that only uses social media sentiments to predict market returns.Relatedly, by using a polarity score identifying the sentiment in Twitter messages, Azar and Lo (2016) show that this measure can predict returns of the Center for Research in Security Prices' (CRSP) value-weighted market index, and can be used to construct trading strategies that significantly outperform buy and hold strategies. Similalrly, Sprenger, Sandner, Tumasjan, and Welpe (2014) examine more than 400,000 S&P 500 stock-related Twitter messages and show that tweets that convey good news do not surprise the markets and that the associated information is largely incorporated in prices ahead of the announcement dates. In contrast, the market significantly reacts to negative news, but the reaction is usually confined to the event day itself. Finally, Yang, Mo and Liu (2015) document a robust correlation between the weighted Twitter financial community sentiment and movements in the major financial market indices such as the Dow Jones, S&P 500, NASDAQ, Russel 3000, and even the market volatility index.

In one of the few firm-specific studies in this area, O'Connor (2012) observes significant correlations between the fan counts (i.e. the number of social media followers) of the 30 most popular consumer brands and their respective brand company stock prices from June 1st, 2010, to June 1st, 2011. The study finds the correlation to be stronger for brands with small ticket and impulse purchases than for brands with larger-ticket items and more complex buying or decision-making processes. The literature strand has recently expanded through several studies that specifically focus on President Trump's tweets. For instance, Borna, Myersa, and Clark (2017) use the abnormal returns of non-media firms on the event day to show that positive (negative) tweets from the President may elicit positive (negative) abnormal returns. Our paper extends their study by differentiating between tweets that mention media and non-media firms, by employing a larger sample of both pre- and post-election tweets, and by using regression analysis to provide a more detailed analysis of the tweet characteristics that influence market prices.

Similar multivariate analyses have also been used in two other studies that explore the market reaction to the President's tweets. Juma'h and Alnsour (2018), for example, employ both event-study and regression analysis and determine that the President's tweets have no significant impact – a finding that is contrary to ours.[14] On the other hand, Ge, Kurov, and Wolfe (2019) study the abnormal returns of 27 non-media firms over 287 days and show that the President's tweets influence stock prices, volatility, trading volume, and institutional investor attention. Our paper differs from these studies by considering a broader range of tweets, by controlling for potential selection biases, by adding Trump's tweets about media firms and by exploring the impact of "old" vs. "new" news based on whether the President repeats information that is already known to the market. An analysis of media firms is more likely to uncover the 'pure' effect of Trump's tweets because his comments about these firms frequently reflect his personal attitudes alone (e.g., the comment "fake news"), whereas those about non-media firms often combine personal attitudes with references to market-relevant information (e.g., negative remarks about the construction of a new plant) or other company-specific information. In the latter case, it may be difficult to discriminate between the impact of the attitudinal and informational

[14] Some of the reasons why Juma'h and Alnsour's (2018) results differ from ours are that first, they started collecting data from the beginning of 2016 when President Trump entered the GOP primaries while we start collecting data when the President gathered enough delegates needed to secure his nomination. Second, their sample is considerably smaller (58 tweets related to 23 public companies), which prevented them from subcategorizing their data.

elements of the tweet.

My second essay explores how natural disasters influence the capital ratio of banks.

In its *Global Risks Report*, the World Economic Forum has long warned about the negative effects changes in the natural environment may have on the world's economy (cf., WEF, 2018). The recent rise in the frequency and severity of natural disasters such as floods, droughts, wildfires, and extreme winds (hurricanes, typhoons, tornadoes, etc.) is often attributed to climate change and climate change itself to our production and consumption behavior (Rummukainen, 2012; Mechler and Bouwer, 2015). In addition, when natural and technological events coincide or interact with each other, they can lead to extreme risks as evidenced by the 2011 Fukushima nuclear disaster.

Because natural disasters primarily affect the real economy, research on their economic effects has mainly focused on their impact on production and growth (Hallegatte, 2014; Arouri et al., 2015; Lesk et al., 2016). Only recently has research started to explore how such disasters affect financial institutions and the broader financial markets. The relevance of natural disasters for the risk and the risk management of individual institutions can be explained through their claims – e.g., via loans, bonds, and stocks – on the real economy. In addition, financial institutions, particularly banks and the banking network, may be exposed to operational risks if disasters hit the institutions' physical locations and computer systems.

Not surprisingly, there is a growing concern among financial regulators and central banks that damages may affect the financial system as a whole (Batten et al., 2016). The *Network for Greening the Financial System* that comprises many of the world's most influential central banks and supervisory authorities has recently outlined the need to incorporate climate risks into financial policies and regulatory frameworks (NGFS, 2018). In addition, the European Union's *High-Level Expert Group on Sustainable Finance* has repeatedly argued that the financial system is a crucial component in any intended moves to shift the overall economy towards a more sustainable system, i.e., a system that balances the needs of our economy, society, and ecology (HLEG, 2018). Financial institutions, especially banks, are expected to provide the financial expertise, backing, and networking necessary for the transition towards sustainability (SFSG, 2018). Despite these efforts to align the financial system with our pursuit of a sustainable natural environment, there is surprisingly little research that explores how, at the same time, the natural environment affects the stability of our financial system. Our study aims to address this gap in the literature.

Whether and how a given financial institution is affected by a natural disaster is difficult to assess. Its claims against exposed counterparties (e.g., mortgage loans, business loans, etc.) may be affected with varying levels of intensity. In addition, even if a given loan has to be written off because, e.g., a firm is forced out of business or a residential property is damaged beyond repair and the homeowners have to default on their loans, the disaster may create new demand for loans as restructuring and rebuilding activities commence (Cortés and Strahan, 2017; Barth et al., 2019).

Moreover, challenges may arise from disasters themselves (physical risks) as well as from changes in the legal framework (transition risks). A further complexity arises from the interconnectivity of different actors in the financial markets that makes them reciprocally vulnerable to risks. For example, interbank lending in the money markets or the participation of banks in insurance companies can indirectly transfer risks among institutions (Battiston et al., 2017).

Banks are among the principal actors in the financial markets and their soundness is considered crucial for the resilience of the financial system. Against the backdrop of the rising frequency and severity of natural disasters in recent years, and the complex effects external shocks have on bank stability, this study aims to explore whether and how damages from natural disasters translate into potential solvency problems for banks and whether the effect varies across different types of banks. Particularly, we address the following research questions:

- to what extent do natural disasters affect bank solvency,
- do natural disasters affect accounting based measures of solvency as much as they affect regulation based measures, and
- are different types of banks affected differently by natural disasters?

This study focuses on bank solvency because a bank's ability to withstand risks and remain solvent even under adverse conditions is existential for both its own stability as well as the soundness of financial system as a whole (Flannery and Giacomini, 2015). Banking regulations typically focus on ensuring that banks maintain sufficient capital. The ability of the banking system to manage risks is driven both by individual institutions' ability to absorb damages and by the diversification of risks within the system (Batten et al., 2016). Although banking regulations have undergone considerable refinements in recent years, particularly after the 2007/2008 subprime mortgage crisis, they are only now starting to consider natural disasters as a potential risk factor (EBA, 2019). Our study aims to shed light on the possibility that natural disasters may pose the next big threat for our economy and for our financial system. That way, banks and bank regulators can anticipate and better prepare themselves without being caught off guard as most were, e.g., in the early days of the current coronavirus pandemic.

Thomson (1998) is one of the first authors to include environmental factors into his risk analysis of banks. He examines the composition of assets of six major banks headquartered in the United Kingdom and assigns risk weights depending on the inclusion of environmentally critical industries. His approach is conceptual with simplified assumptions about the risk characteristics of industries and bank portfolios. In line with this, Klomp (2014) investigates the association between natural disasters and bank stability. His approach focuses on a country's banking system as a whole and on the system's aggregated Z-score. Using data for 169 countries, he concludes that natural disasters increase the likelihood of bank default. Battiston et al. (2017) model the climate risk of the financial system as a whole. Their model is based on the assumption that climate risk affects the equity holdings of financial institutions in carbon risk sensitive industries. They find that first-round effects manifest as losses in critical equity holdings, while second-round effects are driven by the connectivity of financial institutions that have been hurt in the first round.

Cortés and Strahan (2017) investigate the lending behavior of banks in the aftermath of a natural disaster. They ask how banks that operate in multiple local markets adjust their lending when credit demand in a particular local market increases after a natural disaster. Based on data for the mortgage lending of small banks in different counties of the United States (US), they find that these banks tend to cut loans in non-core connected markets and increase the securitization of mortgages. In a similar analysis of US banks, Barth et al. (2019) conclude that natural disasters incentivize institutions to attract more deposits in order to meet the higher loan demand, and that therefore they raise both interest rates on deposits and loans. Koetter et al. (2019) obtain comparable results when analyzing the lending adjustments of German banks with credit relationships to corporates affected by the 2013 flooding of the river Elbe. The authors find that after the flooding, banks lend more to disaster-hit firms (in the form of emergency lending) than to non-affected firms. In addition, banks source their lending primarily through local savings deposits rather than through wholesale funding. Duqi et al. (2021) find that in less competitive markets, banks recover faster after a disaster, and banks with better profitability can generate more mortgage credit.

After differentiating between affected and non-affected banks, Schüwer et al. (2019) apply a similar approach to assess the adjustment strategies of US banks following a catastrophic event. Using Hurricane Katrina as a case study, they examine how natural disasters affect a bank's lending, asset allocation, and capital ratios. The authors further distinguish between independent banks and banks affiliated within bank holding companies (BHCs) and find evidence that suggests that independent banks increase their risk-based capital ratios. In another study in which they examine the impact of multiple disasters on banks in the US, Noth and Schüwer (2018) focus on bank stability and bank performance. They analyze bank accounting ratios such as the return-on-assets, Z-score, and equity-to-assets and find that disasters weaken both bank performance and stability. In another paper, Gramlich et al.(2021) shows that natural disaster has pronounced negative effect on US banks ROE and ROA.

Typically, changes in financial regulation are driven by past experiences and aim to address the vulnerabilities that these experiences have revealed in the financial and economic system.[15] However, it is questionable if this approach is sufficient to avoid future financial crises. Rather, a complete approach that also includes emerging risks is called for. The current solvency requirements should be extended to ensure that banks introduce factors in their capital reserve calculations that account for their susceptibility to the increasing likelihood and severity of natural disasters, particularly with respect to their lending, financing, and investment activities. Accordingly, risk weighted assets should be adjusted while leaving the overall capital requirements at the same level (Van Gelder and Stichele, 2011). This approach is also propagated by Batten et al. (2016) who argue that weather-related natural disasters can trigger financial instability and may cause severe damages to the balance sheets of banks.

A recent report by the *Cambridge Institute for Sustainability Leadership* recommends that the Basel Committee should explicitly acknowledge environmental risk and their increasing impact on the stability of the financial system (CISL, 2016). The report encourages regulators and banking institutions to adopt new practices to address environmental issues and incorporate a forward-looking approach to ensure the sustainability of bank lending activities.

Similarly, in its 2018 report, the *United Nations Environment Programme – Finance Initiative* (UNEP FI, 2018) argues that natural disasters may have severe effects on the world's economies. By referring to the El Niño cycle, the report's author criticizes the current regulatory framework and quotes Dr. Emily Shuckburgh, a climate scientist based at the British Antarctic Survey who noted: "I do not think all decision-makers understand how this can drive inter-connected and highly damaging extremes across the planet, from large scale droughts and wild fires to serious flooding, which would expose the systemic vulnerabilities in our interconnected economies" (pg. 5).

In addition to studies related to banks and banking regulations, recent work has investigated the effect of disasters on other types of institutions as well as on the financial value of investments. These studies frequently call for novel methodological approaches. Building on the new climate-economy literature, Balvers et al. (2017) posit that temperature shocks restrict the growth of companies and impose a higher cost of equity. Based on the arbitrage pricing theory and a specification for expected temperature levels, they consider temperature shocks as a systematic risk factor and examine the loading of asset prices to the temperature risk factor. The loading is negative and equates to a higher cost of equity capital of approximately 0.22%. Another consequence of climate change is the rise of sea

[15] For instance, the Basel III Accord was largely developed in response to the recent subprime mortgage crisis. In line with the accord, the European Union's Capital Requirements Directive (CRD) obliges banks to set aside a minimum percentage of their capital to cover any potential defaults on their loans and investments.

levels with further effects on the price of properties in coastal areas and their use as collateral. Bernstein et al. (2018) categorize properties into buckets of similar size, elevation, and zip code, yet with a different exposure to sea level rise. They find that properties exposed to sea level rise trade at a discount of 6.6% compared to those that are not exposed.

Disruption caused by disasters can have a devastating effect on company's performance. So far, human beings around the world are going through perhaps one of the biggest disasters in human's history, the global pandemic of COVID-19. Indeed, this public health disaster triggered by a viral pandemic severely deteriorated the global economy (Ding et al., 2021). Even though the original cause of the virus has still been mysterious and can yet be identified as a natural disaster, the surprisingly damaging effect from such a disaster leads us to shed light on the damaging effect of natural disasters on corporate business activities.

Among the major disruptions a company has to cope with, disasters from a changing natural environment have become more perceptible and the damaging effect from those natural disasters have been escalating in recent years. Natural disasters comprise extreme climatic and meteorological conditions such as periods of high temperature, flooding and drought or single occurrences such as blizzards, hurricanes and wildfires, and further geological events including earthquakes and seaquakes (Klomp, 2014). Natural disasters do not only destroy the environment and a society's infrastructure, but also trigger significant financial losses.

According to the 2020 CEO/CFO Climate Risk Survey conducted by FM Global, CEOs and CFOs consider natural disasters such as flooding, droughts and wildfires wreak the most financial havoc. In particular, the survey indicates that 76% of the CEOs and CFOs find their company at risk for a climate change disaster and need to be cautious on corporate risk management to avoid further uncertainties after the local area being hit by natural disasters. Similarly, an expert in natural disasters and climate risk at FM Global suggests that "*The combination of being underprepared for natural catastrophes, volatility in financial markets, and the threat of an economic recession couldn't come at a worse time for many companies. Although the loss of revenue might be insured during a business interruption, longer-term market share, shareholder value, reputation and investor confidence will not be*".[16]

It is worth noting that Hsu et al. (2018) indicate that natural disasters are detrimental to the profitability of the firms located in the states hit by natural disasters. As specifically corporation innovation is concerned, natural disasters may also obstruct companies' engagement in research and development (R&D), following decreased corporate financial performance. As stated by Holmstrom (1989), innovative projects, different from corporate routine operations (e.g., mass production and marketing), requires exploring untested and unfamiliar methods with a high likelihood of failure. Given innovation's high level of uncertainty and large amount of financial resources commitment, firm management may prefer to focus on short-term pressure and avoid investing on such risky projects, especially after negative shocks as natural disasters.

Nonetheless, few studies have explored how natural disasters can affect companies' innovation performance. Given the existing rich set and even growing studies on corporate innovation (patents and trademarks), it would be valuable and fruitful to investigate the impediments to corporate innovation pertaining to natural disasters and/or climate change (Hong, Karolyi and Scheinkman, 2020). To our best knowledge, the only exception is the empirical study of Miao and Popp (2014). In this research, they investigate the influence of natural disasters on disaster related innovation output (risk-mitigating innovation) at country-level. Using a rich dataset consisting of the disaster-related patent applications

[16] See spendmatters.com, "Global CEOs and CFOs see climate change risks but feel unprepared to handle them, survey finds." August 5, 2020.

across 30 countries over 25 years, they find that natural disasters can stimulate disaster-related technological innovation that can mitigate the risk of future natural disaster occurrences (e.g., earthquake detection and drought-resistant crop technology). They conclude that human beings constantly learn from their experiences of natural disasters and therefore invent disaster-related technologies to facilitate adaptation to climate change triggering the risk of natural disasters. However, their research only focuses technological innovation at country-level. It is not clear that how much of the innovation is from the private sector. It is likely that those disaster-related patents funded by the public sector and are invented by government funded research institute, rather than privately-owned firms. Hence, it is necessary to investigate how individual firms locate in the disaster zone respond to natural disasters in terms of corporate innovation at firm level. In addition, as the rich set of studies pertaining to the determinants of corporate innovation that do not only limit to specific category of patents (disaster-related technological innovation) but focus on all kinds of utility patens, it is worth exploring the impact of natural disasters on general corporate innovation, not only disaster-related patent activity. We argue that as natural disasters seem to adversely affect corporate financial performance and risk perception for the firms locate in the areas hit by disasters, investigating the impact of natural disasters on general corporate innovation at firm level may produce different outcomes as the study on specifically disaster-related innovation.

In this paper, we investigate the impact of corporate disruption triggered by natural disasters on U.S. public firms' innovation activities. We argue that designing the natural experiment using natural disasters is completely exogenous to corporate innovation activities on the grounds that the vast majority of natural disasters are unpredictable and out of human beings' control. Using major natural disasters in the U.S. from 1990 to 2015 as exogenous shocks to corporate innovation activities, we find significant empirical evidence that natural disasters adversely affect corporate innovation, both technological innovation (proxied by patent activities) and product innovation (proxied by trademarks). The effect is also economically significant. Specifically, our baseline results show that, on average, with a one standard deviation increase in the damage ratio triggered by natural disasters, U.S. public firms headquartered in states hit by natural disasters consequently decrease technological innovation (granted patent counts) approximately by around 1.5% within three years post disaster. It makes sense that the negative effect of the disruption from natural disasters can last three years. Since it takes on average two years from patent applications to patents being granted (Hall, Jaffe, Trajtenberg, 2005), the outcome of the reduction in research commitment may appear in two or three years afterwards. Moreover, on average, a one standard deviation increase in the damage ratio triggers a 0.6% decrease in U.S. firms' product innovation (successfully granted trademark counts) within the three years post disaster for the firms headquartered in disaster zone. It is worth noting that the statistical and economic significance on product innovation is less compared to those on technological innovation. This is in line with our expectation as it takes time to transfer the technological innovation (patents) to commercialized product innovation output (trademarks), the impact within in three years after disasters on product innovation may not be as salient as that on technological innovation. Furthermore, using a variety of alternative measures of technological and product innovation (patent value, patent citation, innovation component, trademark diversity, exploitation trademark, exploratory trademark, marketing trademark, and product trademark), we continue to find an adverse effect of natural disasters on corporate innovation for the firms headquartered in states hit by natural disasters.

To make sure that our baseline results are not driven by outliers, we perform a host of robustness checks. First, we exclude the five states that are most frequently hit by natural disasters. Those states are Alabama, Florida, Georgia, Louisiana, and Mississippi. The results are qualitatively similar to our baseline results. In addition, we only consider the natural disasters with the most severe damage to the disaster zone. The empirical results based on huge natural disasters continue to suggest a negative link between natural disasters and corporate innovation for affected firms.

To cope with the potential issue of selection bias as well as unobserved factors that may bias the causal effect, we employ a difference-in-differences specification based on propensity score matching routine (PSM-DID) to assess the effect of disruption triggered by natural disasters on corporate innovation. The staggered natural disaster shocks enable us to identify firms that are subject to the natural disaster shocks (treated group) versus those who are not (control group). This results from the PSM-DID estimation continue to reveal that natural disasters are associated with significant decline in corporate innovation output.

A further negative effect of natural disaster on corporate innovation, yet less significant, is obtained when relating the damages from disasters in adjacent states to companies located in the neighbor states. This finding suggests a spillover effect of natural disasters on corporate innovation. Moreover, we find that U.S. firms in disaster zone did not significantly reduce their commitment in disaster-related innovation post natural disasters, suggesting such firms recognize the necessity of inventing disaster-related technologies to circumvent the damages from future disasters (Miao and Popp, 2014).

Next, we explore several possible transmission pathways through which natural disasters discourage corporate innovation for affected firms. We firstly address potential reactions from the perspective of the firms themselves, arguing that the higher are damages from disasters, the more cautious managers will behave in terms of financial resources allocation and may try to compensate losses from disasters by reducing their research and development (R&D) commitment. Our results on the link between natural disasters and R&D expenses reveal that following natural disasters, firms in disaster zone significantly cut their spending on research and development.

Second, from the perspective of a company's external context, natural disasters in the state where the company is located adversely affect living conditions in disaster zone. Educated people and employees such as inventors may chose to leave the site and quit the company. Likewise, the ability of the company is obstructed to gain new employees as potential innovators who are willing to relocate into affected states by natural disasters (Gao et al., 2020). Therefore, the inventor mobility can negatively affect the affected companies' innovation output. We show that at the firm level, for the firms affected by natural disasters, less inventors tend to join affected firms whereas more inventors opt to leave the affected firms post natural disasters. In addition, we observe a similar pattern at the state level. Inventors are prone to relocate to the states that are not hit by natural disasters.

Furthermore, we would like to investigate why firms reduce their commitment in research and development following natural disasters? Is it because after natural disasters, managers become more risk averse (Bernile, Bhagwat, and Rau, 2017 and Dessaint and Matray, 2017) and tend to avoid risky projects with high level of uncertainty such as innovation, or because natural disasters significantly undermine firms' profitability (Hsu et al., 2018) and in turn increase firms' financial constraints, and therefore managers are forced to cut risky projects that the value can only be realized in the long-term, or both? To answer this question, we exam two additional transmission channels. The first one is the risk aversion channel. Prior research indicates that firm managers that experience the natural disasters tend to behave more conservatively, such as increasing corporate cash holdings and reducing financial leverage and acquisition activities (Bernile, Bhagwat, and Rau, 2017 and Dessaint and Matray, 2017). If risk aversion channel holds, we would observe affected firms significantly increase their risk aversion post natural disasters. The second one is the financial constraints channel. If the financial constraints channel holds, we would find that affected firms, due to their reduced profitability, are less financially viable to engage in risky projects (Hsu et al., 2018). Our empirical analysis supports the financial constraints channel. That is, following natural disasters, the cash holdings in affected firms significantly decreased, suggesting such firms are too financially constraint to engage in innovation commitment. Nonetheless, we do not find any statistically significant evidence that affected firms become more risk averse post natural disasters. Also, the reduced cash holdings in affected firms itself automatically reject the risk aversion channel, as Dessaint and Matray (2017) indicate that increased risk aversion should be associated with increased cash holdings.

Our research primarily contributes to the emerging string of literature on climate finance. There is a growing number of studies that investigate how natural disasters and climate change affect country-level financial losses (e.g., Kahn, 2005, Raddatz, 2007 and Luechinger & Raschky, 2009); firm-level operating performance as well as stock performance (e.g., Hsu et al., 2018 and Rehse et al., 2019); corporate financing activities (e.g., Bernile, Bhagwat, and Rau, 2017 and Dessaint and Matray, 2017); and financial market participants (e.g., Alok, Kumar, and Wermers, 2020, Choi, Gao, and Jiang, 2020, and Krueger, Sautner, and Starks, 2020). Our study enriches the climate finance by demonstrating that natural disasters discourage affected firms' tendency to engage in risky investment projects post natural disasters, suggesting a negative externality effect of the idiosyncratic environmental shocks.

In addition, our research extends the only research to our best knowledge that linking natural disasters and country-level disaster-related innovation (Miao and Popp, 2014) by examining the influence of natural disasters, with a broader focus, on firm-level all kinds of corporate innovation. Furthermore, our paper makes additional contribution to a rich but growing literature on the determinants of corporate technological innovation (e.g., Aghion et al., 2013, Atanassov, 2013, Fang, Tian, and Tice, 2014, Bernstein, 2015, Cornaggia et al., 2015, Bradley, Kim, and Tian, 2017, Brav et al, 2018, Gao et al., 2020, Moshirian et al., 2021) as well as an emerging strand of studies on production innovation (trademarks) and corporate finance (e.g., Chemmanur et al., 2020, Hsu et al., 2020, Heath and Mace, 2020, and Faurel et al., 2020). Nonetheless, the above-mentioned research focuses only on either technological innovation or product innovation. Our research sheds light on both technological and product innovation.

2. Social Media Posts and Stock Returns: The Trump Factor

2.1 Sample Description and Variable Definitions

2.1.1 Data

Our empirical analysis considers all Twitter messages posted by Donald Trump from May 26th, 2016 (the date he passed the threshold of 1,237 delegates required to guarantee his presidential nomination) to August 30th, 2018. The end point corresponds to the date on which the stock price coverage by Eventus came to an end, i.e., the latest point at which we could access abnormal returns calculated using data directly drawn from the CRSP stock databases at the time of our analysis. We accessed President Trump's tweets through http://www.trumptwitterarchive.com, which provides links to all Twitter messages the President has ever posted. Of the 6,983 presidential tweets during our sample period, we only select messages that mention companies that are publicly traded in the United States for this study. The selected messages are then classified as having a positive, neutral, or negative sentiment. Because the total number of relevant tweets during our sample period only amounts to 513, we did not require any linguistic algorithm for sentiment classification. We believe that this strengthens our data because President Trump uses unique vocabulary that can be better analyzed by humans rather than via classification algorithms. Thus, we selected key words and phrases based on meaning and context rather than having a computer choose them. Table 1 (Panel A) provides an overview of the 513 selected messages, i.e., messages in which specific firms are mentioned, organized by category and time. The date a tweet is posted is labeled as the event date, day 0. If a tweet is posted on a weekend or after the market has closed, we consider the next business day as day 0.

[Insert Table 1 about here]

Of the 513 tweets in which President Trump mentions publicly traded U.S. firms, 82 are positive, 194 are neutral, and 237 are negative. Although ambiguity regarding the sentiment of these messages was rare, each Twitter message in our final sample was reviewed by five independent researchers to ensure consensus interpretations. 432 of the 513 tweets are classified as media-tweets (see our definition below), and 81 are non-media tweets. We count repeated tweets on the same date as one.

Panel B of Table 1 provides a detailed breakdown of media and non-media tweets and lists the names of all public companies in our sample. Specifically, among the firms mentioned in all 513 tweets, 9 are media companies, 31 are non-media companies, and 4 companies are hybrid companies (defined below). As can be seen in Panel B of Table 1, some companies are mentioned more than once, especially media companies.

We define firms as hybrid companies if part of their operation is closely related to the publication of news. The President can post two types of tweets for these companies: a tweet that comments on the quality of their news output (a media tweet) or one that expresses a view on other functions or activities, such as the company's tax status (a non-media tweet). For example, Amazon.com, Inc., a technology company focusing on e-commerce, is closely related to the Washington Post: In 2013, Jeffrey Bezos, founder of Amazon, established Nash Holdings LLC to purchase the media firm. For Amazon, an example of a media tweet is: *"The Fake News Washington Post, Amazon's "chief lobbyist," has another (of many) phony headlines, "Trump Defiant As China Adds Trade Penalties." WRONG! Should read, "Trump Defiant as U.S. Adds Trade Penalties, Will End Barriers And Massive I.P. Theft." Typically bad reporting!"* An example of a non-media tweet for Amazon is: *"Why is the United States Post Office, which is losing many billions of dollars a year, while charging Amazon and others so little to deliver their packages, making Amazon richer and the Post Office dumber and poorer? Should be charging MUCH MORE!"*

[Insert Table 2 about here]

Table 2 shows a list of the key words and phrases that are typical for the President's tweets and are often used by the President when he exhibits positive or negative sentiment. Panel A lists selected key words that can be repeatedly observed in messages with a positive sentiment. The last two keywords/phrases (Back into the United States, No Mexico) are important because in the vocabulary of the President, they can translate into the possibility of no border tariffs for the firms mentioned. The key words and phrases frequently associated with negative tweets are listed in Panel B. Again, the last two key words/phrases (Move to Mexico, Jobs out of the U.S.) were in each case linked to border tariffs for the company mentioned.

2.1.2 Variable Definitions

Table 3 defines the variables we use in our dataset. For each selected tweet, we record several variables such as the name of the firm mentioned, the date and time of the message, and various key words that characterize the message and its sentiment. We then create two dummy variables, POSITIVE_ATTITUDE and NEGATIVE_ATTITUDE, to indicate whether the message has a positive or negative sentiment. Tweets that score zero on both variables are considered to be neutral. We expect the President's media tweets to have a different impact than his non-media tweets, because of their pure evaluative nature as discussed in Section II. To address this, we split our attitude variables (POSITIVE_ATTITUDE and NEGATIVE_ATTITUDE) into four to distinguish between media and non-media tweets: POS_NONMEDIA (positive non-media tweets), NEG_NONMEDIA (negative non-media tweets), POS_MEDIA (positive media tweets) and NEG_MEDIA (negative media tweets).

Furthermore, we employ a dummy variable, REITERATE, to identify messages in which the President repeated information about a company that was already in the public domain. This variable mainly applies to the 81 non-media tweets in our sample. In defining this variable, we consider both the timing and significance of the news. If a firm experienced a significant (positive or negative) shock in the two business days before the President tweeted about the same issue, REITERATE is assigned a value of 1; otherwise 0. We assign a value to this variable by manually searching the Internet for evidence of a significant event that is related to the tweet in question. An example of an observation for which the value of REITERATE is 1 is as follows: On July 18th, 2018, Google (Alphabet Inc.) received a penalty of 5 billion dollars from the European Union for breaking anti-trust laws. On July 19, the President tweeted: *"I told you so! The European Union just slapped a Five Billion Dollar fine on one of our great companies, Google. They truly have taken advantage of the U.S., but not for long!"* This tweet was posted only one business day after the initial news about this significant development; thus REITERATE is assigned a value of 1. Let us consider another example: Rexnord officially announced its decision to move its Indianapolis operations to Monterrey, Mexico, on Nov 14, 2016. On May 7, 2017 the President tweeted: "*Rexnord of Indiana made a deal during the Obama Administration to move to Mexico. Fired their employees. Tax product big that's sold in U.S.*" This tweet was posted more than five months after the initial news announcement; thus REITERATE is assigned a value of zero. Fifty-five out of the 81 non-media tweets made by the President refer to something that happened in the previous two business days (i.e., REITERATE equals 1). The distribution of the variable is shown in Panel B of Table 3.

[Insert Table 3 about here]

Table 4 provides descriptive statistics (i.e., the mean, median, standard deviation, minimum, and maximum) for each variable. The last three variables, VAR (-22,-3), LAG_SPREAD/BID, and LOG_LAG_VOL, are only used in our robustness tests and are based on Bhattacharya et al. (2009). The three variables only have 459 observations, because they depend on data points that ceased to be available from CRSP on June 30, 2018. As mentioned above, the calculation of abnormal returns continued until August 31, 2018. As a result, the sample size for the robustness tests involving these variables decreases from 513 to 459 (while the number of non-media tweets decreases from 81 to 69, and the number of media tweets decreases from 432 to 390). Thus, we only include these three variables in our robustness tests and not in the baseline model.

[Insert Table 4 about here]

2.2 Methodology

2.2.1 Event Study

We employ standard event-study methodology to measure the impact of the President's tweets on stock prices. Event-study methodology analyzes whether stock-price variations can be attributed to chance or whether they reflect the impact of the event being studied, in this case the posting of a tweet by President Trump that mentions a publicly traded firm. Event-study methodology examines abnormal returns defined as the difference between the expected and actual returns at the time of the event.

Because the calculation of abnormal returns depends on the model used to estimate the expected return, we need to examine whether our results are robust across several models. For this purpose, we employ the Capital Asset Pricing Model (CAPM), the CAPM with GARCH (1, 1) errors, the Carhart

(1997) Four Factor[17] model, and the Carhart (1997) Four Factor model with GARCH (1, 1) errors. For brevity, we focus on reporting the results for the Carhart (1997) Four Factor model with GARCH (1, 1) errors. This is one of the more sophisticated models in the repertoire of event-study methodologies.[18]

In addition, we consider several estimation windows spanning 30 days, 80 days, 120 days, 180 days, and 255 days in our empirical analysis. We also employ various end dates for the estimation period, including day -46 (46 days before the tweet), day -11 and day -3. Regardless of the estimation window being used, we find the results to be highly consistent. Again, for reasons of parsimony, we report the results for a single estimation period (180 days ending 11 days before a given tweet) - an estimation period employed in many studies. In summary, the main results remain robust, no matter what model and estimation window we use to calculate the expected returns.

2.2.2 OLS Regression

To examine how the President's tweets influence stock prices, we estimate the following cross-sectional OLS regression model with robust standard errors:

$$\begin{aligned}\mathrm{CAR}(0,1) \text{ or } \mathrm{AR}_0 &= \alpha + \boldsymbol{\beta_1} * \mathbf{ATTITUDE}_{\boldsymbol{s}} + \beta_2 * \mathrm{NEG\_REITERATE} + \beta_3 * \mathrm{POS\_ELECTIONWON} + \beta_4 \\ &\quad * \mathrm{AR}_{-1} + \beta_5 * \mathrm{SP500RETURN} + \boldsymbol{\beta_6} * \mathbf{CONTROL}_{\boldsymbol{l}} + \varphi_{\mathrm{k}} + \pi_t + \varepsilon\end{aligned}$$

We use two variables to measure the short-term performance of a given stock: AR_0 (the abnormal return on day 0) and CAR(0,1) (the cumulative abnormal return on days 0 and 1). $ATTITUDE_s$ is a vector including POS_NONMEDIA, NEG_NONMEDIA, POS_MEDIA, and NEG_MEDIA. To control for the possibility that a non-media tweet may repeat information about news that hit the market recently, we create two dummy variables, NEG_REITERATE and POS_REITERATE, which are the interaction of NEG _NONMEDIA and REITERATE and the interaction of POS _NONMEDIA and REITERATE (see Table 3). In addition, to examine whether the power of media tweets changed after Donald Trump won the election, we create two dummy variables, POS_ELECTIONWON and NEG_ELECTIONWON, which are the interaction of POS_MEDIA and ELECTIONWON and the interaction of NEG_MEDIA and ELECTIONWON. We do not compare non-media tweets before and after the date of the election, because only one non-media tweet was posted before the election. Similarly, as noted above, the President's tweets about media firms were purely evaluative during our sample period and did not repeat market-relevant information. Thus, we only calculate the REITERATE variable for non-media firms. To control for trends in the stock price, we add AR_{-1} (the abnormal return on day -1) to the model. In addition, we include SP500RETURN, the return of the S&P 500 index on the day of the tweet. $\mathrm{CONTROL}_l$ is a vector of firm characteristics and firm-specific variables (ROE, the B/M ratio, the debt ratio, total asset value, the variance of stock returns, the percentage bid-ask spread, and the number of shares traded). All OLS regressions in this paper use robust standard errors.

2.3 Results

2.3.1 Event Study

As shown in Table 5, for the sub-sample of positive tweets, the average abnormal return (AAR) at time 0 is positive and significant at the 5% level, while the results are insignificant for the sub-sample of negative tweets. Similarly, for the sub-sample of positive media tweets, the AAR on day 0 is

[17] Carhart's model extends the previous Fama/French Three Factor Model by adding a momentum factor, which measures the tendency for stock price to continue going up if it is rising and to continue going down if it is declining.

[18] The results for the other models are largely consistent and are available from the authors upon request.

marginally significant (at the 10% level), but it is insignificant for the sub-sample of negative media tweets. One possible explanation for the different findings for positive and negative tweets may be that the President posts many more negative (237) than positive (82) tweets (see Table 1), thus giving the positive tweets more weight.[19]

A similar explanation is likely to underlie the different findings for media and non-media tweets: The President frequently criticizes the news media for reporting negatively about him. For example, on August 30, 2018, the President posted a negative tweet about CNN: "*The hatred and extreme bias of me by @CNN has clouded their thinking and made them unable to function...*" Similarly, on January 14, 2018, the President tweeted positively about Twenty-First Century Fox: "*... "President Trump reversed the policies of President Obama, and reversed our economic decline." Thank you Stuart Varney. @foxandfriends*". There are multiple tweets that are comparable to the first one, in particular. As a result, stock market participants may have become numb to the President's tweets in which he criticizes the media (CNN, the New York Times, CBS, etc.) as being "fake", displaying "hatred" or being "biased". They may also have become somewhat insensitive to the President's tweets in which he praises other media firms (mainly Twenty-First Century Fox). These arguments would explain the findings in Table 5 that negative media tweets do not have a significant effect on day 0 abnormal returns, while positive media tweets only show a weak effect (at the 10% level). For non-media firms, on the other hand, we observe a stronger effect of the President's tweets on stock prices. This is likely due to the fact that the number of non-media tweets is smaller (81 out of 531), and that - as a result - they carry more weight. In addition, these tweets usually include some important information such as "moving to Mexico" or "creating jobs".

Non-media tweets also appear to lead to different stock market reactions depending on their sentiment. For positive non-media tweets, the AAR on day 0 is positive at a 5% significance level. Similarly, for negative non-media tweets, the AAR on day 0 is significantly negative (5%).

One more notable observation about positive media tweets is that after the election, the AAR_0 of positive media tweets is positive and significant at the 5% level, whereas before the election, positive media tweets result in a negative AAR_0 (albeit only significant at the 10% level). This may imply that the market reaction to President Trump's media tweets changed after the election.

[Insert Table 5 about here]

2.3.2 Univariate Analysis

In Table 6, we compare the means of the abnormal return on day 0 (AR_0) for different types of tweets. For the full sample, we observe that the difference in AR_0 between positive and neutral tweets, and between positive and negative tweets, is significant at the 1% level. In contrast, the difference between the mean AR_0 for negative and neutral tweets is insignificant. We have already noted that negative media tweets have a weak (or zero) effect. Because the full sample is composed mainly of media tweets, it is not surprising that the negative-neutral differences are non-significant in the full sample.

Similarly, when we examine the sub-sample of media tweets, the difference between AR_0 for positive and neutral tweets, as well as for positive and negative tweets, is significant (at the 5% level). The difference between AR_0 for negative and neutral tweets is again insignificant. More specifically, the results suggest that Trump's positive media tweets produce a significantly greater abnormal return

[19] For negative tweets, we observe a significantly positive abnormal return on day 2. This is likely due to a market correction that reverses some of the losses observed on the event date and the subsequent trading day (days 0 and 1).

on the day of the tweet than his negative and neutral ones.

After dividing positive media tweets into two sub-samples (Rows 3 and 4 under the heading AR_0 in Table 6, Panel A), we demonstrate that the previous finding (that positive media tweets produce a higher AR_0 than negative and neutral ones) only holds *after* the election. Thus, the post-election media tweets replicate the pattern of results found for all media tweets, and for the full sample of tweets.

Interestingly, when we compare the means of AR_0 for non-media tweets, the difference in the abnormal return is only significant when comparing negative tweets with either positive or neutral tweets ($p < 0.01$), while the mean AR_0 values for neutral and positive tweets are not significantly different. Specifically, the results demonstrate that, when compared to positive and neutral non-media tweets, the President's negative non-media tweets result in a lower abnormal return for the day.

To check the robustness of our results, we also compare the mean values of CAR(0,1) and the median values of both AR_0 and CAR(0,1) (Panel B). In general, for media firms, positive tweets result in better stock performance than negative/neutral tweets, while there is no significant difference between negative and neutral tweets. For non-media firms, the most consistent finding is that negative tweets result in significantly lower returns than positive tweets.

[Insert Table 6 about here]

2.3.3 Multivariate Analysis (OLS Regressions)

To complement our univariate findings, we conduct a multivariate analysis preceded by a correlation analysis. Panels A, B, and C of Table 7 provide the correlation matrix for three regression models. Panel A relates to the regression employing our full sample of tweets; Panel B only relates to tweets about media firms, and Panel C to tweets about non-media firms. Most of the correlation coefficients among the main explanatory and control variables are acceptable (less than 0.4).

However, some correlations among important variables are high and thus require special attention[20]; in Panel B, the correlation between POS_ELECTIONWON and POS_MEDIA is 0.931. Both variables are binary (0, 1) variables. POS_ELECTIONWON (POS_MEDIA* ELECTIONWON) is 1 when POS_MEDIA and ELECTIONWON are each 1. In other words, if the President posts a positive media tweet after the election, POS_ELECTIONWON is 1; otherwise it is 0. To avoid the possibility that these two variables cause any multi-collinearity problems in our regression analysis, we run a separate regression with each of these two variables. In Panel C, the correlation between NEG_REITERATE and NEG_NONMEDIA is also high: 0.514. Both variables are also binary (0, 1) variables. NEG_REITERATE (NEG_NONMEDIA* REITERATE) is 1 when NEG_NONMEDIA and REITERATE are each 1. In other words, if a firm underwent some changes (REITERATE=1) two business days before the President posted a negative non-media tweet (NEG_NONMEDIA=1) about the same topic, this variable is 1; otherwise it is 0. Again, we estimate separate regression models for these two variables to mitigate any potential multi-collinearity problems.

[Insert Table 7 about here]

2.3.3.1 Regression of the Full Sample

Columns 1 and 2 in Table 8 show that the coefficient of POS_MEDIA is positive and significant, confirming that President Trump's positive media tweets increase the abnormal return on the event day relative to negative and neutral tweets. For non-media firms, as foreshadowed in the univariate findings, the coefficient of NEG_NONMEDIA is significant and negative, while that of POS_NONMEDIA is

[20] If we exclude one or all of the highly correlated variables, the results remain qualitatively and quantitatively similar.

significant and positive only in Column 1 (with results becoming insignificant once we control for year and industry fixed effects). These findings suggest that the President's negative non-media tweets generate a lower abnormal return (compared to positive and neutral non-media tweets), while the impact of his positive non-media tweets may be unstable and statistically less reliable. When we use CAR(0,1) as the dependent variable (Columns 3 and 4), the significance of NEG_NONMEDIA decreases to a borderline level (Column 3) or becomes insignificant (Column 4), suggesting that the impact of negative non-media tweets reverses the next day. Yet, the coefficient of POS_MEDIA remains significant, implying that the impact of positive media tweets is more persistent.

[Insert Table 8 about here]

2.3.3.2 Regression Analysis of Media Tweets

Table 9 presents our regression results for media tweets. We analyze media tweets and non-media tweets separately because, as argued in Section II, any effect of non-media tweets on AR_0 may be due to President Trump's evaluation of the company (i.e., a positive or negative view) or to the market information they contain or both. However, the effect of media tweets on AR_0 can only be due to their evaluative content.

For example, at 10:14 a.m. on January 5, 2017, the President tweeted: *"Toyota Motor said they will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build the plant in the U.S. or pay big border tax."* The information in the message (Toyota building a new plant) and the attitude of the President may have an impact on the firm's short-term performance; however, it is difficult to assess their respective influence on it. In comparison, media tweets generally contain less information. For example, at 6:39 a.m. on June 27, 2016, the President tweeted: *"@CNN is all negative when it comes to me. I don't watch it anymore."* The President usually provides positive commentary on positive news reports about himself, and negative comments on negative news reports about himself without providing specific information such as "Toyota's building a new plant." It follows that, if the abnormal returns positively correlate with positive media tweets made by the President, we may reasonably conclude that media companies (and perhaps all companies) can benefit from agreeing with the President.

In Columns 1 to 6 of Table 9, the dependent variable is the day 0 abnormal return, and in Columns 7 to 8, the dependent variable is the (0,1) cumulative abnormal return. We can see that in Columns 1 and 2, the coefficient of POS_MEDIA is positive and significant (at the 5% level), implying an increase in the abnormal returns associated with positive media tweets relative to negative and neutral ones. In Columns 3 and 4, the coefficient of POS_ELECTIONWON is also significant at the 1% and 5% level, respectively. When both variables are included in the model (Columns 5 and 6), the coefficient of POS_MEDIA becomes insignificant. Although POS_MEDIA and POS_ELECTIONWON are highly correlated (0.931), the coefficient of POS_MEDIA is not far from being significant. As expected, these data highlight the significant positive influence of Trump's positive tweets on abnormal returns only after electoral success; presumably this is because the stock market started to take his tweets more seriously at that stage. The coefficient of POS_ELECTIONWON still shows significance or is close to significance in Columns 7 and 8, where the dependent variable is the (0, 1) cumulative abnormal return. Most control variables are not significant.

The R-sqaures are small in table 9. Possible reason is that Ordinary least square regressions of abnormal returns (or cumulative abnormal returns) on explanatory variables such as firm characteristics are often associated with relatively poor adjusted R^2s, unless the returns are very large in magnitude. With social media posts (even if they are made by the President of the United States), abnormal returns are considerably smaller which (due to the parallel influence of various other factors that drive stock returns on a given day) also limits their predictability.

Moreover, one possible reason that the R2 in table 9 is much smaller than table 8 is that the impact of the president's tweets on the media firms may be smaller than that on the non-media firms, because the market may doubt about president's comments on those media reporting news about himself.

In addition, it is worth noting that the longer the event window, the harder it is to explain a firm's abnormal returns (again due to the interference of other factors that drive stock returns in the market). In the first six models of Table 9, we employ the single day return (Ar0) on the event date (day 0), whereas in the last two columns of Table 9, we use the two day cumulative abnormal return (CAR(0,1). This further explains the particularly low and even negative adjusted R2 of those two models.

[Insert Table 9 about here]

2.3.3.3 Regression Analysis of Non-Media Tweets

Table 10 provides our regression results for non-media tweets. INDUSTRY_1DIG represents a series of industry dummies based on the first digit of a firm's SIC code. We use these variables (rather than our previous variables that were based on three-digit SIC codes) to control for industry fixed effects, because the number of non-media tweets is small. In Columns 1 and 2, the coefficients of NEG_NONMEDIA are significant and negative, implying that, when compared to positive and neutral non-media tweets, negative tweets are associated with lower abnormal returns.

In general, the coefficients of NEG_REITERATE are insignificant or borderline significant. The variable NEG_REITERATE takes on a value of 1 if a negative non-media tweet has been posted, and if the tweet contains information about the company that was first published within the previous two days; otherwise it is zero.

The following is an example of a tweet for which NEG_REITERATE equals 1: At 7:51 a.m. on February 8th, 2017, the President tweeted: *"My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!"* The allegedly unfair treatment of Ivanka by Nordstrom occurred right before the tweet and was discussed in the media, thus REITERATE equals 1. Furthermore, the tone of the tweet is negative, meaning that NEG_NONMEDIA is 1, and thus NEG_REITERATE (= NEG_NONMEDIA* REITERATE) equals 1.

The insignificance of the coefficients for NEG_REITERATE demonstrates that negative non-media tweets have no discernible impact on abnormal returns when the tweet repeats recently published, relevant information, even if the President ads a negative commentary. The fact that NEG_NONMEDIA itself has a significant negative coefficient, while the interaction with REITERATE is insignificant implies that the President's negative non-media tweets only have a negative effect on abnormal returns (compared to positive and neutral tweets) when they do not reiterate recent information about the company. In fact, in several cases, the market reaction to the news is positive, despite President Trump's view that the news is negative. This can be seen in the case of the tweet about Nordstrom and Ivanka Trump: the stock market perceives the "issue" (Ivanka's allegedly unfair treatment by Nordstrom) as beneficial to Nordstrom — this can be gleaned from the fact that the abnormal return of Nordstrom on that day is actually positive. When CAR(0,1) is used as the dependent variable (Columns 7 and 8), both the magnitude and the significance level of the coefficient of NEG_NONMEDIA decreases. Together, this suggests that the impact of negative non-media tweets is greater on day 0 than on the following day. Most control variables, other than the concurrent S&P 500 return, are again insignificant in Table 10.

[Insert Table 10 about here]

2.3.4 Robustness Tests

2.3.4.1 Propensity Score Matching

Rather than randomly choosing firms about which to tweet, it is possible that the President may have chosen, knowingly or unknowingly, to comment on firms with specific qualities (a source of a possible selection bias). Further, those qualities may make the selected firms more or less likely to generate abnormal returns than other companies. In addition, the impact of negative and positive tweets on President Trump's selected companies would not be representative of the potential impact of such tweets on companies generally. We therefore employ propensity score matching (PSM) to control for any possible selection biases and to assess the robustness of our results. Specifically, we collect accounting data for 4,522 firms from Compustat and match these firms (1-to-1 matching) with the companies in our sample that attracted the President's non-media tweets. This procedure allows us to compare the impact of tweets on the abnormal returns of President Trump's selected companies with the abnormal returns of a set of companies that were not in the President's set but had very similar characteristics to those that were.

We first perform a probit regression to examine the variables that may influence the President's tweeting choices. The dependent variable is Selection, which takes on a value of 1 for non-media or hybrid companies mentioned in the President's tweets, and a value of 0 for all other companies found in Compustat. Panel A of Table 11 (Column 1) shows that the best predictors of whether a firm is likely to be selected by President Trump are the firm's total assets (Log (Assets)) and its debt ratio. In other words, these findings suggest that the President has a tendency to comment on large companies with lower debt ratios. Using PSM, it is then possible to assemble a matched sample of companies that closely resemble the tweeted-about companies on these characteristics. Column 2 of Panel A demonstrates that after conducting PSM, the coefficient of Log (Assets) decreases and becomes insignificant (the p-value changes from 0.000 to 0.464), and the coefficient of the debt ratio also becomes insignificant (the p-value changes from 0.008 to 0.645). In addition, the pseudo R^2 decreases from 0.405to 0.032, indicating that these two variables are virtually uncorrelated with whether a company is in the selected set or the matched set. The implication of these results is that, to a certain degree and with regard to company-specific characteristics, the influence of any potential selection bias has been controlled.

The results for the matched sample regressions are provided in Panel B of Table 11 and are similar to the results in Table 10. After controlling for potential selection biases, we still find that negative tweets (NEG_NONMEDIA) have a significant negative impact on abnormal returns (Columns 1 to 4). However, contrary to Table 10, we find that the coefficients of POS_NONMEDIA now become significant and positive. This is likely because more firm-day data points without tweets from the President are added to the sample; that is, in the original sample, we compared the impact of negative, neutral, and positive tweets on abnormal returns, but in the matched sample, we compare the impact of each type of tweet with the impact of not being tweeted about. In general, the results show that, in comparison to the abnormal returns of companies with no tweets from the President, the abnormal returns of companies with positive tweets are higher, and the abnormal returns of companies with negative tweets are lower.

[Insert Table 11 about here]

2.3.4.2 Heckman Two Step Regression

A further source of bias may arise from the possibility that the President may choose a specific date (e.g., the date after a firm yields a positive or negative abnormal return) to post a positive/ negative comment about the firm. We control for this possible selection bias by using a Heckman Two Step Regression (Table 12). In the first step, we run a probit regression with NEG_NONMEDIA as the dependent variable and with AR_{-1}, the market return, and other control variables as explanatory variables. In a second step, we regress abnormal returns on POS_NONMEDIA, NEG_NONMEDIA, POS_REITERATE and NEG_REITERATE, with the Mills ratio. Columns 2 to 5 of Table 12 depict the results of these regressions, which correspond to Columns 1, 2, 5 and 6 in Table 10. The results are very similar to those of Table 10, demonstrating that negative non-media tweets continue to produce lower abnormal returns.[21]

[Insert Table 12 about here]

2.3.4.3 Robustness Tests with Additional Control Variables

In another robustness test, we choose three variables (VAR(-22,-3)), LAG_SPREAD/BID, and LOG_LAG_VOL) to control for the potential influence of stock price fluctuations during the days before the tweets were posted (Bhattacharya et al., 2009)[22]. The data source for these three variables is the CRSP database. The effect of including these additional control variables in the model (see Table 13) is neutral; i.e., the coefficients of POS_ELECTIONWON remain significant and positive, and the coefficients of NEG_NONMEDIA remain significant and negative, similar to the results in Tables 9 and 10. Moreover, the three new variables are not significantly correlated with the dependent variables. Thus, the results are robust to the addition of variables that might be expected to influence abnormal returns or to interact with our variables of interest.

[Insert Table 13 about here]

2.3.4.4 Further Robustness Tests (PLS & Subsample Tests)

In Table 14, we divide media tweets into two sub-samples based on whether they occurred prior to or after the election (Columns 1 and 2). In addition, we employ partial least squares structural equation modeling (PLS-SEM) to address any potential multicollinearity problems (Columns 3 to 4). Column 3 provides the results for non-media tweets, and Column 4 provides the results for media tweets.

Our results in Columns 1 and 2 indicate that before the election, the President's positive media tweets are insignificant, but that after the election, the coefficient of the POS_MEDIA becomes highly significant. This supports our earlier conclusion: positive media tweets by President Trump have a greater impact after he won the election. In Column 3, because POS_NONMEDIA and POS_REITERATE as well as NEG_NONMEDIA and NEG_REITERATE are highly correlated, we

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[21] In unreported tests, we also examined positive non-media tweets. The results for those tweets are also similar to our main results but are not reported for expositional brevity.

[22] Till now, we controlled 9 variables besides our main explanatory variables. For non-media tweets, the number of data decrease to 69. To show that limited number of data didn't influence our results, we add appendix 1: In column 1 and 2, The model that only includes four variables continues to support our hypotheses, with the coefficients for each variable remaining quantitatively and qualitatively similar to the reported models in the last two columns of Table 13. And for the model in column 3 and 4, we select the three most important control variables by employing standardized coefficients (whereby standardization involves subtracting the variable's mean from each observed value and then dividing by the variable's standard deviation). This allows us to identify the regressors that have the largest absolute value for their standardized coefficient. These include the variables SP500RETURN, LOG_ASSETS, and DEBT_RATIO. The inclusion of each of these variables also has the strongest positive effect on the R2 of our model (i.e. the variables increase the R2 more than other control variables). Again, the results of our resultant model – now with seven variables (our four variables of interest, plus the three control variables) remain qualitatively and quantitatively similar, with an adjusted R2 of 0.0222 which is highly comparable to the adjusted R2 of the models reported in Table 13.

use the PLS-SEM method and create two latent variables using the weight algorithm introduced by Wold (1982): LV_1, which is calculated as a weighted combination of POS_NONMEDIA (weight: 0.973) and POS_REITERATE (weight: 0.968), and LV_2, which is a weighted combination of NEG_NONMEDIA (weight: 0.990) and NEG_REITERATE (weight: 0.628). The coefficient of LV_2 is significant and negative. Given that both weights (0.99 and 0.628) are positive, the relationship between NEG_NONMEDIA and NEG_REITERATE is cumulative: each variable contributes to a lower abnormal return. In other words, the abnormal return would be lowest if NEG_NONMEDIA and NEG_REITERATE were both 1, and it would be highest if NEG_NONMEDIA and NEG_REITERATE were both 0.

In Column 4, because POS_MEDIA and POS_ELECTIONWON are highly correlated, and because NEG_MEDIA and NEG_ELECTIONWON are highly correlated, we use the same (PLS-SEM) method described above. In this case the latent variables (LV_3 and LV_4) are the weighted combination of POS_MEDIA (weight: 0.981) and POS_ELECTIONWON (weight: 0.985), and the weighted combination of NEG_MEDIA (weight: 0.967) and NEG_ELECTIONWON (weight: 0.922). The coefficient of LV_3 is significant and positive. Again, each variable has the same effect on abnormal returns, in this case contributing to a higher return.

In Column 5, we apply the same method (PLS-SEM) to our full sample and include all four latent variables. The coefficient of LV_2 stays significantly negative, and that of LV_3 significantly positive, further supporting our results in Columns 3 and 4.

[Insert Table 14 about here]

3. After the storm: Natural disasters and bank solvency

3.1 Hypothesis development

This study contributes to the literature by assessing whether and by how much bank solvency is affected by natural disasters. Prior studies in this area discuss different measures of solvency and note that solvency can be expressed from a balance sheet perspective as a form of equity or from a supervisory point of view as a more refined risk-based measure of capital (Flannery and Giacomini, 2015; Hogan, 2015). We thus employ two different types of bank capital ratios in our analysis: (1) the equity ratio and (2) the tier 1 capital ratio. Bank equity comprises all balance sheet components of a bank's proprietary capital including both common equity and preferred equity (Cohen and Scatigna, 2016). It can be interpreted as an institution's risk bearing capacity based on standard accounting principles. In contrast, the tier 1 capital ratio takes a regulatory and specific risk-based point of view, with tier 1 capital generally defined as high-quality equity capital (BCBS, 2011; BCBS, 2017).

In order to obtain numbers that are comparable across banks and years, we standardize the different types of capital. We use the volume of total assets (TA) to standardize the volume-based accounting equity, and the risk-weighted assets (RWA) to standardize tier 1 capital as risk-adjusted capital. Risk-weighted assets are based on the Basel II regulation that in essence have also been retained in the Basel III Accord (Dermine, 2015).

Our first hypothesis is in line with the general assumption that natural disasters have a negative impact on customers and bank operations and may thus cause losses. Specifically, we postulate that:

H_1: Natural disasters negatively affect the solvency of banks, measured via either the equity ratio (Hypothesis H_{1A}) or the tier 1 capital ratio (Hypothesis H_{1B}).

Because the two capital ratios are standardized using a different denominator, we can test the behavior of the simple volume-weighted equity ratio with respect to disasters and compare it to the behavior of the risk-weighted tier 1 capital ratio. On one hand, risk weights are considered more adequate for supervisory risk assessment; however, they may be more complex and less robust on the other hand (Dermine, 2015; Hogan, 2015). Moreover, because tier 1 capital is generally understood to be a more refined measure of a bank's capitalization, we further propose that:

H_2: The regulatory capital ratio is more sensitive to disaster risk than the accounting capital ratio.

We further assume that the magnitude of effects on solvency depends on the characteristics of individual banks. Particularly, the location of banks and their size may affect the damage they are exposed to from natural disasters. Our third hypothesis therefore reads as follows:

H_3: Disasters affect banks differently depending on the individual banks' characteristics.

3.2 Data and data preparation

This study uses data from the Emergency Events Database (EM-DAT) and a merged data set of banks' financial statements from Bankscope and Fitch. EM-DAT is provided by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Leuven, and contains detailed data on damages and other relevant information about various types of catastrophes around the globe. The data is collected from a variety of public and private sources, and since 2000, the centre has enhanced the data by geocoding each disaster (CRED, 2016). Natural (non-technological) disasters include critical meteorological (e.g., droughts, floods, storms) and geo-physical events (e.g., earthquakes, volcanic eruptions). Figure 1 provides an overview of the average annual damages per country caused by recorded disasters during the period 2000–2017. The different shades refer to the weighted damage ratio of each country, i.e., the ratio of the total annual damages in a given country to the country's GDP, averaged across our sample period. Figure 2 provides an overview of the damages caused by different types of disasters during our sample period. The proportion of damages attributable to the three main categories of disasters (earthquakes/tsunamis, floods, and strong winds) varies considerably over time and often depends on one or two 'mega-disasters' that caused most of the damages during a given year. For instance, in 2005, Hurricane Katrina was responsible for a large proportion of the natural disaster-related damages during that year, while in 2011 the earthquake leading to the Fukushima nuclear catastrophe represented a mega-disaster.

***** Insert Figure 1 about here *****

***** Insert Figure 2 about here *****

Bureau van Dijk (Bankscope) and Fitch Solutions (Fitch) provide detailed data on banks' accounting and financial statements. Bankscope includes extensive information for the years 2000 to 2014 yet limits the range of data offered thereafter. Therefore, we merge data from Bankscope through the year 2014 with information from Fitch for the years 2013 to 2017. When matching the two databases, we perform numerous checks to ensure the consistency of institutions and parameters included. A first issue is that the names of banks in Bankscope can differ from those in Fitch. In some cases, banks with similar names may be located in different countries, or banks can have several subsidiaries that are located in different cities in a given country yet display the same name. Furthermore, for some variables, the way Bankscope records or calculates the data can be different from Fitch, and thus variables with the same name in Bankscope and Fitch are not always identical.[23]

In a next step, we employ the year 2013 data on total assets from both Bankscope and Fitch (i.e., the year in which the two databases overlap) and calculate the following variable which we then use to further compare the banks in each database:

$$ADTA = \left|\frac{BTA-FTA}{BTA}\right| \tag{1}$$

where ADTA is the absolute difference in total assets between two banks, BTA is the value of total assets for a bank in Bankscope, and FTA is the value of total assets for a matched bank in Fitch.

The distribution of ADTA is shown in Appendix 1. If the absolute difference in the value of total assets is smaller than 0.1 (10%), we consider the match to be authentic. In contrast, if the absolute difference exceeds 0.1, we drop the matched bank pair.

In addition to total assets, we check the consistency of other variables in Bankscope and Fitch. We again examine the year 2013 data for 2,895 banks in Fitch, and compare the variable values with those of their matched counterparts in Bankscope. We use two different methods for our comparison (see Appendix 2). The first method is based on two correlation measures (the normal correlation and the correlation after trimming each variable at the 1% and 99% levels). The respective results are displayed in columns 1 and 2 of Appendix 2. The second method employs the absolute difference ratio, calculated in the same fashion as the absolute difference in total assets above. If the difference ratio is larger than 0.1 (i.e., a variable value in Fitch is ten percent larger or smaller than in Bankscope), we assign a value of "1" (wrong matching); if not, we assign a value of "0" (correct matching). In addition,

[23] We use the Stata command "matchit" to fuzzy-match the bank names (Stata, 2017). This command calculates similarity scores, ranging from 0 to 1, between every paired bank from Bankscope and Fitch. After matching the names, we ensure that the countries and cities provided as bank locations in the Bankscope database are exactly the same as the matched banks in Fitch. If the locations do not match, we delete the matched banks. Afterwards, we check the rest of the matched banks manually, to ensure that they are very likely to be the same banks.

if the value in Bankscope is 0 (making it impossible to be used as a denominator in our percentage difference calculation), then we assign a value of "0" if the value in Fitch is also 0 (correct matching); otherwise, we assign a value of "1" (wrong matching). The percentage of "1s" (i.e., the percentage of wrong matches) for each variable is shown in column 3 of Appendix 2. We mark the variables we use in this paper in bold and with grey shading. They exhibit good quality matching with a correlation higher than 0.99 and a percentage of difference ratio (at the 0.1 level) of less than 10%.

The Bankscope and Fitch databases include banks from around the world that file their financial statements in different currencies. In total, we have 9,928 banks in our sample with complete data on all variables. These banks are located across 149 different countries. Table 1 reports the geographical distribution.

[Insert Table 16 about here]

Some authors suggest keeping data in the original currency and thus avoid translation effects (Cohen and Scatigna 2016). However, in order to achieve better comparability (e.g., in terms of size), we convert all non-US$ figures at the respective exchange rate at the end of the accounting period. For most of our variables, potential biases caused by exchange rate fluctuations are avoided as we work with standardized data (e.g., capital in absolute terms divided by assets in absolute terms). Hence, any potential biases arising from currency fluctuations in the nominator and denominator should compensate each other.

Appendix 3 provides definitions for all variables used in our analysis and Table 2 reports summary statistics for the variables. The number of observations of the tier 1 capital ratio (124,997) is considerably smaller than that of equity ratio (164,046). The discrepancy is due to the fact that banks have not always been obliged to publish regulatory capital ratios. It is worth noting that the tier 1 capital ratio (tier 1 capital divided by risk-weighted assets) has a median of 14.50%, much higher than the 6% required by Basel III.

[Insert Table 17 about here]

3.3 Methodology

We assess a bank's sensitivity to risk based on a series of ordinary least squares (OLS) and quantile regression approaches. We employ alternative measures of disaster damages as our main independent variables and different specifications of bank solvency as our dependent variables. A major challenge in our analysis is to relate the two types of variables in a meaningful way. For instance, the EM-DAT database we use to assess damages from natural disasters reports disasters over periods of different length, e.g., single-day tornados or blizzards versus longer periods for floods and droughts. In addition, the impact of disasters on banks may be immediate, e.g., if they expose banks to operational risks, or long-term if disasters first affect the banks' customers and then gradually transform into credit risks.

To address these issues, we follow Klomp (2014) and design our main explanatory variable of interest (*Damage Ratio*) as follows: We assume that all banks in one country experience the same repercussions from a given disaster, and further that the impact of the disaster fully materializes and affects banks within one single year or two consecutive years.[24] For example, we assume that the shortest period during which a given disaster occurs and affects a bank is two months (60 days). In

[24] Klomp (2014) also allocates disaster damages to two different years. However, he only uses large-scale disasters and equally assigns 50% of the damage to the disaster year and the subsequent year. In contrast, we include all disasters listed in the EM-DAT database and divide the damages resulting from each disaster into two years based on the specific timing of the disaster during a given year.

addition, we assume that disaster *j* affects country *i* approximately *m* days before the end of year *t*, and that the total number of disasters that occur in year *t* for country *i* is *n*. The proportion of damages attributed to year *t* ($damage_{ijt}$) and year $t+1$ ($damage_{ij(t+1)}$) is thus calculated as follows:

$$If\ m \geq 60\text{: } damage_{ijt} = total\ damage\ of\ disaster\ j\ in\ country\ i$$

$$Otherwise(\ m < 60)\text{: } \begin{cases} damage_{ijt} = \left(\frac{m}{60}\right) * total\ damage\ of\ disaster\ j\ in\ country\ i \\ damage_{ij(t+1)} = \left(\frac{60-m}{60}\right) * total\ damage\ of\ disaster\ j\ in\ country\ i \end{cases} \quad (2)$$

$$DamageRatio_{it} = (\sum_{j=1}^{n} damage_{ijt})/GDP_{it}$$

To account for the different time patterns that characterize both disasters themselves and their effects, we consider periods of varying length during which damages may materialize. Specifically, in addition to the aforementioned 60 days, we also assume that damages manifest within 90 days and 180 days after the beginning of the disaster. Because the results for the different periods are very similar, we only report the results for an impact period of 60 and 180 days, and consider other periods as part of our robustness tests.

Following the prior literature on bank capitalization, we control for several characteristics of banks: Size, measured as the natural logarithm of total assets (Barrios and Blanco, 2003; Brewer et al., 2008; Schepens, 2016), the loan ratio, measured as net loans over total assets (Altunbas et al., 2007; Demirgüç-Kunt et al., 2013; Schepens, 2016), profitability, measured as the ratio of net income over equity (Brewer et al., 2008; Schaeck and Cihák, 2012), and the deposit level, measured as the ratio of total customer deposits over total assets (Barrios and Blanco, 2003; Demirgüç-Kunt et al., 2013).

Furthermore, because country-specific variables can affect each nation's banking system, we include several country-levels controls that have been used in previous research in this area. These include: the level of national development, measured as the natural logarithm of a country's annual real GDP per capita; economic growth, measured as the annual growth in the real GDP, and the credit activity of a country measured as the growth of credit to the private sector. We also examine other country-specific control variables such as the world government index (Kaufmann et al., 2011), a country's trade balance, and changes in each country's exchange rate. The resulting models either suffer from multicollinearity problems or are associated with large reductions in our sample size due to missing values. We thus decided not report the respective regressions here. However, even with these variables included, the results remain similar.

Our resultant regression model can be written as follows:

$$\Delta\, ratio_{kit} = \mu * ratio_{kit-1} + \beta * \mathrm{DR}_{it} + \alpha_m * B^s_{kit} + \gamma_h * C^h_{it} + + \theta_t + \varphi_i + \delta_{kit} + \omega_{kit} + \varepsilon_{kit} \quad (3)$$

and

$$\Delta\, ratio_{kit} = ratio_{kit} - ratio_{kit-1} \quad (4)$$

where $ratio_{kit}$ represents the equity ratio or tier 1 capital ratio for bank *k* in country *i* in year *t*, and $ratio_{kit-1}$ is the corresponding ratio in the preceding year. DR_{it} is our explanatory variable of interest (in this case the weighted damage ratio during the 60 days (or 180 days) following a disaster). B^s_{kit} is a vector of *s* bank-specific control variables, and C^h_{it} is a vector of *h* country-specific control variables. θ_t represents time fixed effects, and φ_i the country fixed effects. δ_{kit} are the accounting standard fixed effects, and ω_{kit} are the bank specialization fixed effects.

3.4 Results

Before commencing with our multivariate analysis, we first examine the Pearson correlation coefficients for all variable pairs in Table 3. All correlations – except for two – between the variables are well below 0.5. The exceptions include the correlation between the lagged tier 1 capital ratio and the lagged equity ratio (0.8206), where a high correlation is expected. The two variables are never employed in the same model, thus mitigating any multicollinearity concerns in our multivariate analysis. Similarly, and again as expected, the damage ratio (60 days) and the damage ratio (180 days) exhibit a high correlation (0.9425). The two variables are used as alternative damage proxies and thus never coexist in one model, again mitigating any multicollinearity concerns.

[Insert Table 18 about here]

We next commence our multivariate analysis by examining how banks' equity ratios are affected by natural disasters (Hypotheses H_{1A} and H_{1B}). In addition, we explore whether the relationship is different when employing the tier 1 capital ratio, instead of the equity ratio, as a dependent variable (Hypothesis H_2). Because the sensitivity to natural hazards is unlikely to be uniform across institutions, we differentiate between banks located in countries with different land masses as well as between different types of banks (based on their business model) as well as different ex-ante capitalization levels of banks.

3.4.1 The sensitivity of banks' equity capital to natural disasters

Table 4 provides our regression results for Hypothesis H_1. To ensure the robustness of our results, we perform separate regressions for our full (worldwide) sample of banks, banks in the United States (US only), and banks in other countries (non-US). Columns 1 to 4 of Table 4 show how the weighted 60-day damage ratio affects the equity ratio (DE/TA) for the three geographical subsamples (with column 4 repeating the full-sample analysis of column 3, but employing a non-winsorized sample). The coefficients for the damage ratio are consistently negative and significant, suggesting that natural disasters indeed have a detrimental effect on banks' capital ratios. Columns 5 to 8 of Table 4 employ the same model specifications as those employed in columns 1 to 4, but use the weighted damage ratio measured over a period of 180 days as the main variable of interest. The results are qualitatively and quantitatively very similar to those in the first four columns.

There are likely several reasons why natural disasters affect a bank's capital ratio. One explanation is that while banks protect their lending activities by requiring assets as collateral, the occurrence of natural disasters may destroy or at least reduce the value of the assets in question, hence reducing the bank's capacity to recover the outstanding loan balance via its collateral. Accordingly, if a borrower defaults on his/her loan and the bank manager realizes that the bank cannot recover the borrowed money through the collateral, the bank has to write off the borrowed amount from its books and, by extension, the bank equity. Consequently, losing collateral as a result of a natural disaster is likely the main channel through which natural disasters affect a bank's equity. Furthermore, disasters may affect banks directly, for instance by damaging a bank's offices or its technical infrastructure. In summary, there is a multitude of reasons why banks that lend in high-risk areas should prepare for and create reserves to protect themselves against natural disasters and prevent any associated deterioration in their capital ratios.[25]

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[25] It is worth noting here that higher capital requirements (e.g., those mandated by Basel III) have been shown to increase banks' lending rates and, consequently, have been blamed for the comparatively slow economic recovery following the 2008/2009 financial crisis and a reduction in global GDP growth, estimated at approximately 0.3% per year.

When examining the other explanatory variables, we observe that bank size (measured by the *natural log of total assets*) negatively correlates with the bank equity ratio, which is in line with prior research on bank solvency (Barrios and Blanco, 2003; Altunbas et al., 2007; Schaeck and Cihák, 2012; Schepens, 2016). Similarly, and also in line with the extant literature, we observe that profitability (measured by the *lagged net income to equity ratio*) is positively related to the equity ratio (Brewer et al., 2008; Schaeck and Cihák, 2012; Panier et al., 2013; Berger et al., 2018); and that the *net loan ratio* (net loans/total assets) is, generally, negatively correlated with the equity ratio (Altunbas et al., 2007; Schepens, 2016).

The prior banking literature exhibits mixed evidence regarding the effect of disruptions on the equity ratio of banks. Studies on financial crises (De Jonghe and Öztekin, 2015, and Gambacorta and Shin, 2018) suggest that the equity ratio of banks is procyclical: when a financial crisis hits the market, the equity ratio of banks increases (likely due to capital injections). Similarly, Koetter et al. (2016) and Bos et al. (2018) argue that capital adequacy (as proxied by the equity ratio) and lending (in the form of total outstanding loans) increase after large-scale natural disasters. In contrast, Noth and Schüwer (2018) find evidence that suggests that US banks that engage in mortgage lending experience a decline in bank capital following a natural disaster. Finally, Klomp (2014) shows that banks' default risk increases (and the equity ratio decreases) in the years following a large natural disaster. Our results complement this research.

[Insert Table 19 about here]

3.4.2 The sensitivity of banks' tier 1 capital to natural disasters

In order to compare the sensitivity of our two solvency measures, we re-estimate the same regressions we employed in Table 4 with the *tier 1 capital ratio* as the independent variable. We thus address our hypothesis (H_2) that suggests that regulatory capital ratios more distinctly reflect changes in risk than accounting based measures of capital. Columns 1 to 3 (4 to 6) of Table 5 show how the weighted 60-day (180-day) damage ratio affects the tier 1 capital ratio of banks in our three geographical subsamples (US banks, non-US banks, and the full sample). Except for the US, the coefficients are not significant and not always negative, suggesting that natural disasters have a smaller effect on regulatory capital ratios than they have on the accounting based equity ratios we examined in Table 4.

[Insert Table 20 about here]

For the subsample of US banks, the coefficients for the damage ratio in our equity capital analyses (Table 4) are considerably larger than those in our regulatory capital regressions (Table 5). We also find that, in general, disasters have a larger impact on the equity ratio of US banks than on the equity ratio of non-US banks. This is likely driven by the fact that since about the 1980s, the damages caused by disasters in the US increased considerably more than those in other countries. For instance, in 2017, the US accounted for 83% of damages from storms worldwide (Munich Re, 2018, p. 52; WEF, 2018, p. 12).

Contrary to Hypothesis H_2, we note that disasters do not have a large impact on the tier 1 capital ratio. If anything, our results show that, in comparison with the equity ratio, the tier 1 capital ratio is less significantly and uniformly influenced by natural disasters. There are several possible reasons: first, regulations may force banks to keep the required amount of tier 1 capital at a specific and constant

A well-measured response to climate change with appropriately defined natural disaster prone risk weightings for banks' assets is therefore called for.

level; second, in order to protect against failure, bank management will, by itself, have an incentive to keep the tier 1 capital ratio at a safe level (Abou-El-Sood, 2015); third, the denominator of the tier 1 capital ratio (a bank's risk-weighted assets), does not sufficiently take natural disaster risk into account, causing regulatory weightings to remain largely unaffected by disasters. Our lack of support for Hypothesis H_2 is in line with prior research findings in this area. For instance, Schüwer et al. (2019) document that the regulatory capital ratio increases (rather than decreases) after a disaster.[26]

We conclude that we cannot find clear evidence of a higher risk sensitivity of the tier 1 capital ratio. Rather, the equity ratio appears to be a more appropriate measure of natural disaster risk and should be considered for regulatory purposes. In addition, as noted above, a revised risk-weighting of assets that does not only take historical credit and liquidity into consideration (as per Basel III), but weighs assets based on their expected susceptibility to natural disasters, may lead to a better inclusion of natural disaster risks in banking regulations. Similar results should be achieved from a fairer risk weighting of assets that takes the geographical lending habits (and thus the proneness to natural disasters) of a given bank into consideration.

With respect to our other explanatory variables, we observe that – in line with previous research in this area (e.g., Brewer et al., 2008) – bank size negatively correlates with the tier 1 capital ratio, and that profitability (the *lagged net income to equity ratio*) positively relates to the equity ratio.

3.4.3 Ex-ante Test

Taking into account the likelihood that banks anticipate natural disasters and respond in advance, we explain the changes in each indicator by using the forward damage ratio (damage ratio one year ahead). We find that, overall, banks do not prepare for future disasters so that there is no significant change in the equity ratio (column 3), tier 1 capital ratio (column 6) or net interest margin (column 9) in the year preceding the disaster.
However, banks in the US (columns 1, 4, and 7), have been more forward-looking and have strengthened their balance sheet by increasing (reducing) equity (debt), injecting liquidity, and expanding the profit margin appropriately. The results have several implications. Firstly, the forward damage ratio significantly affects the asset structure of US banks, which indicates the quality of their prediction and the actions taken to prepare for natural disasters in the United States. Secondly, as can be observed in the aftermath of natural disasters , some governments tend to adopt relatively loose credit policies to support post-disaster reconstruction, which may lead to the increase of banks' bad debt thereafter. However, US banks can effectively mitigate the severe impact of natural disasters on loan quality and credit risk by raising the lending rate in advance, increasing cash reserves, alleviate the panic in the capital market and avoid increasing market risks.

[Insert Table 21 about here]

3.4.4 The influence of bank characteristics

The results up to now provide evidence for our full sample of banks. However, banks around the globe operate under different conditions, pursue divergent business models, and are subject to differing types of disasters as well as variations in country-level factors characterizing each country's legal environment, economic development, and banking regulations. To address these issues, we perform a series of robustness tests in which we examine whether our results hold for different subsamples of our

[26] The authors show that higher risk-based capital ratios are the result of banks prioritizing lower risk-weighted assets such as government securities.

data based on the characteristics of both banks and/or the countries they operate in.

3.4.4.1 Business models

Banks vary considerably with respect to the way they conduct their business, and it is important to explore whether a bank's business model affects its susceptibility to adverse consequences from a natural disaster. We therefore investigate if the risk sensitivity of banks to catastrophic events depends on their respective business models, i.e., their strategy towards customers, products, and regions, and the associated diversification potential. The assumption is that more diversified institutions (whose lending and investment portfolio includes claims with low correlations) are better able to absorb and deal with large damages than undiversified banks. In this respect, damages from disasters may be considered a specific class of risk that allows for diversification effects.

Our analysis focuses on the three predominant business models, namely bank holding companies (BHCs), commercial banks, and savings banks. A bank holding company typically operates across multiple regions and product markets through the participation in different entities. As a result, the potential for geographical diversification is generally higher for BHCs than for commercial banks that also have a broad product portfolio, yet display a smaller network of national and international branches. Savings banks operate under a third type of business model. Their lending portfolio is often regionally focused and they tend to be smaller, increasing their exposure to local disasters. In summary, we expect more diversified (and less concentrated) banks such as BHCs to be less affected by disasters than commercial banks and, in particular, savings banks.

Although our results are not fully as expected, our assumption that a banks' business model matters is confirmed. Table 7 shows that in our global sample, only BHCs exhibit a significant and negative coefficient. In the US sub-sample, BHCs experience the most negative effect from natural disasters whereas commercial banks have a lower, albeit still significant, coefficient. US savings banks exhibit a non-significant and economically small coefficient. Further investigation is needed to explore the causes. In particular, it is likely that a more refined geographical matching of disasters and bank lending activities will affect our results. For instance, there are several thousand savings banks that operate across the US and while a certain proportion of these banks is likely to be severely affected by a disaster, the remainder are likely to be unaffected because they are geographically removed from the disaster. On average, this makes savings banks appear unexposed on average, even though the individual exposures within this group may vary widely. Future research may also consider if business models are still to be conceived as a proxy for diversification as far as damages from natural disasters are concerned. Natural catastrophes represent to a certain extent a systemic risk and traditional patterns of diversification may fail to sufficiently protect the institutions. In addition, it is worth exploring if the benefits from diversification are potentially overcompensated by higher idiosyncratic risks institutions assume with respect to natural disasters.

[Insert Table 22 about here]

3.4.4.2 Capitalization level of different quantiles

Another attribute that may affect the sensitivity of banks to disasters is the extent of their ex-ante capitalization. We expect that banks with higher capital can better mitigate and control damages from disasters as they are better equipped to offset losses. Particularly, single losses may affect large and well-capitalized banks to a lesser extent than smaller institutions with less capital. We consider a bank's total equity as a proxy for size and the equity ratio as a proxy for the bank's equity base. We then use a series of quantile regressions to examine whether our results differ across banks with different ex-ante equity ratios.

Table 8 provides the results for the 0.25, 0.50 and 0.75 quantiles. When examining the coefficients for the damage ratio across all countries and for the US only, we observe that banks with a lower equity ratio (i.e., the 0.25 quantile) exhibit a higher (negative) sensitivity to damages than banks at the 0.75 quantile. The sensitivity decreases continuously from the 0.25 quantile to the 0.75 quantile. In the sub-sample of non-US banks, the coefficients of the damage ratio in the 0.25 and 0.50 quantile regressions are not significant, but become significantly negative in the 0.75 quantile. Overall, these results suggest that higher ex-ante equity ratios appear to reduce the impact of natural disasters on a bank's solvency. Another potential explanation is that banks with a higher capitalization have been hit less frequently by disasters in the past and therefore have been able to maintain higher levels of equity capital.

[Insert Table 23 about here]

3.4.4.3 Bank location

From a spatial perspective, the severity of disasters and the magnitude of the associated damages may vary among countries and affect some banks more than others based on their location. In addition, natural disasters of the same magnitude may hit smaller countries more extensively while their impact on large countries may be comparatively small. For example, a single tsunami may destroy much of the infrastructure of any Caribbean state. In contrast, the 2008 earthquake in China's Sichuan province had a destructive effect on this province, but had a relatively small impact on banks in surrounding provinces, because they are geographically far removed.

For smaller countries, the reduced land mass increases the likelihood that a disaster affects one or more of a bank's clients. Second, banks in smaller countries are less likely to be diversified. As a result, a country's land mass should be negatively related to a bank's post-disaster solvency.

Table 6 provides empirical evidence for several tests that address this issue. We divide our sample into two subsamples based on whether the land mass of their respective countries falls above or below the sample median. In column 1, we can see that disaster damages have a significantly negative impact on the equity ratio of banks in countries with a comparatively small land size. However, regardless of whether we include banks in the US, the results are insignificant for larger countries (see columns 2 and 3). As before, disasters appear to have no impact on the tier 1 capital ratio for either small or large countries.

[Insert Table 24 about here]

Then, we estimate a weighted regression in which we assign a weight equal to one divided by the square root of a country's 2017 surface area (based on data from the World Bank Indicators Database, https://data.worldbank.org/indicator) to all observations in that country. Our results remain robust as regards this methodological variation.

As the size of the country increases, it is more likely for the country to cover the location of natural disasters, and the vulnerable population will increase. We adjust the natural disaster variable for the country's geographic area to rule out any endogeneity bias, and the results remain robust. In the full sample, the banks' equity is significantly reduced after experiencing natural disasters (column 1 and 2), but the capital adequacy ratio is not significantly curtailed due to the requirements of the Basel Accord (column 3).

[Insert Table 25 about here]

We group countries into quintiles based on the 2017 GDP per capita in said country, again employing data provided by the World Bank Indicators Database. In rare instances where 2017 data was not available, we employ the most recent available GDP per capita for that country and then extrapolate it to the year 2017 (i.e., to the end of our sample period) using the GDP per capita growth rate during the previous five years as a growth factor. We then assign dummy variables to each of the five quintiles and estimate a ‘wealth fixed effect regression’ in which we include dummy variables for four of the five quintiles in our model (excluding the center quintile). The coefficients for the dummy variables denoting the lowest two GDP per capita quintiles are significantly negative, suggesting that banks in poorer countries (i.e., countries with the lowest GDP per capita figures) experience the largest decline of solvency following a natural disaster.

[Insert Table 26 about here]

Considering that the occurrence of natural disasters closely relates to the geographical location of banks, we divided the sample into 6 groups according to their continent. The results show that the equity ratio of banks in Africa was most significantly negatively affected (column 1), which may be attributed to a relatively imperfect banking system, followed by the small adjustment of bank assets in Oceania and North America (columns 5 and 4). Even so, there is no significant change in the tier 1 capital ratio on any continent, supporting our main hypothesis (columns 7-12). That is to say, that banks in all continents have met the requirements of capital adequacy for regulatory reasons, and there is not much change after the natural disaster. , However, it also reveals that the Basel Accord fails to take into account the capital requirements in the case of natural disasters. Consequently, we should expect that the value of T1R should have been calibrated but it has not changed suitably.

[Insert Table 27 about here]

3.4.4.4 Different types of disasters

Finally, we aimed to analyze the consequences of different types of disasters. In all disaster types, floods have the most significant impact on capital (column 2), followed by storms (column 1), whereas earthquakes have no significant impact (column 3). As Benson and Clay (2004) point out, geological disasters such as earthquakes are likely to cause Schumpeter’s "creative destruction" and thus stimulate post-disaster economic development. Yet meteorological and hydrological disasters such as storm and flood that occur more frequently are more likely to destroy the investment atmosphere, leading to a significant contraction in the equity ratio.

[Insert Table 28 about here]

3.4.5 Additional tests

To further ensure the robustness of our results, we perform some additional sensitivity checks. First, we are interested whether and how much any potential damages from the previous year can influence the equity ratio of the current year. We therefore regress the change in the equity ratio of the current year against the damage ratio of the previous year (Damage ratio$_{t-1}$). Our results, presented in columns 1 and 2 of Table 9, show that, regardless of whether we use the damage ratio over 60 or 180 days, its significance level decreases relative to our main regression results in Table 4, although the coefficient remains negative. This suggests that damages affect a bank’s capitalization relatively quickly and that, as time passes, the impact decreases.

[Insert Table 29 about here]

Next, we examine whether our results stay robust if we do not control for the equity ratio in the previous year. We estimate the respective regressions in column 3 and 4. The coefficients of both the 60- and 180-day damage ratio remain negative and highly significant. Finally, we employ a system GMM approach to estimate our regressions. The coefficients are still significantly negative. However, it is worth noting in this context that with fixed effect dummies (or any other dummy with many 0s or

1s), the results of a system GMM can be biased.[27]

3.4.6 Economic significance of our research

At last, our results remain robust after standardizing all variables, that is, for every standard deviation change in damage ratio, the equity ratio decreases by 0.004 standard deviation (column 3). Although 0.004 is a small number, the damage from disaster can be surprisingly big: the highest damage ratio is 148.38%, which is about 192.70 times of the standard deviation (0.77%).

[Insert Table 30 about here]

27 For additional details, please refer to Roodman (2009).

4. How Companies Respond to Natural Disasters? Evidence from Corporate Innovation

4.1 Data and sample

We elaborate the process of data collection and sample construction, followed by the descriptive statistics in this section.

4.1.1 Data on natural disasters

We obtain the data pertaining to natural disasters from the Spatial Hazard Events and Losses Database (SHELDUS) that is held and maintained by Arizona State University. We firstly define the severity of each natural disaster using the personal and property damage caused by a natural disaster between 1990 and 2015. Specifically, we compute the aggregate damage data (personal as well as property damage) for each U.S. state in each year between 1990 and 2015. Next, based on the aggregate damage data, we construct our main explanatory variable, *Damage ratio*, which is calculated as the aggregate damage of the natural disasters occurred within a U.S. state in a given year scaled by the annual state GDP in the prior fiscal year. In addition, for robustness check, we follow Barrot and Sauvagnat (2016) to identify the most disastrous 36 disasters (*Huge disaster*) occurred between 1990 and 2015.

4.1.2 Data on technological innovation

Existing studies have documented that patent activity is a reliable measure of the quality of firms' technological (Lanjouw et al., 1998; Hall et al., 2001, and Bernstein, 2015). We collect the data on patents from several databases. The market value of successfully granted patents are retrieved from the website of https://iu.app.box.com/v/patents, provided by Kogan et al. (2017). In addition, we collect patent information from National Bureau of Economic Research (NBER) Patent Database. However, since the patent data is available only until 2006 in NBER Patent Database, we complement the patent data from 2007 to 2015 by using the website of Patents View (https://www.patentsview.org) supported by USPTO (the United States Patent and Trademark Office). Because we find no data available to merge U.S. companies with assignees of all patents after 2006 (although NBER Patent Database provides a bridge file linking patent assignees to Compustat up to 2006), we employ a "fuzzy matching" procedure. Specifically, we apply an algorithm to compute the similarity score between patent assignees' name with U.S. firms' name available in Compustat. Next, we manually verify whether the matched pair of companies are indeed the same firm. Finally, we count the cumulative number of patents granted to each U.S. firm in each fiscal year. Based on the collected patent data, we construct several proxies for U.S. firms' technological innovation. Following Kogan et al. (2017), we construct our first proxy of corporate technological innovation that captures the market value created by firms' successfully granted patents (*Patent value*). Explicitly, it measures the stock market response to the announcements of patents being successfully granted to U.S. firms. As indicated by Kogan et al. (2017), the abnormal returns created by newly granted patents can effectively reflect patents' real value and quality. Our second measure of technological innovation is *Ln(1+Patent)*, which is the natural logarithm one plus a firm's granted patent count in a fiscal year[28]. Our third proxy of technological innovation is the citations of firms' granted patents, as Griliches (1990) and Bernstein (2015) state that simple patent counts cannot reflect breakthrough innovation as well as incremental discoveries. We follow Hall et al. (2001) and Bernstein (2015) to calculate the truncations adjusted number of citations

[28] Given that distributions of patents and patent citations are highly right skewed, we take the natural logarithm of patent counts and patent citations. When taking the natural logarithm, we add the value of one to the actual number of patent counts and patent citations to prevent losing observations without any patents and citations.

of a granted patent, to mitigate the issue of truncation bias[29]. Hence, the third measure is constructed as the natural logarithm of one plus the truncation adjusted total citations of a firm's granted patents in a fiscal year, *Ln(1+Citation)*.

4.1.3 Data on product innovation

Base on existing literature pertaining to product innovation, corporate successfully registered trademarks are considered effective proxy of product innovation (Mendonça, Pereira, and Godinho, 2004; Sandner and Block, 2011; Hsu et al., 2018; Chemmanur et al., 2020; Faurel et al., 2020; Heath and Mace, 2020; Hsu et al., 2020). We obtain trademark data from Trademark Case Dataset, available at USPTO. The Trademark Case Dataset contains a rich set of information on 9.1 million trademark applications as well as registrations from 1870 to the present. The detailed information of trademarks include classification, filing date, ownership, and registration date. According to the above-mentioned literature, we only count trademarks that were successfully registered. Similar to patent data, no bridge file is available to pair the trademark owner and U.S. firms in *Compustat*, we employ the fuzzy matching algorithm to match U.S. firms available in *Compustat* with trademark information. In addition, we manually verify each matching pair to ensure the matched two firms are indeed identical. Based on the trademark data, we construct six proxies of product innovation in total. The basic measure is the natural logarithm of a firm's successfully registered trademark counts in a fiscal year, *Ln(1+Trademark)*. In addition to the simply the quantity of registered trademarks, we construct several variables to measure the diversity as well as the quality of a firm's product innovation. Following Hsu et al. (2020), we construct five additional variables, with *Ln(1+Diversity)* measuring the diversity of corporate product innovation whilst *Ln(1+Exploitation), Ln(1+Exploratory), Ln(1+Marketing), and Ln(1+Product)* capturing the quality of product innovation. Furthermore, we perform the principal component analysis (PCA) for technological and product innovation and use the first PCA component to measure a firm's overall innovation output (*Innovation component*). Detailed definitions of these measures are specified in Table A1, Appendix A.

4.1.4 Control variables

Following previous studies, we include a set of firm specific characteristics as control variables[30]. The data of firm specific variables are collected from *Compustat*. Explicitly, our baseline control variables are financial leverage (*Leverage*), growth opportunities (*Tobin's q*), Herfindahl-Hirschman Index (*HHI*), profitability (*ROA*), corporate cash holdings (*Cash holdings*), firm size (*Firm size*), number of years being included in *Compustat* (*Firm age*), and research and development expense ratio (*R&D ratio*). We provide detailed definition for all variables in Table A1 in Appendix.

4.1.5 Sample and descriptive statistics

Our baseline sample includes 12,184 U.S. public firms from 1990 to 2015, the total firm-year observations are 99,521. We provide the summary statistics in Table 1. From Table 1, we can see that the mean value of the damage ratio caused by all natural disasters in a given year is 0.12% of state GDP. The average value may not be too high because not all the U.S. states are hit by natural disasters. This phenomenon is well exhibited in Figure 1. Figure 1 indicates that major financial damages caused by natural disasters are clustered in the South of the U.S. This is in line with our expectation given that the southern states are frequently hit by hurricanes. Also, states in the Midwest and California have

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[29] For example, in our sample, we can only count the citations of a patent granted in 2010 up to 2015, but there will be citations after 2015 (Hall et al., 2001).

[30] To explore the transmission channels through which natural disasters affect corporate innovation, we also employ variables of *Inventor comer, Inventor leaver, CEO vega, Systematic risk*, and *Unsystematic risk* respectively. To examine the state-level inventor mobility, we include a set of state specific variables: state unemployment, state population, state minimum wage, and state GDP. Variable definitions are provided in Table A1 in Appendix.

significant financial loss triggered by natural disasters. The average value of the huge disaster dummy suggests that nearly 20% of the natural disasters are considered ones that triggered severe financial damages. The descriptive statistics pertaining to technological and product innovation show that the distribution of patents as well as trademarks are skewed to the right, given the positive value of means whilst zero value of medians. This finding is reasonable as only a limited number of firms are innovation intensive. Figure 2 and Figure 3 exhibit the fact that innovation intensive firms tend to be clustered in both the east and west coasts, as well as the Great Lakes area.

[Insert Table 35 and Figure 3-5 about here]

Prior to moving on to our multivariate regression analysis, we review the correlation matrix for the variables in our sample in Table 2. Generally, Table 2 raises few concerns about potential multicollinearity in our subsequent regression analysis. Specifically, as we want to investigate the impact of natural disasters on corporate innovation in the following three years, we need to include the lagged damage ratios up to three years. The correlation coefficients among the damage ratio and the lagged one to three years damage ratios in Table 2 suggest that including them all together in the regression analysis do not cause the problem of multicollinearity.

[Insert Table 36 about here]

4.2 Empirical results

4.2.1 Natural disasters and corporate innovation

Our multivariate regression analysis begins from the baseline analysis on the relationship between natural disasters and U.S. firms' technological as well as product innovation. To empirically test the impact of natural disasters on corporate innovation, we employ pooled OLS panel regression. Our interest is to find out the consequences of natural disasters on corporate innovation up to the third year after the disaster year.

$$Innovation_{jt} = \beta_1 \cdot Damage\ ratio_{it} + \beta_2 \cdot Controls_{jt} + Year\ FE + Industry\ FE + State\ FE + \varepsilon_{jt} \quad (1)$$

The dependent variables are the baseline proxies of technological innovation (*Ln (1+Patent)*), product innovation (*Ln (1+Trademark)*), as well as the innovation factor obtained from PCA analysis (*Innovation component*), at firm *j* in year *t*. The explanatory variable is *Damage ratio*$_t$, which is the total damage of all natural disasters in state *i* divided by the annual state GDP in the previous year. We also include the control variables that are measured at the prior year. Furthermore, to address unobserved heterogeneity over time and across industries as well as states, we include year, industry, and state fixed effects[31].

We present the empirical results of using Equation (1) to investigate the impact of natural disasters on corporate innovation in Table 3. In Column (1) and (2), we report the results of how natural disaster affect U.S. firms' technological innovation. We can see clearly that the coefficients of *Damage ratio* are negative and statistically significant at 1% level in the disaster year, as well as in the three years thereafter. These results are economically significant, suggesting that the impact of natural disasters on U.S. firms' patent activities is significantly negative. On average, after controlling for several fixed effects, one standard deviation increase in the damage ratio caused by natural disasters leads to 1.6% decease in patent activities among U.S. firms headquartered in disaster zones in the natural disaster year. In addition, in the following years, the reductions in technological innovation are 1.7%, 1.5%, and 1.3% respectively. In Column (3) and (4), we present the results pertaining to the influence of natural disasters on product innovation. The coefficients of *Damage ratio* are negative and statistically

[31] Industry is classified based on 3-digit SIC code.

significant at conventional levels within our observation period. With regards to the economic significance, the results reveal that, on average, the U.S. firms located in areas hit by natural disasters reduce their trademark activities by approximate 6% along with one stand deviation increase in the damage ratio in the disaster year as well as in the three years subsequently. Column (5) and (6) indicate the results of the impact of natural disasters on the overall innovation output of U.S. firms. Similarly, the coefficients of *Damage ratio* remain negative and statistically significant at 1% level. These results further confirm that natural disasters discourage U.S. firms' commitments in corporate innovation. Pertaining to the control variables, we find consistent results with existing literature on corporate innovation. Generally, firms with higher profitability, firms that are less prone to financial distress, larger firms, and research-intensive firms are associated with higher innovation output.

[Insert Table 37 about here]

4.2.2 Alternative proxies of corporate innovation

The empirical results using additional proxies of corporate innovation are reported in Table 4. In terms of technological innovation, we can see that among the firms locate in disaster zones, the market value of patents (*Patent value*) as well as the patent quality (*Ln (1+Citation)*) decrease significantly in the three years post natural disasters. Similarly, in terms of product innovation, Column (3) to (7) report that the coefficients of damage ratio within the three years post natural disasters are statistically significant at conventional levels to a large extent, suggesting that the diversity and quality of trademarks of the firms being affected by natural disasters significantly decreased. We interpret above findings as further support for our hypothesis that natural disasters adversely affect corporate innovation for the firms located in disaster hitting areas.

[Insert Table 38 about here]

4.2.3 Robustness Checks

In addition to the baseline results, we perform several robustness tests in this section. Firstly, we acknowledge the negative effect of natural disasters on corporate innovation could be driven by outliers. Given the fact that natural disasters as hurricanes in the U.S. are clustered in several southern states, it is possible the reduced innovation output is among the firms headquartered in such states. To ensure that the causal link between natural disasters and corporate innovation is not driven by outliers, we exclude the firms locate in the southern states that are frequently hit by hurricanes. Those states are Alabama, Florida, Georgia, Louisiana, and Mississippi. The empirical results after excluding the firms in the five states above are reported in Colum (1)-(3), Table 5. We can see clearly that negative link between natural disasters and corporate innovation remain robust after excluding possible outliers. Secondly, we only consider the impact of those natural disasters causing severe financial damages (huge disasters). Following Barrot and Sauvagnat (2015), we define huge disasters as a group of natural disasters causing more than $1 billion loss (in 2015 constant dollars) within 31 days. Based on the information of huge natural disasters, we create an indicator variable (*Huge disaster*) that takes the value of 1 if there is one huge disaster happened in the state in a fiscal year, and 0 otherwise. Column (4)-(6) in Table 5 report the empirical results. From these empirical results, we can still see that natural disasters significantly hinder corporate innovation for the firms in disaster zone.

[Insert Table 39 about here]

4.2.4 PSM-DID analysis

To better identify the causal effect and eliminate potential selection bias, we apply the difference-in-differences estimation post propensity score matching routine (PSM-DID) to estimate the treatment effect of natural disasters on corporate innovation more effectively. Firstly, we perform the propensity score matching (PSM) routine. To facilitate the PSM, we only consider the huge disasters using the huge disaster dummy (*Huge disaster*). Specifically, we match firms in the states hit by huge natural disasters with firms in the states that are not affected by any natural disasters on a vector of firm characteristics using one-to-one nearest neighbor matching each year, without replacement. We use the same set of controls variables as our baseline model to perform the PSM. The PSM routine yields us 11,084 firms in total (5,542 treated firms and 5,542 controls). Next, we perform the post-matching DID estimation base on the matched sample[32]. Our sample of the DID estimation covers all the firms over the three years prior to natural disasters and three years post natural disasters. We estimate the following regressions:

$$Innovation_{jt} = \beta_1 \cdot Treat_{it} * Post_{it} + \beta_2 \cdot Treat_{it} + \beta_3 \cdot Post_{it} + \beta_4 \cdot Controls_{jt} + Year\ FE + Industry\ FE + State\ FE + \varepsilon_{jt} \quad (2)$$

whilst *Innovation*, control variables and the included fixed effects are the same as those in Equation (1). The dummy variable $Treated_{it}$ equals one for firms headquartered in the states hit by natural disasters, and zero for matched firms that locate in the states are not affected by natural disasters. The dummy variable $Post_{it}$ takes the value of 1 for innovation output produced within 3 years after the natural disasters, and the value of 0 if the innovation output that is produced within 3 years prior to the disaster. Our main variable of interest is the interaction between treated firms and the post natural disaster period $(Treated_{it} \times Post_{it})$. The coefficient on the interaction term, β_3, captures the incremental change in corporate innovation from the pre to the post natural disaster period for firms in the disaster zone relative to the change for firms in the control group. A negative coefficient on β_3 reveals that natural disasters trigger higher degree of innovation reduction for the firms located in disaster zone. Table 5 report the empirical results of the PSM-DID estimation. We can observe that the coefficients of the DID estimators are negative and statistically significant at the 5% level in the latter two specifications, which are largely consistent with our expectation and further confirm the causal link between natural disasters and corporate innovation[33].

[Insert Table 40 about here]

4.2.5 Further analysis

4.2.5.1 Spillover effects

In this section, we discuss the possible spillover effects stemming from natural disasters. That is, when a natural disaster occurs in a state, will the negative influence on corporate innovation spread to the neighboring states? Prior research has shown a spillover effect of natural disasters. Dessaint and Matray (2017) indicate that even firms in the neighboring states of the state with natural disaster occurrence indirectly suffer from the natural disasters. Specifically, corporate managers of the firms locate in the neighbors of the disaster zone become more risk averse post disaster than before. Consequently, such corporate managers specifically mention their concerns toward natural disasters in 10-Ks/10Qs and in turn increase corporate cash holdings, although there is no change in the overall firm-level risk. Therefore, we intend to investigate whether corporate managers in the neighboring states overact to the natural disasters by cutting down corporate innovation activities. The empirical results in Table 7 provide limit evidence on the possible spillover effect. It is plausible that firms in the adjacent states of the disaster zone overact to natural disasters and decrease their commitment in risky

[32] In unreported tests, we perform the balanced test (t-test) on our matching variables and find no significant differences in most of the matching variables between treated firms and controls. We therefore conclude that the PSM routine successfully eliminate the differences between the two groups of firms.

[33] We also perform the PSM-DID estimations using our alternative measures of corporate technological as well as product innovation in our unreported tests. The results are largely similar as those reported in Table 5.

projects as innovation. However, the results are not robust as we find no statistical evidence on the negative link when including year, industry, and state fixed effects.

[Insert Table 41 about here]

4.2.5.2 Natural disaster related innovation

So far, our empirical evidence that natural disasters discourage innovation has been based on general corporate innovation including various categories of innovation. However, Miao and Popp (2014) argue that natural disaster is the "mother" of innovation. They provide country-level evidence that natural disasters can catalyze disaster related innovation activities that are used to prevent future occurrence of natural disasters. As Miao and Popp (2014)'s empirical analysis is based on country-level patent activities that are largely from government funded research institutes, it is not fully clear how private sector, publicly listed firms, responds to natural disasters in terms of innovation commitment. If the whole society indeed commit to focus on disaster related innovation that can circumvent the occurrence of natural disasters in the future, we should observe publicly listed firms increase or at least do not decrease their innovation commitment on disaster related innovation. The empirical results in Table 8 suggest that U.S. firms do not cut down disaster related innovation within the three years post disasters. We argue that the reduced innovation commitment post natural disasters are mainly for general corporate innovation other than disaster related innovation.

[Insert Table 42 about here]

4.2.6 Exploring transmission channels

Through the above comprehensive empirical analysis, we have presented robust evidence that natural disasters indeed discourage affected firms' innovation activities. In this section, we explore potential transmission channels through which natural disasters impede corporate innovation.

4.2.6.1 Corporate R&D spending post natural disasters

We know that patents and trademarks are considered the successful outcome of corporate innovation commitment. To successfully produce innovation output, companies have to make sufficient financial commitment on research and development. Hsu et al. (2018) indicate that the profitability of the firms that are directly affected by natural disasters substantially decreased post disasters. Hence, after natural disasters, such firm tend to face higher level of financial constraint than before. With significantly reduced profitability, it is very likely that firms in the areas hit by natural disasters tend to be cautious on corporate spending and in turn cut spending on risky projects, such as the research and development (R&D) expenses. In line with our expectation, the empirical results in Table 9 indicate that firms headquartered in disaster zone significantly reduce their R&D spending within the three years post natural disasters.

[Insert Table 43 about here]

4.2.6.2 Inventor mobility post natural disasters

It has been documented by existing research that educated people, such as inventors, prefer to work in areas with better living conditions. Gao et al. (2020) state that inventors generally prefer a smoke free working environment and therefore are willing to join companies headquartered in the states implementing smoking ban in workplace. Natural disasters can significantly deteriorate the living quality of affected areas in the short term. Firms in disaster zone may face the difficulty of hiring new employees as inventors because potential inventors prefer workplace in more livable areas. Likewise, current inventors may choose to relocate to safer areas with better living conditions by joining other companies. Thus, we argue that the inventor mobility can negatively affect the affected companies' innovation output. In our empirical analysis, we examine the inventor mobility at both firm-level and state-level. The results in Panel A, Table 10 reveal that at the firm level, less inventors tend to join affected firms whereas it is not sure whether inventors opt to leave the affected firms post natural disasters in the disaster year. At the same time, according to column 5 and 6, the number of net comer is negatively influenced by disasters. We also observe a similar pattern at the state level, which is exhibited in Panel B, Table 10. Inventors are less likely to move to the states with the risk of natural disasters within the three years following disasters.

[Insert Table 44 about here]

4.2.6.3 Corporate risk-taking post natural disasters

From the above analysis pertaining to the transmission pathways via which natural disasters hinder corporate innovation. We would like to further identify the reason why firms in the areas hit by natural disasters cut down their spending on research and development. There could be two possible reasons. First, as we argue above, the reduced profitability as well as the increase financial constraints (Hsu et al., 2018) force corporate managers to prioritize firm performance and reduce investments in risky projects. Hence, they have to reduce their financial commitment on R&D. Second, it is likely that following natural disasters, corporate managers become more risk averse and tend to overact to salient risk (Bernile, Bhagwat, and Rau, 2017 and Dessaint and Matray, 2017) than before. As innovation itself is considered risky activity with high likelihood of failure, corporate managers may behave cautious and intentionally avoid risky activities. Nonetheless, we admit these two possibilities are not mutually exclusive, the reduced innovation commitment could be associated to both possibilities. To empirically answer this question, we investigate two additional transmission mechanisms. For the first one, the risk aversion channel, following prior studies, we measure corporate risk taking by CEO vega, which is the change in the dollar value of the CEO wealth (in $thousands) for a one percentage change in the annualized standard deviation of stock returns in a fiscal year (Coles, Daniel, and Naveen, 2006). If corporate managers become more risk averse after natural disasters, we should observe reduced CEO vega post natural disasters. Additionally, following Armstrong and Vashishtha (2012), we examine the change of corporate risk taking by looking at the change in firms' systematic risk as well as firm-specific risk. To calculate the two types of risk, we collect operating segments and the book value of assets in those segments from the Compustat Industry Segment Database[34]. We firstly identify the number of industry segments (n) in which a firm operates at in a fiscal year. Next, we calculate the monthly return $R_{i,t}$ of industry segment i in month t, calculated as the value-weighted average of the monthly returns of all firms in Compustat operating exclusively in segment i in a fiscal year.[35] The equation for calculating return $R_{j,t}$ is developed as follow:

$$R_{j,t} = \sum_{i=1}^{n} \frac{Ai,j}{Aj} R_{i,t} \qquad (3)$$

where $A_{i,j}$ is the book value of total assets in segment i of firm j and A_j represents the book value of total assets of firm j. In addition, we compute the firm total risk, which is the variance of monthly return $R_{j,t}$ across the prior 60 months. We require there are at least 20 months. Next, we decompose the systematic risk and unsystematic (firm-specific) risk by regressing the monthly returns $R_{j,t}$ on Fama-French three factors model (Fama and French, 1993). Specifically, systematic risk is computed as the square root of the explained variance whilst unsystematic risk is computed as the square root of the unexplained variance. Table 11 provide the empirical results. We find no statistical evidence that risk aversion among the firms hit by natural disasters significantly decreases following natural disasters. Hence, the reduced commitment in corporate innovation cannot be explained by the risk aversion channel.

[Insert Table 45 about here]

[34] Industry segment is defined at the two-digit SIC level.

[35] We compute $R_{i,t}$ only for those segment years for which there are at least three firms operating exclusively in industry i.

4.2.6.4 Corporate cash holdings post natural disasters

Since the negative impact of natural disasters on corporate innovation cannot be explained well by the risk aversion channel, we next investigate the other channel, the financial constraint channel. After the areas being hit by natural disasters, affected firms in these areas become less profitable and therefore more financially constraint after being hit by natural disasters. Therefore, such firms are less financially viable to engage in risky investment projects, such as innovation. If the financial constraint channel holds, we should observe affected firms have less cash holdings available following natural disasters. We can see that to a large extent, the coefficients of damage ratio within the three years post disasters are negative and statistically significant at conventional levels. Such results reveal that following natural disasters, corporate cash holdings significantly decline among the firms in the areas hit by natural disasters. Furthermore, it is worth noting that the declined cash holdings in affected firms once again reject the risk aversion channel. According to Dessaint and Matray (2017), increased risk aversion should be associated with increased cash holdings owing to precautionary motivation.

[Insert Table 46 about here]

5. Conclusions

The first essay investigates the influence of U.S. President Donald Trump's Twitter messages on stock prices. By performing an event-study analysis and estimating a series of cross-sectional regressions, we find that positive tweets about media firms lead to positive abnormal returns and are more influential than negative and neutral tweets. Moreover, the influence of positive tweets on the stock prices of media firms became significantly stronger after President Trump's election. For non-media firms, we observe an even more pronounced impact of tweets on stock prices, particularly when a tweet has a negative sentiment. Specifically, negative tweets lead to negative abnormal returns which are more significant on the first day than neutral and positive tweets, but this effect partially reverses the next day, likely due to the market correcting for an initial overreaction. Additionally, if the President posts a negative tweet about a non-media firm in which he reiterates news about the firm that was previously made public, the abnormal return appears to be driven not only by the information contained in the news release, but also by the President's attitude towards the issue. Overall, we can conclude that the President's tweets clearly affect the stock price returns of different kinds of firms. This finding raises the question how public figures should use social media platforms given that their comments may disturb and unduly influence the market and its participants.

There are a number of additional studies that could usefully be developed following this research. Firstly, the analysis should be replicated using a larger sample size, possibly including multiple high-profile figures from various different countries. Secondly, the explanatory power of tweeting behaviour may be improved if additional variables such as the number of retweets and the number of likes are included in the models. A further improvement might be obtained by examining the social ranking of influential people who post tweets and then applying regression analysis to determine the impact of their combined tweets. Finally, the scope of our study could be improved by examining the impact of tweets on abnormal volatility and abnormal trading volume in addition to abnormal returns. It should be noted that some previous studies (as discussed in Section II) have examined the relationship between social media posts and the volatility of stock returns, but we are only aware of one study that explores the effect of tweets on abnormal volume (Kurov and Wolfe, 2019).

The second essay examines whether and how natural disasters affect bank solvency. Specifically, using a sample of 9,928 banks located in 149 countries and data on natural disasters that occurred around the globe during the period 2000–2017 we examine how natural disaster damages affect banks' equity ratios and tier 1 capital ratios.

Our major finding is that damages from natural disasters negatively affect bank solvency. The relationship varies across regions and among different types of banks, but provides compelling evidence that natural disasters represent a significant threat for the financial soundness of individual banks and, by extension, the stability of our financial system as a whole.

We hypothesized that the tier 1 capital ratio – as a regulatory measure of bank solvency – would be more sensitive to natural disaster damages than the accounting based equity ratio. However, natural disasters appear to affect the tier 1 capital ratio to a lesser extent than the corresponding accounting ratio. Although this issue calls for further investigation, we conclude that the regulatory weights attributed to risky assets in the tier 1 capital ratio specification are not adequate in capturing a bank's exposure to natural disasters. The regulatory risk weights stem from historical evidence and rely primarily on economic drivers of risk. However, the observable increase in the frequency and severity of natural disasters is a more recent phenomenon with roots that largely lie outside the financial system.

The results of our study have important implications for financial regulators and risk managers. In particular, financial regulators should consider modifying the assessment and weighting of solvency risks in light of the increasing damages caused by natural disasters. For instance, they may consider explicitly including disasters as a source of operational risk and to increase the risk weights for customers which are particularly exposed to these risks. Similarly, managers of institutions that lend in disaster-prone areas should include the expected damages from disasters in their calculations of the risk premium of loans. If the premium is priced correctly, i.e., when it accounts for higher damages from natural disasters, any losses in a bank's lending business should be largely compensated by the premium.

The negative effect of natural disasters on bank solvency varies depending on the specific profile of banks. Banks located in countries where damages from natural disasters have a relatively high impact (as compared to the GDP) show a higher degree of affectedness. This is also the case for banks with a low ex-ante capitalization. In contrast, our study does not find significant and consistent results for banks with different business models. We conclude that natural disasters may exhibit a different propagation pattern and may affect regions, infrastructures, and institutions as a whole. Consequently, traditional diversification patterns appear to be irrelevant in this case.

A potential direction for further research on the link between bank solvency and natural disasters is to address the underlying transmission process of damages. This is challenging as causes and effects may unfold in various forms. Natural disasters primarily affect a bank's customers but may, at the same time, jeopardize the infrastructure of banks themselves. Depending on the risk management strategies both banks and their customers employ, the effect of disasters on bank solvency may be different. In addition, the frequency and magnitude of disasters may change over time. Future research has to cope with this high degree of complexity and the dynamic nature of disasters.

The third essay extends the understanding of the economic and social disruptions caused by natural disasters by showing the negative implications of weather-related disasters on corporate innovation. Even though prior studies suggest natural disasters can be the "mother" of invention, our empirical analysis provides strong evidence that natural disasters discourage general innovation activities at firm level.

Using 12,184 U.S. public firms between 1990 and 2015, our empirical evidence reveals that firms headquartered in the areas hit by major weather-related disasters significantly reduce their technological innovation as well as product innovation. Moreover, it is plausible that the negative influence can spill over to the neighbors of disaster zone. We provide limit empirical evidence that the salient risk of natural disasters also has some negative influence on corporate innovation among the firms locate in adjacent states of the areas hit by natural disaster. Our analysis on the transmission channels via which natural disasters discourage corporate innovation indicates that after natural disasters, firms in disaster areas tend to be too financially constraint to touch risky investment projects such as innovation and therefore cut their financial commitment on the input of corporate innovation. In addition, since natural disasters significantly deteriorate the living conditions of disaster areas, inventors prefer to relocate to other areas without the influence of natural disasters. Hence, it is difficult for the firms in disaster zone to hire new employees as potential innovators. Our research can provide important policy implications pertaining to the interplay of climate change and natural disasters. The costs of natural disasters are not only the property damages, casualties, and associated financial loss, but can also spread the disruption on corporate innovation. Innovation is pivotal to economic growth as well as the well beings of the society, it is therefore crucial for the policy makers to exert efforts to cope with climate change risk.

References

Abou-El-Sood, H. (2016). Are regulatory capital adequacy ratios good indicators of bank failure? Evidence from US banks. International Review of Financial Analysis, 48, 292-302.

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. American economic review 103(1), 277-304.

Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. The Review of Financial Studies 33(3), 1146-1183.

Altunbas, Y./ Carbo, S./ Gardener, E. P./ Molyneux, P. (2007). Examining the relationships between capital, risk and efficiency in European banking. European Financial Management, 13 (1), 49-70.

Armstrong, C. S., & Vashishtha, R. (2012). Executive stock options, differential risk-taking incentives, and firm value. Journal of Financial Economics 104(1), 70-88.

Arouri, M./ Nguyen, C./ Youssef, A.B. (2015). Natural disasters, household welfare, and resilience: Evidence from rural Vietnam. World Development, 70, 59-77.

Atanassov, J. (2013). Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. The Journal of Finance 68(3), 1097-1131.

Azar, P.D., and Lo, A.W., 2016. The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds. The Journal of Portfolio Management, Special Issue 2016, 42 (5), pg. 123-134.

Balvers, R./ Du, D./ Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. Journal of Banking & Finance, 77, 18-34.

Barrios, V. E./ Blanco, J. M. (2003). The effectiveness of bank capital adequacy regulation: A theoretical and empirical approach. Journal of Banking & Finance, 27 (10), 1935-1958.

Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics 131(3), 1543-1592.

Barth, J. R./ Sun, Y./ Zhang, S. (2019). Banks and natural disasters, Working Paper (August 16, 2019).

Batten, S./ Sowerbutts, R./ Tanaka, M. (2016). Let’s talk about the weather: The impact of climate change on central banks, Bank of England Staff Working Paper No. 603, London, U.K.

Battiston, S./ Mandel, A./ Monasterolo, I./ Schütze, F./ Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change, (7), 283-288.

BCBS (2011) – Basel Committee on Banking Supervision. Basel III: A global regulatory framework for more resilient banks and banking systems, Basel, Switzerland.

BCBS (2017) – Basel Committee on Banking Supervision. Basel III: Finalising post-crisis reforms, Basel, Switzerland.

Benson, C., & Clay, E. J. (2004). Understanding the economic and financial impacts of natural disasters (No. 4). World Bank Publications.

Berger, A.N./ Öztekin, Ö./ Roman, R.A. (2019). How does competition affect bank capital structure? Evidence from a natural experiment. Working Paper (February 19, 2019).

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. The Journal of Finance 72(1), 167-206.

Bernstein, A./ Gustafson, M. T./ Lewis, R. (2018). Disaster on the horizon: The price effect of sea level rise. Journal of Financial Economics, 134 (2), 253-272.

Bernstein, S. (2015). Does going public affect innovation? The Journal of finance 70(4), 1365-1403.

Bhattacharya, U., Galpin, N., Ray, R., and Yu, X., 2009. The role of the media in the Internet IPO

bubble. Journal of Financial and Quantitative Analysis, 44(3), pg. 657-682.
Bollen, J., Maoa, H., and Zeng, X., 2011. Twitter mood predicts the stock market. Journal of Computational Science, 2(1), pg. 1-8.
Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), pg. 307-327.
Born, J.A., Myers, D.H., and Clark, W., 2017. Trump tweets and the efficient market hypothesis. Algorithmic Finance, 6(3-4), pg. 1-7.
Bos, J./ Li, R./ Sanders, M. (2018). Hazardous lending: The impact of natural disasters on banks' asset portfolio, Working Paper (August 27, 2018).
Bourdeau-Brien, M./ Kryzanowski, L. (2017). The impact of natural disasters on the stock returns and volatilities of local firms. Quarterly Review of Economics and Finance, 63 (February), 259-270.
Bradley, D., Kim, I., & Tian, X. (2017). Do unions affect innovation? Management Science 63(7), 2251-2271.
Brav, A., Jiang, W., Ma, S., & Tian, X. (2018). How does hedge fund activism reshape corporate innovation? Journal of Financial Economics 130(2), 237-264.
Brewer I. E./ Kaufman, G. G./ Wall, L. D. (2008). Bank capital ratios across countries: Why do they vary? Journal of Financial Services Research, 34 (2-3), 177-201.
Carhart, M.M., 1997. On persistence in mutual fund performance. The Journal of Finance, 52(1), pg. 57-82.
Chemmanur, T. J., Rajaiya, H., Tian, X., & Yu, Q. (2020). Trademarks in Entrepreneurial Finance. Unpublished Working Paper. Available at: SSRN: https://ssrn.com/abstract=3183879.
Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. The Review of Financial Studies 33(3), 1112-1145.
CISL – Cambridge Institute for Sustainability Leadership (2016). Environmental risk analysis by financial institutions – A review of global practice, Cambridge, U.K.
Cohen, B. H./ Scatigna, M. (2016). Banks and capital requirements: Channels of adjustment. Journal of Banking & Finance, 69 (August), Supplement 1, S56-S69.
Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. Journal of Financial Economics 79(2), 431-468.
Cornaggia, J., Mao, Y., Tian, X., & Wolfe, B. (2015). Does banking competition affect innovation? Journal of Financial Economics 115(1), 189-209.
Cortés, K. R./ Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. Journal of Financial Economics 125 (1), 182-199.
CRED – Centre for Research on the Epidemiology of Disasters (2016). The EM-DAT higher resolution disaster data. CRED Crunch No. 43, July, 1-2.
De Jonghe, O./ Öztekin, Ö. (2015). Bank capital management: International evidence. Journal of Financial Intermediation, 24 (2), 154-177.
Demirgüç-Kunt, A./ Detragiache, E./ Merrouche, O. (2013). Bank capital: Lessons from the financial crisis. Journal of Money, Credit and Banking, 45 (6), 1147-1164.
Dermine, J. (2015). Basel III leverage ratio requirement and the probability of bank runs. Journal of Banking & Finance, 53 (April), 266-277.
Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. Journal of Financial Economics 126(1), 97-121.
Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. Journal of Financial Economics 141(2), 802-830.

Dougal, C., Engelberg, J., Garcia, D., and Parsons, C.A., 2012. Journalists and the stock market. The Review of Financial Studies, 25(3), pg. 639-679.
Duqi, A., McGowan, D., Onali, E., & Torluccio, G. (2021). Natural disasters and economic growth: The role of banking market structure. Journal of Corporate Finance, 102101.
Dyck, A., Volchkova, N., and Zingales, L., 2008. The corporate governance role of the media: Evidence from Russia. The Journal of Finance, 63(3), pg. 1093-1135.
EBA (2019) – European Banking Authority. Action plan on sustainable finance, Paris, France.
Engelberg, J.E., and Parsons, C.A., 2011. The causal impact of media in financial markets. The Journal of Finance, 66(1), pg. 67-97.
Fama, E. F., & Kenneth, R. (1993). French, 1993, Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33(1), 3-56.
Fama, E.F., and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), pg. 3-56.
Fang, V. W., Tian, X., & Tice, S. (2014). Does stock liquidity enhance or impede firm innovation? The journal of Finance 69(5), 2085-2125.
Faurel, L., Li, Q., Shanthikumar, D. M., & Teoh, S. H. (2020). Bringing Innovation to Fruition: Insights from New Trademarks. Unpublished Working Paper. Available at: SSRN: https://ssrn.com/abstract=2585804.
Financial Times (2020, September 17). Wildfires, hurricanes and vanishing sea ice: the climate crisis is here. Available at: https://www.ft.com/content/6a6bab93-21fc-4bd6-b309-86e394e3869b (accessed on May 1, 2021).
Flannery, M. J./ Giacomini, E. (2015). Maintaining adequate bank capital: An empirical analysis of the supervision of European banks. Journal of Banking & Finance, 59 (October), 236-249.
Gambacorta, L./ Shin, H. S. (2018). Why bank capital matters for monetary policy. Journal of Financial Intermediation, 35, 17-29.
Gao, H., Hsu, P. H., Li, K., & Zhang, J. (2020). The real effect of smoking bans: evidence from corporate innovation. Journal of Financial and Quantitative Analysis 55(2), 387-427.
Ge, Q., Kurov, A., and Wolfe, M., 2019. Do investors care about presidential company-specific tweets? The Journal of Financial Research, 42(2), pg. 213-242.
Gentzkow, M., 2006. Television and voter turnout. The Quarterly Journal of Economics, 121(3), pg. 931-972.
Griliches, Z. (1991). The search for R&D spillovers. NBER Working Paper.
Gramlich, D., Walker, T., Xu, Y., Zhao, Y.(2021) The Impact of Natural Disasters on the Performance of U.S. banks. Working Paper
Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Paper.
Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. RAND Journal of Economics, 16-38.
Hallegatte, S. (2014). Modeling the role of inventories and heterogeneity in the assessment of the economic costs of natural disasters. Risk Analysis, 34 (1), 152-167.
Heath, D., & Mace, C. (2020). The strategic effects of trademark protection. The Review of Financial Studies 33(4), 1848-1877.
HLEG – EU High-Level Expert Group on Sustainable Finance (2018). Financing a sustainable European economy: Final 2018 report by the High-Level Expert Group on Sustainable Finance, European Commission, Brussels, Belgium.
Ho, C.S., Damien, P., Gu, B., and Konana, P., 2017. The time-varying nature of social media

sentiments in modeling stock returns. Decision Support Systems, 101(C), pg. 69-81.
Hogan, T. L. (2015). Capital and risk in commercial banking: A comparison of capital and risk-based capital ratios. Quarterly Review of Economics and Finance, 57 (August), 32-45.
Holmstrom, B. (1989). Agency costs and innovation. Journal of Economic Behavior & Organization 12(3), 305-327.
Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate finance. The Review of Financial Studies 33(3), 1011-1023.
Hosono, K./ Miyakawa, D./ Uchino, T./ Hazama, M./ Ono, A./ Uchida, H./ Uesugi, I. (2016). Natural disasters, damage to banks, and firm investment. International Economic Review, 57 (4), 1335-1370.
Hsu, P. H., Lee, H. H., Peng, S. C., & Yi, L. (2018). Natural disasters, technology diversity, and operating performance. Review of Economics and Statistics 100(4), 619-630.
Hsu, P. H., Li, D., Li, Q., Teoh, S. H., & Tseng, K. (2021). Valuation of new trademarks. Management Science, forthcoming.
Jong, P., Elfayoumy, S., and Schnusenberg, O., 2017. From returns to tweets and back: An investigation of the stocks in the Dow Jones Industrial Average. Journal of Behavioral Finance, 18(1), pg. 54-64.
Juma'h, A., and Alnsour, Y., 2018. Using social media analytics: The effect of President Trump's tweets on companies' performance. Journal of Accounting and Management Information Systems, 17(1), pg. 100-121.
Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. Review of Economics and Statistics 87(2), 271-284.
Kaufmann, D./ Kraay, A./ Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. Hague Journal on the Rule of Law, 3 (2), 220-246.
Klomp, J. (2014). Financial fragility and natural disasters. An empirical analysis. Journal of Financial Stability, 13 (August), 180-192.
Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. Journal of Financial Stability 13, 180-192.
Koetter, M./ Noth, F./ Rehbein, O. (2019). Borrowers under water! Rare disasters, regional banks, and recovery lending. Journal of Financial Intermediation, forthcoming.
Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics 132(2), 665-712.
Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. The Review of Financial Studies 33(3), 1067-1111.
Lanjouw, J. O. (1998). Patent protection in the shadow of infringement: Simulation estimations of patent value. The Review of Economic Studies 65(4), 671-710.
Lesk, C./ Rowhani, P./ Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. Nature, 529 (7584), 84-87.
Luechinger, S., & Raschky, P. A. (2009). Valuing flood disasters using the life satisfaction approach. Journal of Public Economics 93(3-4), 620-633.
Malkiel, B.G., and Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), pg. 383-417.
Mechler, R./ Bouwer, L. M. (2015). Understanding trends and projections of disaster losses and climate change: Is vulnerability the missing link? Climatic Change, 133 (1), 23-35.
Mendonça, S., Pereira, T. S., & Godinho, M. M. (2004). Trademarks as an indicator of innovation and industrial change. Research Policy 33(9), 1385-1404.

Miao, Q., & Popp, D. (2014). Necessity as the mother of invention: Innovative responses to natural disasters. Journal of Environmental Economics and Management 68(2), 280-295.
Moshirian, F., Tian, X., Zhang, B., & Zhang, W. (2021). Stock market liberalization and innovation. Journal of Financial Economics 139(3), 985-1014.
Munich Re (2018). Topics Geo 2017, Munich, Germany.
NGFS – Central Banks and Supervisors Network for Greening the Financial System (2018). NGFS First Progress Report, Paris, France.
Nofer, M., and Hinz, O., 2015. Using Twitter to predict the stock market: Where is the mood effect? Business & Information Systems Engineering, 57(4), pg. 229-242.
Noth, F./ Schüwer, U. (2018). Natural disasters and bank stability: Evidence from the U.S. financial system. SAFE Working Paper No. 167 (April 25, 2018).
O'Connor, A.J., 2012. The power of popularity: An empirical study of the relationship between social media fan counts and brand company stock prices. Social Science Computer Review, 31(2), pg. 229-235.
Panier, F./ Pérez-González, F./ Villanueva, P. (2013). Capital structure and taxes: What happens when you (also) subsidize equity? Working Paper, Stanford University.
Peress, J., 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. The Journal of Finance, 69(5), pg. 2007-2043.
Raddatz, C. (2007). Are external shocks responsible for the instability of output in low-income countries? Journal of Development Economics 84(1), 155-187.
Rehse, D., Riordan, R., Rottke, N., & Zietz, J. (2019). The effects of uncertainty on market liquidity: Evidence from Hurricane Sandy. Journal of Financial Economics 134(2), 318-332.
Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9 (1), 86-136.
Rosenbaum, P.R., and Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), pg. 41-55.
Rummukainen, M. (2012). Changes in climate and weather extremes in the 21st century. Wiley Interdisciplinary Reviews: Climate Change, 3 (2), 115-129.
Sandner, P. G., & Block, J. (2011). The market value of R&D, patents, and trademarks. Research Policy 40, 969-985.
Schaeck, K./ Cihák, M. (2012). Banking competition and capital ratios. European Financial Management, 18 (5), 836-866.
Schepens, G. (2016). Taxes and bank capital structure. Journal of Financial Economics, 120 (3), 585-600.
Schüwer, U./ Lambert, C./ Noth, F. (2019). How do banks react to catastrophic events? Evidence from Hurricane Katrina. Review of Finance 23 (1), 75-116.
SFSG – G20 Sustainable Finance Study Group (2018). Sustainable Finance Synthesis Report.
Sprenger, T.O., Sandner, P.G., Tumasjan, A., and Welpe, I.M., 2014. News or noise? Using Twitter to identify and understand company-specific news. Flow Journal of Business Finance & Accounting, 41(7) & (8), pg. 791-830.
Stata (2017). Stata user's guide, Release 15. College Station, TX, USA.
Sul, H.K., Dennis, A.R., and Yuan, L., 2017. Trading on Twitter: Using social media sentiment to predict stock returns. Journal of Decision Sciences 48(3), pg. 454-488.
Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance, 62(3), pg. 1139-1168.
Thompson, P. (1998). Assessing the environmental risk exposure of UK banks. International Journal

of Bank Marketing, 16 (3), 129-139.
Veldkamp, L.L., 2006. Media frenzies in markets for financial information. American Economic Review, 96(3), pg. 577-601.
WEF – World Economic Forum (2018). The global risks report 2018. Geneva, Switzerland.
Wold, H., 1982. Soft modeling: The basic design and some extensions, in: Systems under indirect observations: Part II, Jöreskog, K.G., and Wold, H. (eds.), North-Holland: Amsterdam, pp. 1-54.
Yang, S.Y., Yin, S., Mo, K., & Liu, A., 2015. Twitter financial community sentiment and its predictive relationship to stock market movement. Quantitative Finance, 15(10), pg. 1637-1656.

Figures

Figure 1: Ratios of disaster damages/GDP – Country-level averages for the 18-year-period (2000–2017), grey indicates that no data is available

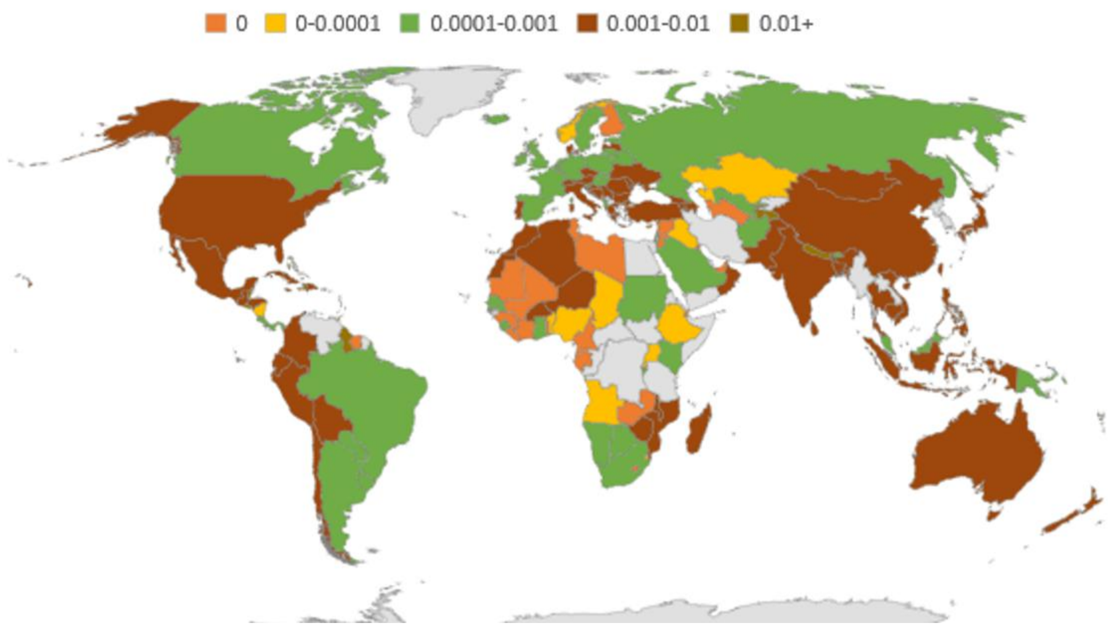


Figure 2: Distribution of worldwide disaster damages across different types of disasters, by year (US$ billion)

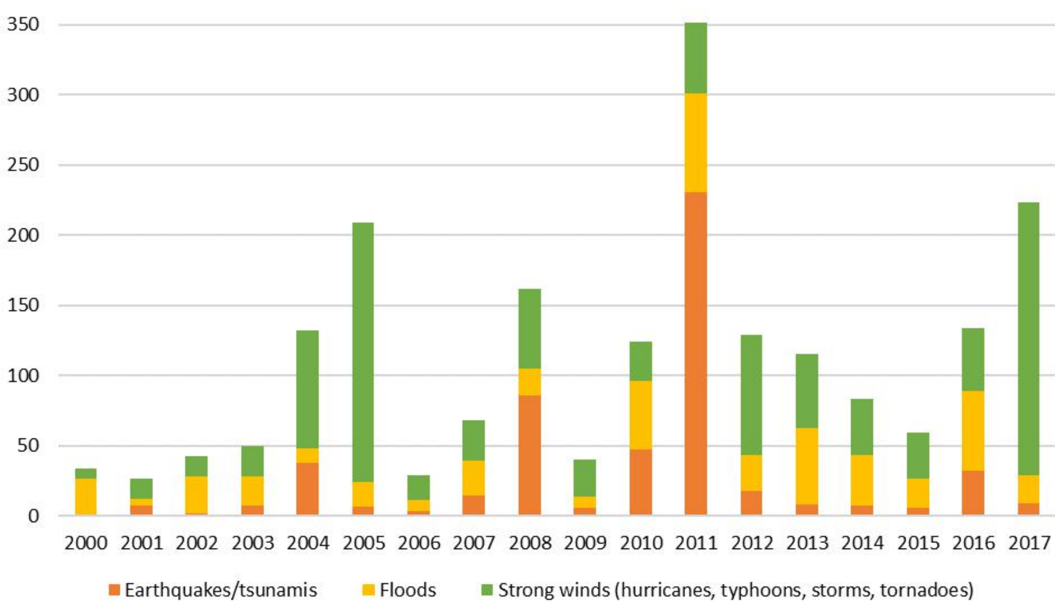


Figure 3. Damage ratio from natural disasters in United States

This figure presents the average damage ratio caused by natural disasters across different states in United States from 1990 to 2015. The average damage ratio is measured with the mean value of total damage of all natural disasters in a state scaled by the annual state GDP in different fiscal years between 1990 and 2015.

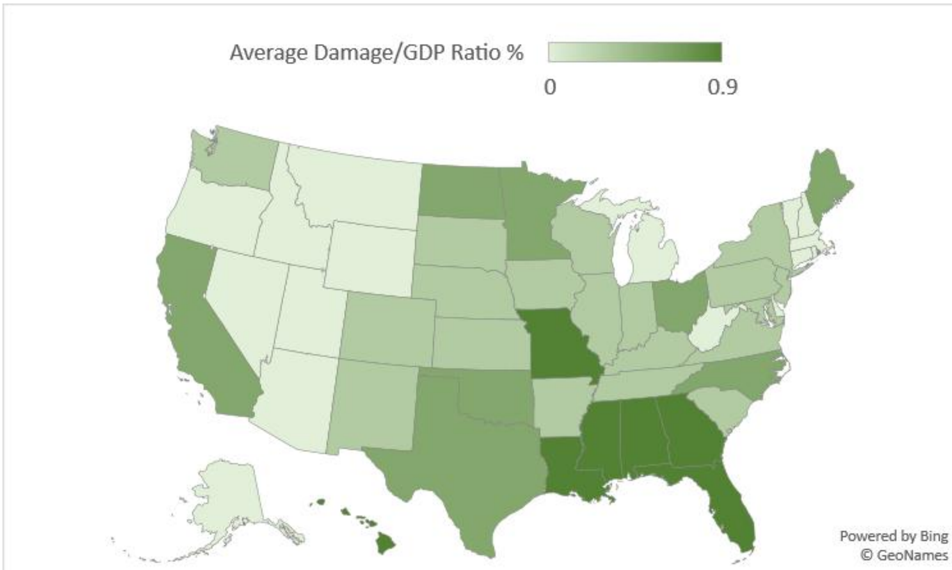


Figure 4. Technological innovation of U.S. firms

This figure presents the average technology innovation output of U.S. public firms at state-level from 1990 to 2015. The average technology innovation output is measured with the average number of granted patents per year from the firms in a given state.

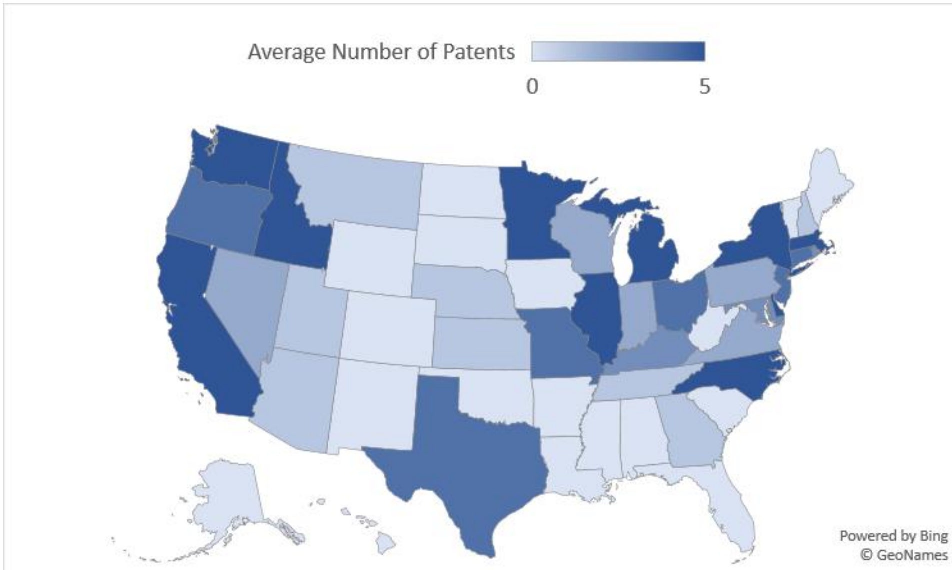
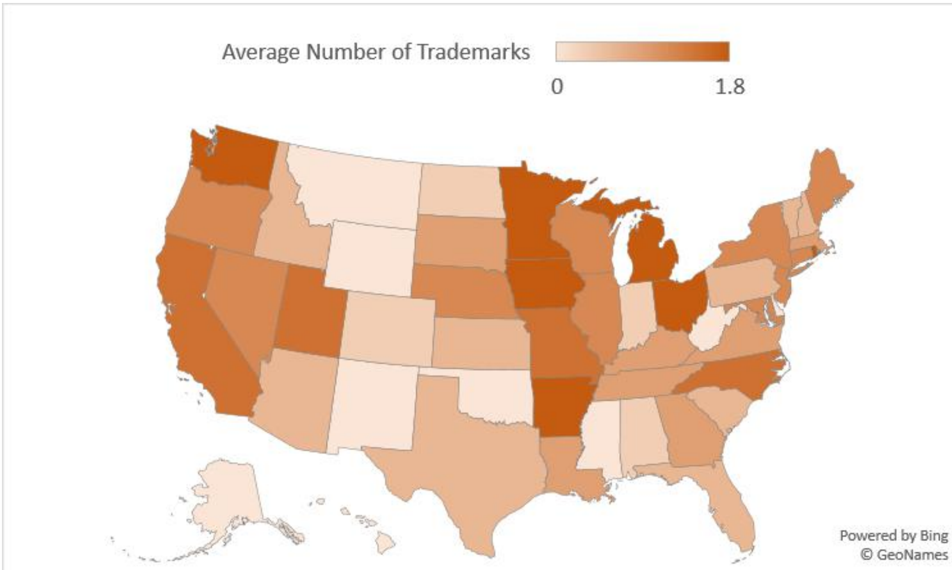


Figure 5. Product innovation of U.S. firms

This figure presents the average product innovation output of U.S. public firms at state-level from 1990 to 2015. The average product innovation output is measured with the average number of granted trademarks per year from the firms in a given state.



Tables

Table 1: Summary Statistics

Panel A provides descriptive statistics of our tweet sample organized by sentiment (negative, neutral, and positive), industry (media and non-media), and time period (by quarter and before vs. after the election). Columns 1-3 report the number of negative, neutral, and positive tweets. Columns 4 and 5 show the number of non-media tweets and media tweets, respectively. Panel B provides a breakdown of the firms named in media, hybrid, and non-media tweets.

Panel A:

	(1)	(2)	(3)	(4)	(5)	(6)
Time Period	**Negative Tweets**	**Neutral Tweets**	**Positive Tweets**	**Non-Media**	**Media**	**Total**
2016-Q2	13	9	1	0	23	23
2016-Q3	25	38	3	1	65	66
2016-Q4	26	14	5	8	37	45
2017-Q1	37	20	20	25	52	77
2017-Q2	21	15	3	2	37	39
2017-Q3	17	14	5	5	31	36
2017-Q4	33	22	5	3	57	60
2018-Q1	14	12	28	13	41	54
2018-Q2	29	25	5	12	47	59
2018-Q3	22	25	7	12	42	54
Before Election	49	55	5	1	108	109
After Election	188	139	77	80	324	404
Total	237	194	82	81	432	513

Panel B:

	Company Names in Non-Media Tweets	**No. of Tweets**	**Company Names in Media Tweets**	**No. of Tweets**
Media Firms			CBS Corp.	8
			Comcast Corp.	63
			Facebook Inc.	11
			Gannett Co. Inc.	4
			New York Times Co.	59
			News Corp.	6
			Time Warner Inc.	69
			21st Century Fox	168
			Twitter Inc.	1
Hybrid Firms	AT&T Inc.	1	AT&T Inc.	5
	Alphabet Inc.	4	Alphabet Inc.	1
	Amazon.Com Inc.	6	Amazon.Com Inc.	15
	Walt Disney Co.	1	Walt Disney Co.	22
Non-Media Firms	Abbott Laboratories	1		
	Aetna Inc.	2		
	Apple Inc.	3		
	Boeing Co.	4		
	Broadcom Ltd.	1		
	Delta Air Lines Inc.	1		
	Enbridge Inc.	1		
	Energy Transfer Partners	1		
	Exxon Mobil Corp.	3		
	Fiat Chrysler Automobiles	5		

Ford Motor Co.	5		
General Motors Co.	3		
Goldman Sachs Group Inc.	1		
Harley Davidson Inc.	5		
Intel Corp.	1		
International Speedway	3		
JPMorgan Chase & Co.	1		
Lockheed Martin	3		
Marathon Petroleum	1		
Merck & Co.	2		
Microsoft Corp.	2		
Nordstrom Inc.	1		
Pfizer Inc.	3		
Phillips 66	1		
Rexnord Corp.	2		
Speedway Motorsports Inc.	3		
Tesla Inc.	2		
Toyota Motor Corp.	4		
Transcanada Corp.	2		
Wal-Mart Stores Inc.	1		
Wells Fargo & Co.	1		
TOTAL	81	TOTAL	432

Table 2: Positive and Negative Sentiment Key Words and Phrases

Panel A lists the key words and phrases frequently used in Twitter messages having a positive sentiment. Panel B lists representative key words and phrases used in Twitter messages having a negative sentiment. Although ambiguity was rare, each Twitter message was reviewed by five different researchers to ensure consensus interpretations.

Atanassov, J. (2013). Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting

Azar, P.D., and Lo, A.W., 2016. The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Tw

Balvers, R./ Du, D./ Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perc

Barrios, V. E./ Blanco, J. M. (2003). The effectiveness of bank capital adequacy regulation: A theoretical and empirical appro

Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. Th

Barth, J. R./ Sun, Y./ Zhang, S. (2019). Banks and natural disasters, Working Paper (August 16, 2019).

Batten, S./ Sowerbutts, R./ Tanaka, M. (2016). Let's talk about the weather: The impact of climate change on central banks, B

Battiston, S./ Mandel, A./ Monasterolo, I./ Schütze, F./ Visentin, G. (2017). A climate stress-test of the financial system. Natu

BCBS (2011) – Basel Committee on Banking Supervision. Basel III: A global regulatory framework for more resilient banks

BCBS (2017) – Basel Committee on Banking Supervision. Basel III: Finalising post-crisis reforms, Basel, Switzerland.

Benson, C., & Clay, E. J. (2004). Understanding the economic and financial impacts of natural disasters (No. 4). World Bank

Berger, A.N./ Öztekin, Ö./ Roman, R.A. (2019). How does competition affect bank capital structure? Evidence from a natural

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters

Bernstein, A./ Gustafson, M. T./ Lewis, R. (2018). Disaster on the horizon: The price effect of sea level rise. Journal of Financ

Bernstein, S. (2015). Does going public affect innovation? The Journal of finance 70(4), 1365-1403.

Bhattacharya, U., Galpin, N., Ray, R., and Yu, X., 2009. The role of the media in the Internet IPO bubble. Journal of Financia

Bollen, J., Maoa, H., and Zeng, X., 2011. Twitter mood predicts the stock market. Journal of Computational Science, 2(1), pg

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), pg. 307-327.

Born, J.A., Myers, D.H., and Clark, W., 2017. Trump tweets and the efficient market hypothesis. Algorithmic Finance, 6(3-4)

Table 3: Variable Definitions

Panel A shows the definitions and sources for all variables used in our empirical analysis. Panel B shows the distribution of the REITERATE variable across non-media tweets of different sentiments.

Panel A: Variable Definitions and Sources

Variable	Definition	Source
CAR(0,1)	Cumulative abnormal return on days (0, 1) around the event date (day 0). Calculated by Eventus	CRSP, Eventus
AR_t	Abnormal return on day t (if a tweet was posted when the market was closed, we consider the next business day as day t). Calculated by Eventus	CRSP, Eventus
POS_NONMEDIA	Positive non-media tweet, binary variable (0 or 1)	Twitter, authors' evaluation
NEU_NONMEDIA	Neutral non-media tweet, binary variable (0 or 1)	Twitter, authors' evaluation
NEG_NONMEDIA	Negative non-media tweet, binary variable (0 or 1)	Twitter, authors' evaluation
POS_MEDIA	Positive media tweet, binary variable (0 or 1)	Twitter, authors' evaluation
NEG_MEDIA	Negative media tweet, binary variable (0 or 1)	Twitter, authors' evaluation
REITERATE	A variable used to identify tweets in which the President repeated known information that was previously reported in the news. If news about a given change in a company was reported within 2 days before the tweet, the variable is assigned a value of 1; otherwise it is 0	Twitter, authors' evaluation
POS_REITERATE	Interaction of POS _NONMEDIA and REITERATE	Authors' calculations
NEG_REITERATE	Interaction of NEG _NONMEDIA and REITERATE	Authors' calculations
ELECTIONWON	If a tweet was posted before the date of the presidential election this variable is 0; otherwise it is 1	Twitter, authors' calculations
POS_ELECTIONWON	Interaction of POS_MEDIA and ELECTIONWON	Authors' calculations
NEG_ELECTIONWON	Interaction of NEG_MEDIA and ELECTIONWON	Authors' calculations
SP500RETURN	The daily return of the S&P 500	S&P Dow Jones Indices LLC
BM_RATIO	The accounting value of equity divided by the market value of equity at the end of the previous quarter (quarterly)	Compustat
DEBT_RATIO	The value of debt divided by total assets at the end of the previous quarter (quarterly)	Compustat

ROE	Return on equity, i.e., the value of gross profits divided by equity at the end of the previous quarter (quarterly)	Compustat
LOG_ASSETS	Natural log of the value of total assets at the end of the previous quarter (quarterly)	Compustat
VAR(-22,-3) (robustness test)	Variance of stock returns in the twenty days from day -22 to day -3	CRSP
LAG_SPREAD/BID (robustness test)	Bid-ask spread/bid price on day -1	CRSP
LOG_LAG_VOL (robustness test)	Natural log of the number of shares traded on day -1	CRSP
INDUSTRY_3DIG	Industry dummies based on the first three digits of a firm's SIC code	Compustat
INDUSTRY_1DIG	Industry dummies based on the first digit of a firm's SIC code	Compustat

Panel B: Distribution of the REITERATE Variable across Non-Media Tweets and Sentiments

	Negative Tweets	**Neutral Tweets**	**Positive Tweets**	**Total**
Non-Reiterated Tweets	17	4	5	26
Reiterated Tweets	9	10	36	55
Total	26	14	41	81

Table 4: Descriptive Statistics

This table provides summary statistics (the number of observations as well as the mean, median, standard deviation, minimum and maximum) for all main variables used in our analysis. The last three variables are only used in our robustness tests.

VARIABLE NAME	Obs.	Mean	Std. Dev.	Min.	Median	Max.
CAR(0,1) (%)	513	0.13	1.72	-6.13	0.02	9.34
AR_0 (%)	513	0.15	1.32	-6.57	0.08	8.97
AR_{-1} (%)	513	-0.02	1.47	-5.52	-0.05	15.15
POS_NONMEDIA	513	0.08	0.27	0.00	0.00	1.00
NEG_NONMEDIA	513	0.05	0.22	0.00	0.00	1.00
POS_REITERATE	513	0.07	0.26	0.00	0.00	1.00
NEG_REITERATE	513	0.02	0.13	0.00	0.00	1.00
POS_MEDIA	513	0.08	0.27	0.00	0.00	1.00
NEG_MEDIA	513	0.41	0.49	0.00	0.00	1.00
POS_ELECTIONWON	513	0.15	0.36	0.00	0.00	1.00
NEG_ELECTIONWON	513	0.37	0.48	0.00	0.00	1.00
LOG_ASSETS	513	10.79	1.42	7.27	10.91	14.78
DEBT_RATIO	513	0.63	0.14	0.09	0.63	1.01
BM_RATIO	513	0.48	1.54	-0.01	0.32	18.99
ROE	513	0.07	0.47	-1.96	0.05	10.19
SP500RETURN (%)	513	0.09	0.66	-4.10	0.09	2.72
VAR(-22,-3)	459	0.03	0.08	0.00	0.01	1.17
LAG_SPREAD/BID (%)	459	1.86	1.15	0.43	1.54	10.46
LOG_LAG_VOL	459	15.46	1.21	10.01	15.68	18.17

Table 5: Short Term Abnormal Performance of Firms Mentioned in President Trump's Twitter Messages

This table provides the results for an event study of the short-term abnormal returns around different kinds of tweets. Our calculations of abnormal returns follow the Carhart (1997) Four Factor model with GARCH (1,1) errors and an estimation period of (-191,-11). Betas and market risk premiums are calculated based on the CRSP equally weighted index. P-values are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Sample	N	(-2,-2)	(-1,-1)	(0,0)	(1,1)	(2,2)
All Positive Tweets	82	0.06%	0.23%	**0.61%****	0.05%	**-0.09%****
		(0.1155)	(0.4629)	(0.0107)	(0.2249)	(0.0291)
All Negative Tweets	237	-0.02%	**-0.17%***	0.01%	-0.03%	-0.10%
		(0.4738)	(0.0863)	(0.2376)	(0.2376)	(0.4476)
Positive Media Tweets	41	0.10%	-0.14%	**0.53%***	0.15%	**-0.28%****
		(0.1558)	(0.2902)	(0.0926)	(0.4052)	(0.0171)
Negative Media Tweets	211	0.06%	**-0.10%***	0.11%	-0.04%	-0.11%
		(0.4365)	(0.0876)	(0.4540)	(0.2106)	(0.4646)
Positive Media Tweets Before the Election	5	0.66%	0.18%	**-0.04%***	**-0.17%***	-0.84%
		(0.4073)	(0.2534)	(0.0591)	(0.0591)	(0.2534)
Positive Media Tweets After the Election	36	0.02%	-0.19%	**0.61%****	0.20%	**-0.20%****
		(0.1605)	(0.3657)	(0.0231)	(0.3727)	(0.0221)
Positive Non-Media Tweets	41	0.03%	0.60%	**0.69%****	**-0.06%***	0.09%
		(0.2470)	(0.3551)	(0.0266)	(0.0953)	(0.2857)
Negative Non-Media Tweets	26	-0.67%	-0.76%	**-0.84%****	0.09%	0.01%
		(0.3952)	(0.2552)	(0.0339)	(0.4463)	(0.2580)

Table 6: Preliminary Examination of Abnormal Returns

This table provides results for a series of univariate tests designed to compare the mean and median stock price performance of media and non-media firms that were the subject of negative, neutral, and positive tweets posted before/after the 2016 election. In Panel A, we run a series of one-tailed t-tests to examine the significance of the mean differences in abnormal returns between different pairs of tweets, where the numbers refer to (1) negative, (2) neutral, and (3) positive tweets. In Panel B, we employ a series of Kruskal-Wallis tests to examine differences in the respective medians. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Means

	(1)	(2)	(3)			
AR_0	**Negative**	**Neutral**	**Positive**	**P-value of (1) vs. (2)**	**P-value of (2) vs. (3)**	**P-value of (1) vs. (3)**
Full sample	0.007	0.132	0.611	0.162	**0.003*** **	**0.000*** **
Media tweets	0.111	0.088	0.534	0.571	**0.024** **	**0.019** **
Media tweets before the election	0.093	0.107	-0.038	0.469	0.641	0.624
Media tweets after the election	0.116	0.080	0.614	0.588	**0.025** **	**0.016** **
Non-media tweets	-0.836	0.701	0.688	**0.004*** **	0.513	**0.000*** **
CAR(0,1)	**Negative**	**Neutral**	**Positive**	**P-value of (1) vs. (2)**	**P-value of (2) vs. (3)**	**P-value of (1) vs. (3)**
Full sample	-0.020	0.095	0.658	0.243	**0.006*** **	**0.001*** **
Media tweets	0.070	0.102	0.685	0.422	**0.022** **	**0.010** **
Media tweets before the election	-0.058	0.075	-0.212	0.274	0.689	0.636
Media tweets after the election	0.109	0.114	0.809	0.490	**0.021** **	**0.011** **
Non-media tweets	-0.750	-0.003	0.631	0.161	0.137	**0.008*** **

Panel B: Medians

	(1)	(2)	(3)			
AR_0	**Negative**	**Neutral**	**Positive**	**P-value of (1) vs. (2)**	**P-value of (2) vs. (3)**	**P-value of (1) vs. (3)**
Full sample	-0.080	0.185	0.330	**0.044** **	**0.018** **	**0.000*** **
Media tweets	-0.020	0.140	0.290	0.382	**0.073* **	**0.016** **
Media tweets before the election	0.060	0.145	-0.310	0.432	0.362	0.698
Media tweets after the election	-0.070	0.135	0.330	0.595	**0.039** **	**0.009*** **
Non-media tweets	-0.760	0.520	0.400	**0.001*** **	0.685	**0.000*** **
CAR(0,1)	**Negative**	**Neutral**	**Positive**	**P-value of (1) vs. (2)**	**P-value of (2) vs. (3)**	**P-value of (1) vs. (3)**
Full sample	-0.190	0.030	0.725	0.222	**0.005*** **	**0.000*** **
Media tweets	-0.110	0.020	0.720	0.435	**0.022** **	**0.001*** **
Media tweets before the election	-0.090	0.190	-0.480	0.207	0.327	0.591
Media tweets after the election	-0.115	-0.060	0.750	0.830	**0.010** **	**0.001*** **

Non-media tweets	-0.780	0.240	0.740	0.165	0.156	**0.011****

Table 7: Correlation Matrix

The three panels of this table report the correlation coefficients among all main variables used in our three different regression analyses, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: All tweets

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	CAR(0,1)											
(2)	AR_0	0.674***										
(3)	AR_{-1}	0.045	0.135***									
(4)	POS_NONMEDIA	0.095**	0.085*	-0.026								
(5)	NEG_NONMEDIA	-0.030	-0.025	-0.048	-0.246***							
(6)	POS_NONMEDIA	0.086*	0.120***	0.125***	-0.087**	-0.246***						
(7)	NEG_NONMEDIA	-0.119***	-0.172***	-0.116***	-0.068	-0.193***	-0.068					
(8)	LOG_ASSETS	0.002	-0.029	0.033	-0.017	-0.182***	0.149***	0.037				
(9)	DEBT_RATIO	0.011	-0.005	0.006	0.015	-0.070	0.062	0.183***	0.162***			
(10)	BM_RATIO	0.020	0.026	0.023	-0.028	-0.076*	0.258***	0.067	0.131***	-0.031		
(11)	ROE	0.012	0.011	0.021	-0.018	-0.049	-0.023	0.047	0.049	0.155***	-0.023	
(12)	SP500RETURN	0.020	0.084*	-0.067	-0.096**	-0.016	-0.022	-0.033	0.056	0.049	0.006	0.026

Panel B: Media tweets

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	CAR(0,1)											
(2)	AR_0	0.645***										
(3)	AR_{-1}	0.038	0.087*									
(4)	POS_MEDIA	0.109**	0.102**	-0.024								
(5)	NEG_MEDIA	-0.043	-0.024	-0.040	-0.316***							
(6)	POS_ELECTIONWON	0.125***	0.114**	-0.034	**0.931****	-0.295***						
(7)	NEG_ELECTIONWON	-0.016	-0.016	-0.047	-0.251***	**0.793****	-0.234***					
(8)	LOG_ASSETS	-0.023	-0.071	0.023	0.006	-0.148***	0.003	-0.066				
(9)	DEBT_RATIO	0.043	0.001	-0.013	0.047	-0.013	0.023	-0.012	0.107**			
(10)	BM_RATIO	-0.039	-0.073	-0.039	0.014	0.099**	0.018	0.003	-0.072	-0.190***		
(11)	ROE	0.022	-0.003	0.025	-0.021	-0.053	-0.026	0.042	0.435***	0.095**	-0.292***	
(12)	SP500RETURN	-0.017	0.038	-0.127***	-0.105**	-0.023	-0.100**	0.012	0.023	0.065	-0.091*	0.085*

		Panel C: Non-media tweets										
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	CAR(0,1)											
(2)	AR_0	0.763***										
(3)	AR_{-1}	0.064	0.239**									
(4)	POS_NONMEDIA	0.258**	0.295***	0.193*								
(5)	NEG_NONMEDIA	-0.262**	-0.426***	-0.273**	**-0.696***							
(6)	POS_REITERATE	0.201*	0.269**	0.215*	**0.883***	**-0.615***						
(7)	NEG_REITERATE	-0.029	-0.076	-0.188*	-0.358***	**0.514***	-0.316***					
(8)	LOG_ASSETS	0.093	0.095	0.032	0.102	-0.139	0.052	-0.168				
(9)	DEBT_RATIO	-0.055	-0.027	0.014	-0.119	0.187*	-0.202*	0.341***	0.221**			
(10)	BM_RATIO	0.052	0.057	0.021	0.141	-0.069	0.167	-0.101	0.219**	-0.100		
(11)	ROE	0.024	0.019	0.021	-0.149	-0.024	-0.171	0.058	-0.003	0.220**	-0.053	
(12)	SP500RETURN	0.188*	0.296***	0.116	-0.055	-0.091	0.037	-0.132	0.239**	0.016	0.046	0.060

Table 8: OLS Regression Results for the Whole Sample

This table reports the results for a series of OLS regressions in which we regress the abnormal returns during different event windows around a tweet against various factors that characterize the firm and President Trump's tweet about the firm. Columns 1 and 2 use the abnormal return (AR) on day 0 as the dependent variable. Columns 3 and 4 use the cumulative abnormal return (CAR) on days 0 and 1 as the dependent variable. P-values based on robust standard errors are listed in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	AR_0	**AR_0**	**CAR(0,1)**	**CAR(0,1)**
POS_MEDIA	0.005**	0.005**	0.006**	0.006**
	(0.026)	(0.025)	(0.015)	(0.028)
NEG_MEDIA	-0.000	0.001	-0.000	-0.000
	(0.960)	(0.668)	(0.916)	(0.801)
POS_NONMEDIA	0.005**	-0.001	0.005	0.004
	(0.032)	(0.692)	(0.139)	(0.372)
NEG_NONMEDIA	-0.009**	-0.011***	-0.008*	-0.005
	(0.017)	(0.000)	(0.093)	(0.261)
AR_{-1}	0.103*	0.067	0.030	-0.005
	(0.059)	(0.203)	(0.688)	(0.942)
LOG_ASSETS	-0.000	-0.002	-0.000	-0.001
	(0.302)	(0.263)	(0.784)	(0.751)
DEBT_RATIO	0.001	0.005	0.003	0.006
	(0.727)	(0.533)	(0.614)	(0.590)
BM_RATIO	0.000	0.000	0.000	0.000
	(0.643)	(0.574)	(0.708)	(0.534)
ROE	0.001	0.001	0.001	0.002*
	(0.344)	(0.176)	(0.488)	(0.061)
SP500RETURN	0.200**	0.153*	0.073	0.036
	(0.021)	(0.079)	(0.539)	(0.755)
CONSTANT	0.005	0.022	0.001	0.005
	(0.323)	(0.210)	(0.908)	(0.752)
INDUSTRY_3DIG		Yes		Yes
YEAR		Yes		Yes
N	513	513	513	513
Adjusted R^2	0.054	0.094	0.012	0.065

Table 9: OLS Regression Results for Media Tweets

This table provides OLS regression results for our sub-sample of media tweets. Columns 1 to 6 use the abnormal return (AR) on day 0 as the dependent variable. Columns 7 and 8 use the cumulative abnormal return (CAR) on days 0 and 1 as the dependent variable. P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR_0	**AR_0**	**AR_0**	**AR_0**	**AR_0**	**AR_0**	**CAR(0,1)**	**CAR(0,1)**
POS_MEDIA	0.005**	0.005**			-0.001	-0.000	-0.004	-0.002
	(0.018)	(0.029)			(0.683)	(0.995)	(0.377)	(0.672)
NEG_MEDIA	0.000	0.001			0.000	0.001	-0.002	-0.000
	(0.786)	(0.640)			(0.859)	(0.442)	(0.428)	(0.956)
POS_ELECTIONWON			0.006***	0.005**	0.007**	0.005	0.011**	0.008
			(0.008)	(0.026)	(0.032)	(0.143)	(0.021)	(0.111)
NEG_ELECTIONWON			0.000	0.000	0.000	-0.001	0.002	-0.000
			(0.798)	(0.942)	(0.970)	(0.588)	(0.420)	(0.897)
AR_{-1}	0.097*	0.095*	0.099*	0.096*	0.099*	0.095*	0.054	0.052
	(0.077)	(0.081)	(0.072)	(0.077)	(0.072)	(0.077)	(0.417)	(0.442)
LOG_ASSETS	-0.001	-0.005	-0.001	-0.005	-0.001	-0.005	-0.001	-0.000
	(0.208)	(0.267)	(0.200)	(0.299)	(0.212)	(0.269)	(0.460)	(0.971)
DEBT_RATIO	-0.001	-0.004	-0.001	-0.004	-0.001	-0.004	0.006	0.021
	(0.742)	(0.851)	(0.797)	(0.849)	(0.807)	(0.831)	(0.377)	(0.441)
BM_RATIO	-0.006*	0.004	-0.006*	0.003	-0.006*	0.004	-0.003	0.006
	(0.073)	(0.630)	(0.079)	(0.694)	(0.079)	(0.681)	(0.697)	(0.609)
ROE	0.002	0.006	0.002	0.007	0.002	0.007	0.012	0.018
	(0.909)	(0.764)	(0.905)	(0.744)	(0.899)	(0.740)	(0.699)	(0.579)
SP500RETURN	0.001	0.001	0.001	0.001	0.001	0.001	-0.000	-0.000
	(0.192)	(0.191)	(0.181)	(0.188)	(0.188)	(0.181)	(0.854)	(0.898)
CONSTANT	0.011*	0.065	0.011*	0.064	0.011*	0.066	0.004	-0.018
	(0.085)	(0.326)	(0.084)	(0.350)	(0.092)	(0.322)	(0.642)	(0.809)
INDUSTRY_3DIG		Yes		Yes		Yes		Yes
YEAR		Yes		Yes		Yes		Yes
N	432	432	432	432	432	432	432	432
Adjusted R^2	0.015	0.012	0.018	0.014	0.013	0.010	0.000	-0.007

Table 10: OLS Regression Results for Non-Media Tweets

This table provides OLS regression results for our sub-sample of non-media tweets. Columns 1 to 6 use the abnormal return (AR) on day 0 as the dependent variable. Columns 7 and 8 use the cumulative abnormal return (CAR) on days 0 and 1 as the dependent variable. P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AR_0	AR_0	AR_0	AR_0	AR_0	AR_0	CAR(0,1)	CAR(0,1)
POS_NONMEDIA	0.002	0.005			0.005	0.007	0.019***	0.022**
	(0.621)	(0.236)			(0.258)	(0.186)	(0.005)	(0.012)
NEG_NONMEDIA	-0.013***	-0.012***			-0.016***	-0.016***	-0.008	-0.009
	(0.001)	(0.008)			(0.000)	(0.002)	(0.217)	(0.245)
POS_REITERATE			0.008**	0.011***	-0.004	-0.003	-0.011**	-0.011
			(0.015)	(0.005)	(0.392)	(0.511)	(0.044)	(0.182)
NEG_REITERATE			0.004	0.005	0.013	0.015	0.015	0.018
			(0.607)	(0.581)	(0.135)	(0.108)	(0.231)	(0.187)
AR_{-1}	0.074	0.063	0.122	0.102	0.091	0.084	-0.001	-0.014
	(0.512)	(0.519)	(0.341)	(0.351)	(0.441)	(0.422)	(0.996)	(0.920)
LOG_ASSETS	-0.000	-0.001	0.000	0.000	-0.000	-0.001	0.001	-0.000
	(0.747)	(0.419)	(0.809)	(0.987)	(0.943)	(0.623)	(0.732)	(0.837)
DEBT_RATIO	0.005	0.014	-0.002	0.009	-0.003	0.008	-0.012	0.003
	(0.629)	(0.362)	(0.799)	(0.522)	(0.785)	(0.562)	(0.312)	(0.919)
BM_RATIO	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.001
	(0.725)	(0.336)	(0.999)	(0.654)	(0.687)	(0.318)	(0.835)	(0.401)
ROE	-0.000	0.000	0.001	0.001	-0.000	-0.000	0.001	0.001
	(0.862)	(0.963)	(0.413)	(0.513)	(0.785)	(0.957)	(0.469)	(0.294)
SP500RETURN	0.007**	0.008**	0.008**	0.007**	0.008**	0.009**	0.008*	0.009*
	(0.016)	(0.018)	(0.018)	(0.021)	(0.013)	(0.010)	(0.084)	(0.057)
CONSTANT	0.007	0.010	-0.005	-0.010	0.007	0.003	-0.002	-0.004
	(0.642)	(0.658)	(0.722)	(0.678)	(0.614)	(0.890)	(0.913)	(0.914)
INDUSTRY_1DIG		Yes		Yes		Yes		Yes
YEAR		Yes		Yes		Yes		Yes
N	81	81	81	81	81	81	81	81
Adjusted R^2	0.182	0.224	0.095	0.137	0.206	0.259	0.033	0.118

Table 11: Propensity Score Matching

Panel A provides details about our matching routine for firms the President tweeted about. The dependent variable of both columns is Selection, which takes on a value of 1 for non-media or hybrid companies mentioned in the President's tweets and a value of 0 for all other companies listed in the Compustat database. Column 1 of Panel A (labeled "Before PSM") reports the parameter estimates for the probit model used in estimating the propensity scores of the treated and control groups. These estimates are then used to generate the propensity scores for each firm. Column 2 (labeled "After PSM") contains the parameter estimates of the probit model estimated using the subsample of matched treatment-control pairs after matching. We use one-to-one nearest neighbor propensity score matching, without replacement. Panel B provides the result of a regression analysis with the matched sample. Columns 1 and 2 use the abnormal return on day 0 as the dependent variable. Columns 3 and 4 use the cumulative abnormal return (CAR) on days 0 and 1 as the dependent variable. P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: PSM Matching Routine

	(1)	(2)
	Before PSM	**After PSM**
LOG_ASSETS	0.527***	-0.048
	(0.000)	(0.464)
ROE	0.013	0.080
	(0.123)	(0.136)
DEBT_RATIO	-1.258***	0.272
	(0.008)	(0.645)
BM_RATIO	-0.002	0.082
	(0.689)	(0.122)
CONSTANT	-6.474***	0.257
	(0.000)	(0.673)
N	4,519	162
Pseudo R^2	0.405	0.032
χ^2test (p-value)	0.000	0.126

Panel B: OLS Regression Analysis of AR_0 and CAR(0,1) Using the PSM Matched Sample

	(1)	(2)	(3)	(4)
	AR_0	**AR_0**	**CAR(0,1)**	**CAR(0,1)**
POS_NONMEDIA	0.008**	0.005	0.013***	0.016**
	(0.020)	(0.213)	(0.000)	(0.023)
NEG_NONMEDIA	-0.013***	-0.016***	-0.013**	-0.013*
	(0.000)	(0.000)	(0.013)	(0.054)
POS_ REITERATE	-0.004	-0.001	-0.010**	-0.010
	(0.383)	(0.745)	(0.027)	(0.148)
NEG_REITERATE	0.013	0.016*	0.013	0.016
	(0.139)	(0.095)	(0.286)	(0.214)
AR_{-1}	0.097	0.099	0.043	0.057
	(0.317)	(0.292)	(0.773)	(0.695)
LOG_ASSETS	-0.000	-0.000	0.000	-0.001
	(0.631)	(0.871)	(0.937)	(0.606)
ROE	-0.000	-0.000	-0.001	-0.000
	(0.195)	(0.463)	(0.131)	(0.553)
DEBT_RATIO	-0.004	-0.017	-0.003	-0.016
	(0.510)	(0.126)	(0.706)	(0.285)
BM_RATIO	0.000	-0.000	0.000	0.000
	(0.670)	(0.997)	(0.647)	(0.528)
SP500RETURN	0.370**	0.356*	0.369	0.390
	(0.049)	(0.073)	(0.155)	(0.136)
CONSTANT	0.021**	0.040***	0.008	0.043***
	(0.026)	(0.002)	(0.451)	(0.005)
INDUSTRY_1DIG		Yes		Yes
YEAR		Yes		Yes
N	162	162	162	162
Adjusted R^2	0.138	0.145	0.028	0.060

Table 12: Heckman Two Step Regressions

This table provides Heckman two step regression results for non-media tweets. Column 1 provides result for the first step regression with the NEG_NONMEDIA dummy as the dependent variable. Columns 2 to 5 use the abnormal return on day 0 as the dependent variable. P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	NEG_NONMEDIA	**AR_0**	**AR_0**	**AR_0**	**AR_0**
POS_NONMEDIA		0.003	0.005	0.007	0.007
		(0.429)	(0.222)	(0.142)	(0.182)
NEG_NONMEDIA		-0.014***	-0.011**	-0.017***	-0.016***
		(0.001)	(0.013)	(0.000)	(0.002)
POS_ REITERATE				-0.004	-0.003
				(0.316)	(0.550)
NEG_REITERATE				0.014*	0.016*
				(0.097)	(0.084)
AR_{-1}	-29.816**	0.336*	0.371	0.368**	0.501
	(0.044)	(0.071)	(0.467)	(0.041)	(0.260)
LOG_ASSETS	-0.190	0.000	0.001	0.001	0.002
	(0.113)	(0.743)	(0.863)	(0.485)	(0.527)
DEBT_RATIO	0.926	-0.005	0.005	-0.013	-0.005
	(0.593)	(0.648)	(0.807)	(0.280)	(0.759)
BM_RATIO	0.030	0.000	0.000	0.000	-0.000
	(0.545)	(0.964)	(0.897)	(0.925)	(0.999)
ROE	-0.014	0.000	0.000	0.000	0.000
	(0.929)	(0.757)	(0.910)	(0.749)	(0.956)
SP500RETURN	0.122	0.008**	0.007**	0.008***	0.008**
	(0.697)	(0.015)	(0.040)	(0.010)	(0.023)
MILLS RATIO		-0.011*	-0.013	-0.012*	-0.017
		(0.091)	(0.538)	(0.060)	(0.348)
CONSTANT	0.703	0.016	0.012	0.017	0.009
	(0.605)	(0.308)	(0.482)	(0.266)	(0.538)
INDUSTRY_1DIG	Yes		Yes		Yes
YEAR	Yes		Yes		Yes
N	81	81	81	81	81
Adj. or Pseudo R^2	0.207	0.208	0.218	0.237	0.259

Table 13: Robustness Test with Three Added Variables

In this table, we include three additional variables in our model. The dependent variable is the abnormal return on day 0 (AR_0). Specifically, the added variables include the variance of stock returns during the twenty days ranging from day -22 to day -3 prior to the tweet (VAR(-22,-3)), the bid-ask spread divided by the bid price on day -1 (LAG_SPREAD/BID), and the natural log of the number of shares traded on day -1 (LOG_LAG_VOL). P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Media AR_0	**Media AR_0**	**Non-media AR_0**	**Non-media AR_0**
POS_MEDIA	-0.002	-0.001		
	(0.423)	(0.708)		
NEG_MEDIA	0.000	0.002		
	(0.861)	(0.218)		
POS_ELECTIONWON	0.009**	0.007*		
	(0.019)	(0.089)		
NEG_ELECTIONWON	-0.000	-0.002		
	(0.773)	(0.323)		
POS_NONMEDIA			0.008	0.008
			(0.270)	(0.230)
NEG_NONMEDIA			-0.014***	-0.019***
			(0.003)	(0.004)
POS_REITERATE			-0.005	-0.004
			(0.466)	(0.463)
NEG_REITERATE			0.009	0.015*
			(0.299)	(0.098)
AR_{-1}	0.080	0.074	0.251*	0.232
	(0.154)	(0.188)	(0.097)	(0.146)
LOG_ASSETS	-0.002	-0.006	-0.002	-0.004*
	(0.102)	(0.201)	(0.302)	(0.075)
DEBT_RATIO	-0.001	-0.004	0.013	0.023*
	(0.736)	(0.818)	(0.297)	(0.087)
BM_RATIO	-0.007	0.004	0.000	0.001
	(0.173)	(0.671)	(0.809)	(0.167)
ROE	0.005	0.010	-0.002*	-0.001
	(0.802)	(0.623)	(0.088)	(0.208)
SP500RETURN	0.001	0.002	0.010***	0.011***
	(0.140)	(0.104)	(0.006)	(0.004)
VAR(-22,-3)	0.353	0.240	-17.758*	-10.660
	(0.353)	(0.375)	(0.051)	(0.207)
LAG_SPREAD/BID	-0.143	-0.187	0.012	-0.052
	(0.346)	(0.219)	(0.935)	(0.689)
LOG_LAG_VOL	0.001	0.002	0.000	0.002
	(0.283)	(0.179)	(0.821)	(0.260)
CONSTANT	0.006	0.048	0.016	0.004
	(0.672)	(0.468)	(0.326)	(0.796)
INDUSTRY_1DIG				Yes
YEAR		Yes		Yes
INDUSTRY_3DIG		Yes		

N	390	390	69	69
Adjusted R^2	0.016	0.019	0.268	0.289

Table 14: Additional Robustness Tests

This table shows the results for subsample regressions (Columns 1 and 2) and partial least squares regressions (Columns 3 and 4), using the abnormal return (AR_0) as a dependent variable. The first two columns use sub-samples of media tweets (media tweets before the election & media tweets after the election, respectively). For the partial least squares regressions, we create four latent variables: Latent Variable 1 (LV_1) is calculated as a weighted combination of POS_NONMEDIA (weight: 0.973) and POS_REITERATE (weight: 0.968). Latent Variable 2 (LV_2) is calculated as a weighted combination of NEG_NONMEDIA (weight: 0.990) and NEG_REITERATE (weight: 0.628). Latent Variable 3 (LV_3) is calculated as a weighted combination of POS_MEDIA (weight: 0.981) and POS_ELECTIONWON (weight: 0.985). Latent Variable 4 (LV_4) is calculated as a weighted combination of NEG_MEDIA (weight: 0.967) and NEG_ELECTIONWON (weight: 0.922). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Pre-election Media AR_0	**Post-election Media AR_0**	**Non-media AR_0**	**Media AR_0**	**Full-sample AR_0**
POS_MEDIA	-0.000	0.006**			
	(0.871)	(0.016)			
NEG_MEDIA	0.000	0.000			
	(0.932)	(0.916)			
LV_1 (POS_NONMEDIA&POS_REITERATE)			0.07		0.044
			(0.629)		(0.388)
LV_2 (NEG_NONMEDIA&NEG_REITERATE)			-0.314**		-0.131***
			(0.040)		(0.004)
LV_3 (POS_MEDIA&POS_ELECTIONWON)				0.126**	0.122**
				(0.013)	(0.017)
LV_4 (NEG_MEDIA&NEG_ELECTIONWON)				0.016	0.000
				(0.757)	(0.997)
AR_{-1}	0.058	0.090	0.107	0.098**	0.116***
	(0.471)	(0.138)	(0.322)	(0.043)	(0.009)
LOG_ASSETS	-0.015***	0.012	-0.043	-0.08	-0.054
	(0.000)	(0.124)	(0.707)	(0.137)	(0.225)
DEBT_RATIO	-0.069***	0.058**	0.062	-0.012	0.016
	(0.000)	(0.035)	(0.591)	(0.812)	(0.725)
BM_RATIO	-0.000	-0.013	0.022	-0.072	0.012
	(0.998)	(0.332)	(0.837)	(0.158)	(0.784)
ROE	-0.041	0.022	-0.004	0.007	0.019
	(0.527)	(0.316)	(0.974)	(0.896)	(0.659)
SP500RETURN	0.001	0.001	0.260**	0.059	0.100**
	(0.229)	(0.344)	(0.018)	(0.227)	(0.022)
CONSTANT	0.229***	-0.124*			
	(0.000)	(0.075)			
INDUSTRY_3DIG	Yes	Yes			
YEAR	Yes	Yes			
N	108	324	81	432	513
Adjusted R^2	0.053	0.017	0.16	0.017	0.052

Table 15: Robustness Test with Only 7 variables

This table provides OLS regression results for non-media tweets. All columns use the abnormal return (AR) on day 0 as the dependent variable. Column 1 and 2 use only four main explanatory variables of interest (POS_NONMEDIA, NEG_NONMEDIA, POS_REITERATE, and NEG_REITERATE) as independent variables. Columns 3 and 4 use four main explanatory variables of interest as independent variables and three control variables that have the largest absolute value for their standardized coefficients. P-values based on robust standard errors are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Non-media	**Non-media**	**Non-media**	**Non-media**
	AR_0	**AR_0**	**AR_0**	**AR_0**
POS_NONMEDIA	-0.001	0.000	0.005	0.007
	(0.722)	(0.989)	(0.269)	(0.211)
NEG_NONMEDIA	-0.019***	-0.018***	-0.017***	-0.017***
	(0.000)	(0.001)	(0.000)	(0.001)
POS_REITERATE	0.001	0.003	-0.003	-0.001
	(0.729)	(0.547)	(0.528)	(0.777)
NEG_REITERATE	0.010	0.012	0.013	0.014
	(0.273)	(0.248)	(0.159)	(0.135)
LOG_ASSETS			-0.000	-0.000
			(0.953)	(0.748)
DEBT_RATIO			-0.002	0.005
			(0.825)	(0.686)
SP500RETURN			0.008**	0.009***
			(0.012)	(0.010)
CONSTANT	0.007***	0.007	0.006	0.003
	(0.003)	(0.340)	(0.629)	(0.903)
INDUSTRY_1DIG		Yes		Yes
YEAR		Yes		Yes
N	81	81	81	81
adj. R-sq	0.169	0.212	0.222	0.270

Table 16: Sample distribution: The number of banks per country

This table reports the distribution of our sample of 9,928 banks across 149 countries. We list countries alphabetically and report the number of banks (N) for each country.

Seq	Country	N	Seq	Country	N	Seq	Country	N	Seq	Country	N
1	Afghanistan	5	39	Egypt	19	76	Liberia	1	113	Romania	17
2	Albania	12	40	El Salvador	9	77	Libya	2	114	Russian	54
3	Algeria	2	41	Estonia	8	78	Lithuania	6	115	Rwanda	6
4	Angola	4	42	Ethiopia	1	79	Luxembourg	27	116	Saint Kitts	1
5	Antigua	1	43	Finland	23	80	Macau	5	117	Saint Lucia	1
6	Argentina	1	44	France	33	81	Madagascar	1	118	Saudi Arabia	10
7	Armenia	11	45	Gabon	2	82	Malawi	6	119	Senegal	4
8	Australia	23	46	Gambia	2	83	Malaysia	43	120	Serbia	10
9	Austria	119	47	Georgia	11	84	Maldives	2	121	Seychelles	3
10	Azerbaijan	22	48	Germany	1,211	85	Mali	3	122	Sierra Leone	3
11	Bahamas	6	49	Ghana	20	86	Malta	4	123	Singapore	12
12	Bahrain	15	50	Greece	5	87	Mauritania	1	124	Slovakia	8
13	Bangladesh	38	51	Grenada	1	88	Mauritius	11	125	Slovenia	12
14	Barbados	1	52	Guatemala	2	89	Mexico	20	126	South Africa	12
15	Belarus	10	53	Guinea	1	90	Moldova	7	127	Spain	49
16	Belgium	13	54	Guyana	3	91	Mongolia	2	128	Sri Lanka	15
17	Benin	1	55	Haiti	1	92	Montenegro	6	129	Sudan	5
18	Bhutan	2	56	Honduras	1	93	Morocco	4	130	Suriname	3
19	Bolivia	6	57	Hong Kong	16	94	Mozambique	10	131	Sweden	66
20	Bosnia	16	58	Hungary	15	95	Namibia	7	132	Switzerland	79
21	Botswana	7	59	Iceland	2	96	Nepal	2	133	Tajikistan	2
22	Brazil	59	60	India	9	97	Netherlands	22	134	Thailand	21
23	Bulgaria	15	61	Indonesia	56	98	New Zealand	4	135	Togo	1
24	Burundi	1	62	Iraq	1	99	Nicaragua	4	136	Trinidad	4
25	Cambodia	15	63	Ireland	9	100	Niger	1	137	Tunisia	3
26	Canada	3	64	Israel	7	101	Nigeria	15	138	Turkey	18
27	Cape Verde	3	65	Italy	338	102	Norway	93	139	Uganda	13
28	Chile	18	66	Jamaica	5	103	Oman	9	140	Ukraine	6
29	China	104	67	Japan	231	104	Pakistan	21	141	Emirates	22
30	Congo	2	68	Jordan	14	105	Panama	18	142	United Kingdom	95
31	Costa Rica	11	69	Kazakhstan	24	106	New Guinea	2	143	United States	6,010
32	Croatia	24	70	Kenya	24	107	Paraguay	2	144	Uruguay	14
33	Cyprus	8	71	South Korea	7	108	Peru	3	145	Vanuatu	2
34	Denmark	53	72	Kuwait	3	109	Philippines	11	146	Venezuela	14
35	Djibouti	2	73	Latvia	14	110	Poland	23	147	Vietnam	8
36	Dominica	1	74	Lebanon	19	111	Portugal	77	148	Yemen	5

37	Dominican Rep.	24	75	Lesotho	2	112	Qatar	10	149	Zambia	13
38	Ecuador	15								Total	9,928

Table 17: Summary statistics

This table provides summary statistics for our sample. For each variable, we report the number of bank-year observations, together with the mean, standard deviation, median, 5^{th} percentile, and 95^{th} percentile. The number of bank-year observations varies due to missing data for some banks.

Variable name	No. of Observations	Mean	Std. Dev.	Median	5^{th} Percentile	95^{th} Percentile
Equity ratio	164,046	0.1166	0.0945	0.0973	0.0448	0.2253
Tier 1 capital ratio	124,997	0.1812	0.1359	0.1450	0.0914	0.3688
Damage ratio (60 days)	194,186	0.0023	0.0078	0.0009	0.0000	0.0072
Damage ratio (180 days)	194,186	0.0022	0.0068	0.0010	0.0000	0.0097
Total assets (in US$ billion)	164,056	3.2179	11.3531	0.2753	0.0295	14.9945
Net loans ratio	163,168	0.5978	0.1853	0.6258	0.2363	0.8522
Customer deposits ratio	161,893	0.7581	0.1744	0.8127	0.3893	0.9105
Net income to equity ratio	163,865	0.0730	0.0892	0.0705	-0.0467	0.2075
Real GDP growth rate	194,157	0.0204	0.0675	0.0227	-0.1035	0.1260
Growth rate of credit to private sector	172,545	0.0128	0.0619	0.0097	-0.0886	0.0920
Real GDP per capita (in US$ thousands)	194,186	32.0650	14.0286	37.0949	0.7586	42.0992

Table 18: Correlation matrix

This table presents the Pearson correlation coefficients between the dependent variables (the annual change in the equity ratio and the annual change in the tier 1 capital ratio), and the explanatory variables. Although the lagged tier 1 capital ratio is highly correlated (**0.8206**) with the lagged equity ratio, they never coexist in one model. Similarly, the damage ratio (60 days) and the damage ratio (180 days) exhibit a high correlation (**0.9425**), but are not jointly used in any model. * indicates significance at the 10% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Change in equity ratio	1											
(2)	Lagged equity ratio	-0.3068*	1										
(3)	Lagged tier 1 capital ratio	-0.2712*	**0.8206***	1									
(4)	Damage ratio (60 days)	-0.0036	0.0050*	0.0111*	1								
(5)	Damage ratio (180 days)	-0.0046*	0.0057*	0.0094*	**0.9425***	1							
(6)	Log (total assets)	0.0414*	-0.2452*	-0.2774*	-0.0328*	-0.0352*	1						
(7)	Net loans ratio	-0.0045*	-0.2795*	-0.4838*	0.0062*	0.0056*	0.0304*	1					
(8)	Customer deposits ratio	-0.0138*	-0.3933*	-0.3165*	0.0468*	0.0498*	-0.2616*	0.1929*	1				
(9)	Lagged net income to equity ratio	0.0999*	-0.0505*	-0.1180*	0.0266*	0.0295*	0.0508*	0.0209*	0.0237*	1			
(10)	Real GDP growth rate	-0.0072*	-0.0304*	0.0203*	0.0272*	0.0289*	0.0019	0.0153*	0.0264*	0.0464*	1		
(11)	Growth rate of credit to private sector	-0.0340*	0.0851*	0.0315*	-0.0163*	0.0074*	-0.0339*	-0.0020	-0.0590*	0.1581*	0.0955*	1	
(12)	Log (real GDP per capita)	0.0264*	-0.1599*	-0.0262*	-0.0056*	-0.0111*	-0.1318*	0.1866*	0.2486*	-0.1112*	0.0737*	-0.2081*	1

Table 19: The effect of natural disasters on banks' equity ratios, employing damage ratios calculated over 60 and 180 days

This table presents the results from regressing the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in columns (1) to (3) and (5) to (7) is the change in the equity ratio (winsorized). The dependent variable in columns (4) and (8) is the change in the equity ratio (not winsorized). In columns (1) to (4), the independent variable at interest is the damage ratio calculated over a period of 60 days; in columns (5) to (8), the independent variable of interest is the damage ratio calculated over a period of 180 days. Columns (1) and (5) report results for the US-only subsample; columns (2) and (6) report results for the non-US subsample; and columns (3), (4), (7), and (8) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Damage Period: 60 Days				Damage Period: 180 Days			
Dependent variable: ΔE/TA	(1) US Only	(2) Non-US	(3) Full Sample	(4) Full Sample	(5) US Only	(6) Non-US	(7) Full Sample	(8) Full Sample
	ΔE/TA winsorized			ΔE/TA not winsorized	ΔE/TA winsorized			ΔE/TA not winsorized
Damage ratio	-0.359***	-0.012**	-0.016**	-0.018**	-0.522***	-0.013*	-0.019***	-0.022**
	(0.000)	(0.037)	(0.011)	(0.016)	(0.000)	(0.051)	(0.007)	(0.011)
Lagged equity ratio	-0.304***	-0.187***	-0.222***	-0.237***	-0.304***	-0.187***	-0.222***	-0.237***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.024***	-0.006***	-0.015***	-0.023***	-0.024***	-0.006***	-0.015***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.112***	-0.032***	-0.059***	-0.083***	-0.112***	-0.032***	-0.059***	-0.083***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.001	0.029***	0.025***	0.036***	0.001
	(0.000)	(0.000)	(0.000)	(0.500)	(0.000)	(0.000)	(0.000)	(0.500)
Real GDP growth rate	0.068***	0.001	-0.004**	-0.002	0.063***	0.001	-0.004**	-0.002
	(0.000)	(0.714)	(0.047)	(0.390)	(0.000)	(0.751)	(0.042)	(0.395)
Growth rate of credit to private sector	-0.012***	-0.018***	-0.016***	0.000	-0.008***	-0.019***	-0.017***	0.000
	(0.000)	(0.000)	(0.000)	(0.453)	(0.000)	(0.000)	(0.000)	(0.452)
Log (real GDP per capita)	0.048***	0.003**	0.003**	0.003**	0.050***	0.003**	0.003**	0.003**
	(0.000)	(0.016)	(0.022)	(0.040)	(0.000)	(0.017)	(0.024)	(0.041)
Country FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	142,063	88,918	53,145	142,063	142,063
Adjusted R^2	0.316	0.154	0.217	0.215	0.316	0.154	0.217	0.215

Table 20: The effect of natural disasters on banks' tier 1 capital ratios, employing damage ratios calculated over 60 and 180 days

This table presents the results from regressing the tier 1 capital ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 107,832 firm-year observations in our sample for which data on the tier 1 capital ratio is available. The dependent variable is the change in the tier 1 capital ratio (winsorized). In columns (1) to (3), the independent variable of interest is the damage ratio calculated over a period of 60 days; in columns (4) to (6), the independent variable of interest is the damage ratio calculated over a period of 180 days. Columns (1) and (4) report results for the US-only subsample; columns (2) and (5) report results for the non-US subsample; columns (3) and (6) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔT1R/TA (winsorized)	Damage Period: 60 Days			Damage Period: 180 Days		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample
Damage ratio	-0.292***	0.003	-0.019	-0.407***	-0.003	-0.024
	(0.000)	(0.935)	(0.625)	(0.000)	(0.954)	(0.582)
Lagged tier 1 capital ratio	-0.217***	-0.183***	-0.192***	-0.218***	-0.183***	-0.192***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.004***	-0.003***	-0.004***	-0.004***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.089***	-0.044***	-0.074***	-0.089***	-0.044***	-0.074***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.121***	-0.024***	-0.086***	-0.121***	-0.024***	-0.086***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.041***	0.028***	0.054***	0.041***	0.028***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.083***	0.009	-0.005	0.078***	0.009	-0.005
	(0.000)	(0.181)	(0.287)	(0.000)	(0.180)	(0.285)
Growth rate of credit to private sector	-0.016***	-0.048***	-0.035***	-0.013***	-0.048***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.064***	-0.004	-0.009***	0.066***	-0.004	-0.009***
	(0.000)	(0.177)	(0.000)	(0.000)	(0.175)	(0.000)
Country FE		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes
N	86,231	21,601	107,832	86,231	21,601	107,832
Adjusted R^2	0.238	0.265	0.177	0.238	0.265	0.177

Table 21: Ex-ante Test

This table presents the results from regressing the change in equity ratio, tier 1 capital ratio, and net interest margin of banks on the forward damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on which data on the equity ratio (tier 1 capital ratio or net interest margin) is available. The dependent variable in columns (1) to (3) is the change in the equity ratio (winsorized). The dependent variable in columns (4) to (6) is the change in the tier 1 capital ratio (winsorized). The dependent variable in columns (7) to (9) is the change in the net interest margin (winsorized). Columns (1), (4), and (7) report results for the US-only subsample; columns (2), (5), and (8) report results for the non-US subsample; and columns (3), (6), and (9) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)			Dependent variable: ΔT1R/TA (winsorized)			Dependent variable: ΔNIM (winsorized)		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample	(7) US Only	(8) Non-US	(9) Full Sample
Lagged equity ratio	-0.305***	-0.195***	-0.228***						
	(0.000)	(0.000)	(0.000)						
Lagged tier 1 capital ratio				-0.257***	-0.226***	-0.235***			
				(0.000)	(0.000)	(0.000)			
Lagged Net Interest Margin							-0.032	-0.012**	-0.016***
							(0.182)	(0.010)	(0.003)
Forward 1 Damage ratio	0.038*	0.006	0.006	0.210***	0.069	0.043	0.090***	-0.010	-0.009
	(0.084)	(0.335)	(0.352)	(0.000)	(0.326)	(0.482)	(0.000)	(0.175)	(0.228)
Log (total assets)	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***	-0.004***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.280)	(0.000)
Net loans ratio	-0.024***	-0.006***	-0.016***	-0.091***	-0.047***	-0.078***	0.004***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.112***	-0.031***	-0.060***	-0.091***	-0.023***	-0.071***	-0.002***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.559)	(0.148)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.040***	0.030***	0.051***	-0.010***	-0.006***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Real GDP growth rate	0.045***	-0.000	-0.006***	0.055***	0.011	-0.005	-0.002	-0.003**	-0.002***
	(0.000)	(0.933)	(0.009)	(0.000)	(0.138)	(0.317)	(0.252)	(0.015)	(0.000)
Growth rate of credit to private sector	-0.008***	-0.017***	-0.015***	-0.013***	-0.048***	-0.033***	-0.001**	0.001	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.286)	(0.019)
Log (real GDP per capita)							-		
	0.047***	0.004***	0.003***	0.061***	-0.003	-0.008***	0.016***	-0.000	0.000
	(0.000)	(0.008)	(0.007)	(0.000)	(0.375)	(0.009)	(0.000)	(0.615)	(0.874)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88918	53145	142063	86231	21601	107832	87636	48767	136403
Adjusted R^2	0.317	0.162	0.224	0.254	0.192	0.240	0.065	0.038	0.075

Table 22: The effect of natural disasters on banks' equity ratios – Commercial banks vs. bank holding companies and savings banks
This table presents the results from regressing the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period, for different subsamples of our dataset based on the business model of each bank. The dependent variable is the change in the equity ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) to (3) report the result for the subsample of commercial banks. Columns (4) to (6) report the result for the subsample of bank holding companies, and columns (7) to (9) report the result for the subsample of savings banks. Columns (1), (4), and (7) report results for the US sample; columns (2), (5), and (8) report results for the non-US sample; and columns (3), (6), and (9) report results for the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔE/TA (winsorized)	Commercial banks			Bank holding companies			Savings banks		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample	(7) US Only	(8) Non-US	(9) Full Sample
Damage ratio	-0.360***	-0.012**	-0.014**	-0.406***	0.062	0.120	-0.083	-0.157***	-0.022
	(0.000)	(0.047)	(0.021)	(0.000)	(0.478)	(0.274)	(0.359)	(0.008)	(0.721)
Lagged equity ratio	-0.346***	-0.235***	-0.267***	-0.142***	-0.175***	-0.146***	-0.189***	-0.052***	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.003***	-0.006***	-0.003***	-0.001***	-0.006***	-0.002***	-0.003***	-0.000**	-0.002***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.012)	(0.000)
Net loans ratio	-0.025***	-0.005**	-0.017***	-0.012***	0.012	-0.008***	-0.021***	-0.002**	-0.014***
	(0.000)	(0.012)	(0.000)	(0.000)	(0.202)	(0.000)	(0.000)	(0.014)	(0.000)
Customer deposits ratio	-0.132***	-0.041***	-0.079***	-0.033***	-0.058***	-0.041***	-0.077***	-0.003**	-0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.038)	(0.000)
Lagged net income to equity ratio	0.029***	0.025***	0.036***	0.014***	0.037	0.022***	0.019**	0.009*	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.202)	(0.000)	(0.015)	(0.059)	(0.000)
Real GDP growth rate	0.071***	0.004	0.000	0.018	0.012	-0.009	0.078***	0.019**	-0.005
	(0.000)	(0.273)	(0.973)	(0.111)	(0.448)	(0.534)	(0.000)	(0.018)	(0.150)
Growth rate of credit to private sector	-0.014***	-0.021***	-0.022***	-0.011***	-0.031*	-0.042***	0.016**	-0.010	0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.054)	(0.001)	(0.015)	(0.166)	(0.606)
Log (real GDP per capita)	0.048***	0.003	-0.000	0.021***	0.017	0.006	0.056***	-0.008**	0.005**
	(0.000)	(0.118)	(0.900)	(0.000)	(0.140)	(0.476)	(0.000)	(0.033)	(0.011)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	71,106	20,985	92,091	10,314	1,060	11,374	7,423	11,206	18,629
Adjusted R^2	0.370	0.182	0.264	0.097	0.108	0.114	0.168	0.122	0.119

Table 23: The effect of natural disasters on banks' equity ratios – Quantile regression results for the 0.25, 0.50, and 0.75 quantiles

This table presents the results from regressing (using quantile regressions) the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all models is the change in the equity ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) to (3) provide the results for the 0.25 quantile regression, columns (4) to (6) provide the results for the 0.50 quantile regression, and columns (7) to (9) provide the results for the 0.75 quantile regression. Columns (1), (4), and (7) report results of the US sample, columns (2), (5), and (8) report results of the non-US sample, and columns (3), (6), and (9) report results for the full sample. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: ΔE/TA (winsorized)	0.25 Quantile			0.5 Quantile			0.75 Quantile		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample	(7) US Only	(8) Non-US	(9) Full Sample
Damage ratio	-0.294***	-0.003	-0.022***	-0.243***	-0.006	-0.018***	-0.190***	-0.012**	-0.014***
	(0.000)	(0.688)	(0.002)	(0.000)	(0.244)	(0.000)	(0.000)	(0.046)	(0.002)
Lagged equity ratio	-0.139***	-0.135***	-0.132***	-0.051***	-0.038***	-0.031***	-0.056***	-0.017***	-0.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (total assets)	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.004***	0.005***	0.001*	-0.003***	0.001***	-0.001***	-0.004***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.098)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.019***	0.001	-0.004***	-0.023***	-0.002***	-0.009***	-0.025***	-0.007***	-0.012***
	(0.000)	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.020***	0.015***	0.020***	0.008***	0.006***	0.010***	-0.001***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.790)	(0.654)
Real GDP growth rate	0.063***	0.002*	-0.006***	0.050***	0.002*	-0.005***	0.034***	0.000	-0.006***
	(0.000)	(0.076)	(0.000)	(0.000)	(0.073)	(0.000)	(0.000)	(0.712)	(0.000)
Growth rate of credit to private sector	-0.015***	-0.011***	-0.013***	-0.015***	-0.011***	-0.013***	-0.015***	-0.010***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.017***	0.000	0.002***	0.006***	-0.000	0.001***	0.004***	-0.001	0.002***
	(0.000)	(0.852)	(0.000)	(0.000)	(0.703)	(0.000)	(0.000)	(0.360)	(0.000)
Country FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	88,918	53,145	142,063	88,918	53,145	142,063

Table 24: The effect of natural disasters on banks' equity and tier 1 capital ratios – Small vs. large countries

This table presents the results from regressing the capital ratio (i.e., either the equity ratio or the tier 1 capital ratio) of banks on the weighted damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on the size of the country in which each bank is headquartered. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the tier 1 capital ratio (winsorized). The independent variable of interest is the damage ratio calculated over a period of 60 days. Columns (1) and (3) report the result for the subsample of banks in countries whose land mass is smaller than the median of all countries. Columns (2) and (4) report the result for the subsample of banks in countries (including the US) whose land mass is larger than the median of all countries. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1) Small countries	(2) Large countries (incl. US)	(3) Small countries	(4) Large countries (incl. US)
Damage ratio	-0.018***	-0.011	-0.101	-0.013
	(0.010)	(0.499)	(0.522)	(0.725)
Lagged equity ratio	-0.213***	-0.228***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.224***	-0.235***
			(0.000)	(0.000)
Log (total assets)	-0.005***	-0.003***	-0.005***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.007***	-0.016***	-0.032***	-0.080***
	(0.004)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.041***	-0.063***	-0.035***	-0.073***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.023***	0.038***	0.025***	0.052***
	(0.000)	(0.000)	(0.008)	(0.000)
Real GDP growth rate	0.006	-0.005**	0.017	0.002
	(0.373)	(0.017)	(0.323)	(0.699)
Growth rate of credit to private sector	-0.019***	-0.015***	-0.061***	-0.023***
	(0.001)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.004	0.003**	-0.011	-0.011***
	(0.105)	(0.037)	(0.242)	(0.000)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes
N	13,471	128,592	4,681	103,151
Adjusted R^2	0.180	0.228	0.199	0.239

Table 25: The effect (area adjusted) of natural disasters on banks' equity and tier 1 capital ratios

This table presents the results from regressing the change in equity ratio and tier 1 capital ratio of banks on the damage ratio (area adjusted) and other control variables over the 2000–2017 period for different subsamples of our dataset based on which data on the equity ratio (tier 1 capital ratio or net interest margin) is available. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the Tier 1 capital ratio (winsorized). Columns (2) and (4) report results with fixed effects of country, year, specialization, and accounting standard. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Full Sample
Lagged equity ratio	-0.191***	-0.223***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.205***	-0.231***
			(0.000)	(0.000)
Damage ratio（/Area）	-0.002***	-0.003**	-3.581	-7.203*
	(0.009)	(0.013)	(0.112)	(0.085)
Log (total assets)	-0.002***	-0.003***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.014***	-0.015***	-0.068***	-0.077***
	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.040***	-0.059***	-0.051***	-0.069***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.034***	0.036***	0.035***	0.050***
	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.011***	-0.004**	-0.004	-0.004
	(0.000)	(0.042)	(0.202)	(0.379)
Growth rate of credit to private sector	-0.011***	-0.017***	-0.028***	-0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.000	0.003**	0.003***	-0.007***
	(0.134)	(0.011)	(0.000)	(0.003)
Country FE		Yes		Yes
Year FE		Yes		Yes
Specialization FE		Yes		Yes
Accounting standard FE		Yes		Yes
N	142063	142063	107832	107832
Adjusted R^2	0.178	0.217	0.189	0.233

Table 26: The effect of natural disasters on banks' equity and tier 1 capital ratios – Wealthy vs. Poor countries

This table presents the results from regressing the change in equity ratio and tier 1 capital ratio of banks on the damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on which data on the equity ratio (tier 1 capital ratio) is available. The dependent variable in columns (1) and (2) is the change in the equity ratio (winsorized). The dependent variable in columns (3) and (4) is the change in the Tier 1 capital ratio (winsorized). Columns (1) and (3) report results for the lower GDP per capita subsample; columns (2) and (4) report results for the higher GDP per capita subsample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		Dependent variable: ΔT1R/TA (winsorized)	
	(1)	(2)	(3)	(4)
	GDP low	GDP high	GDP low	GDP high
Lagged equity ratio	-0.197***	-0.259***		
	(0.000)	(0.000)		
Lagged tier 1 capital ratio			-0.217***	-0.245***
			(0.000)	(0.000)
Damage ratio	-0.113*	-0.539*	-0.126	-0.366
	(0.059)	(0.088)	(0.775)	(0.559)
Log (total assets)	-0.004***	-0.003***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.006***	-0.019***	-0.048***	-0.083***
	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.035***	-0.086***	-0.026***	-0.087***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.031***	0.035***	0.036***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.001	-0.008***	0.009	-0.031***
	(0.799)	(0.005)	(0.265)	(0.000)
Growth rate of credit to private sector	-0.020***	-0.020***	-0.051***	-0.017*
	(0.000)	(0.000)	(0.000)	(0.056)
Log (real GDP per capita)	0.004***	-0.004**	-0.004	-0.004
	(0.005)	(0.047)	(0.229)	(0.379)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes
N	41194	100869	17409	90423
Adjusted R^2	0.160	0.274	0.185	0.254

Table 27: The effect of natural disasters on banks' equity and tier 1 capital ratios – different continents

This table presents the results from regressing the change in equity ratio and tier 1 capital ratio of banks on the damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on which data on the equity ratio (tier 1 capital ratio) is available. The dependent variable in columns (1) to (6) is the change in the equity ratio (winsorized). The dependent variable in columns (7) to (12) is the change in the Tier 1 capital ratio (winsorized). Columns (1) and (7), (2) and (8), (3) and (9), (4) and (10), (5) and (11), (6) and (12) report results for the Africa, Asia, Europe, North America, Oceania, and South America subsample respectively. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)						Dependent variable: ΔT1R/TA (winsorized)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	africa	asia	europe	northam	oceania	southam	africa	asia	europe	northam	oceania	southam
Lagged equity ratio	-0.320***	-0.242***	-0.158***	-0.298***	-0.070	-0.184***						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.229)	(0.000)						
Lagged tier 1 capital ratio							-0.483***	-0.218***	-0.160***	-0.255***	-0.202***	-0.385***
							(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Damage ratio	-0.376***	0.044	-0.028	-0.010**	-0.030***	-0.021	0.001	0.028	-0.071	-0.406	0.176	0.018
	(0.005)	(0.365)	(0.702)	(0.021)	(0.007)	(0.174)	(0.998)	(0.629)	(0.615)	(0.125)	(0.413)	(0.769)
Log (total assets)	-0.006***	-0.004***	-0.002***	-0.003***	-0.001*	-0.008***	-0.012***	-0.006***	-0.002***	-0.004***	-0.002	-0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.055)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.138)	(0.000)
Net loans ratio	0.021***	-0.013***	-0.005***	-0.020***	-0.005	-0.010	-0.133***	-0.063***	-0.031***	-0.087***	0.004	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.469)	(0.142)	(0.000)	(0.000)	(0.000)	(0.000)	(0.849)	(0.000)
Customer deposits ratio	-0.063***	-0.050***	-0.025***	-0.111***	-0.002	-0.053***	-0.130***	-0.027***	-0.014***	-0.096***	-0.004	-0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.661)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.821)	(0.000)
Lagged net income to equity ratio	0.042***	0.024***	0.020***	0.036***	0.021	0.030**	0.082***	0.048***	0.019**	0.052***	-0.017	0.040
	(0.000)	(0.000)	(0.000)	(0.000)	(0.197)	(0.013)	(0.005)	(0.000)	(0.012)	(0.000)	(0.528)	(0.225)
Real GDP growth rate	0.011	-0.004	0.013	0.008	-0.051**	-0.015	0.042	-0.010	0.012	-0.079	-0.030	0.054
	(0.152)	(0.484)	(0.139)	(0.515)	(0.027)	(0.225)	(0.196)	(0.323)	(0.479)	(0.318)	(0.517)	(0.121)

Growth rate of credit to private sector	-0.024***	-0.014*	-0.017***	-0.001	0.028	-0.037***	-0.025	-0.038***	-0.038***	-0.048	-0.073	0.014
	(0.001)	(0.088)	(0.005)	(0.919)	(0.234)	(0.009)	(0.390)	(0.001)	(0.001)	(0.352)	(0.373)	(0.823)
Log (real GDP per capita)	0.004	0.001	-0.001	0.014**	0.017	0.011***	0.005	-0.005	0.001	0.005	0.044	0.017
	(0.375)	(0.668)	(0.787)	(0.040)	(0.513)	(0.004)	(0.821)	(0.252)	(0.834)	(0.851)	(0.626)	(0.412)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3137	10048	35893	90680	294	2011	962	5244	14261	86597	184	577
Adjusted R^2	0.301	0.205	0.122	0.319	0.193	0.144	0.355	0.195	0.133	0.265	0.187	0.274

Table 28: The effect of natural disasters on banks' equity-different disasters

This table presents the results from regressing the change in equity ratio of banks on the various types of natural disasters and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all columns is the change in the equity ratio (winsorized) from the full sample. Columns (1), (2), and (3) report results for storm, flood, and earthquake damage respectively to the full sample. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)		
	(1) Full Sample	(2) Full Sample	(3) Full Sample
Lagged equity ratio	-0.222***	-0.222***	-0.222***
	(0.000)	(0.000)	(0.000)
Storm damage ratio	-0.011*		
	(0.087)		
Flood damage ratio		-0.050*	
		(0.060)	
Earthquake damage ratio			-0.009
			(0.418)
Log (total assets)	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.015***	-0.015***	-0.015***
	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.059***	-0.059***	-0.059***
	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.036***	0.036***	0.036***
	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.004**	-0.004**	-0.004**
	(0.038)	(0.040)	(0.040)
Growth rate of credit to private sector	-0.017***	-0.016***	-0.017***
	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	0.003**	0.002**	0.003**
	(0.022)	(0.027)	(0.022)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes
N	142,063	142,063	142,063
Adjusted R^2	0.217	0.217	0.217

Table 29: The effect of natural disasters on banks' equity ratios – Additional robustness tests

This table presents the results from regressing the equity ratio of banks on the weighted damage ratio and other control variables over the 2000–2017 period for the 142,063 firm-year observations in our sample for which data on the equity ratio is available. The dependent variable in all models is the change in the equity ratio (winsorized). In columns (1) and (2), the independent variable of interest is the lagged damage ratio. In columns (3) and (4), the independent variable of interest is still the damage ratio, but the lagged equity ratio is excluded from the control variables. In columns (5) and (6), the independent variable of interest is also the damage ratio, but we use system GMM regressions. In columns (1), (3), and (5), we use the damage ratio calculated over a period of 60 days, and in columns (2), (4) and (6), we use the damage ratio calculated over a period of 180 days. P-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	OLS Regressions				System GMM Regressions	
Dependent variable: ΔE/TA (winsorized)	(1) Damage Period: 60 Days	(2) Damage Period: 180 Days	(3) Damage Period: 60 Days	(4) Damage Period: 180 Days	(5) Damage Period: 60 Days	(6) Damage Period: 180 Days
Lagged Damage ratio	-0.015*	-0.011				
	(0.050)	(0.229)				
Damage ratio			-0.016***	-0.019***	-0.789**	-0.807**
			(0.010)	(0.008)	(0.016)	(0.037)
Lagged equity ratio	-0.222***	-0.222***			-0.725***	-0.689***
	(0.000)	(0.000)			(0.000)	(0.000)
Log (total assets)	-0.003***	-0.003***	0.000***	0.000***	-0.012***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.015***	-0.015***	-0.001	-0.001	-0.000	-0.002
	(0.000)	(0.000)	(0.235)	(0.235)	(0.977)	(0.833)
Customer deposits ratio	-0.059***	-0.059***	-0.005***	-0.005***	0.054***	0.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.036***	0.036***	0.048***	0.048***	-0.362***	-0.332***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	-0.004**	-0.004**	-0.004	-0.004	0.056***	0.052***
	(0.045)	(0.042)	(0.106)	(0.108)	(0.001)	(0.000)
Growth rate of credit to private sector	-0.016***	-0.016***	-0.021***	-0.021***	-0.062**	-0.046**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.040)	(0.032)
Log (real GDP per capita)	0.003**	0.003**	-0.000	-0.000	-0.032	-0.053
	(0.023)	(0.023)	(0.872)	(0.867)	(0.456)	(0.167)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting Standard FE	Yes	Yes	Yes	Yes	Yes	Yes

N	142,063	142,063	142,063	142,063	142,063	142,063
Adjusted R^2	0.217	0.217	0.034	0.034		
Hansen's p-value					0.360	0.148
Arelanno–Bond AR(1) p-value					0.000	0.000
Arelanno–Bond AR(2) p-value					0.557	0.086

Table 30: Economic significance

This table presents the results from regressing the standardized change in equity ratio and tier 1 capital ratio of banks on the standardized damage ratio and other control variables over the 2000–2017 period for different subsamples of our dataset based on which data on the equity ratio (tier 1 capital ratio) is available. The dependent variable in columns (1) to (3) is the change in the equity ratio (winsorized). The dependent variable in columns (4) to (6) is the change in the Tier 1 capital ratio (winsorized). Columns (1), (4), and (7) report results for the US-only subsample; columns (2), (5), and (8) report results for the non-US subsample; and columns (3), (6), and (9) report results for the full sample. All the variables are standardized. Robust p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: ΔE/TA (winsorized)			Dependent variable: ΔT1R/TA (winsorized)		
	(1) US Only	(2) Non-US	(3) Full Sample	(4) US Only	(5) Non-US	(6) Full Sample
Lagged equity ratio	-0.832***	-0.510***	-0.607***			
	(0.000)	(0.000)	(0.000)			
Lagged tier 1 capital ratio				-0.668***	-0.552***	-0.605***
				(0.000)	(0.000)	(0.000)
Damage ratio	-0.096***	-0.003**	-0.004**	-0.049***	-0.000	-0.003
	(0.000)	(0.037)	(0.011)	(0.000)	(0.935)	(0.625)
Log (total assets)	-0.169***	-0.217***	-0.186***	-0.157***	-0.163***	-0.167***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net loans ratio	-0.151***	-0.035***	-0.098***	-0.402***	-0.198***	-0.339***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer deposits ratio	-0.660***	-0.190***	-0.347***	-0.374***	-0.099***	-0.285***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged net income to equity ratio	0.110***	0.105***	0.128***	0.104***	0.072***	0.117***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real GDP growth rate	0.091***	-0.001	-0.011***	0.072***	0.012	-0.010
	(0.000)	(0.714)	(0.047)	(0.000)	(0.181)	(0.287)
Growth rate of credit to private sector	-0.025***	-0.038***	-0.032***	-0.022***	-0.062***	-0.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (real GDP per capita)	1.990***	0.152**	0.103**	1.831***	-0.110	-0.208***
	(0.000)	(0.016)	(0.022)	(0.000)	(0.177)	(0.000)
Country FE		Yes	Yes		Yes	Yes
Year FE		Yes	Yes		Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes
Accounting standard FE	Yes	Yes	Yes	Yes	Yes	Yes
N	88,918	53,145	142,063	86,231	21,601	107,832
Adjusted R^2	0.316	0.154	0.217	0.238	0.265	0.177

Table 31: Absolute differences in total assets (ADTA) between Fitch and Bankscope

This table examines differences in observations between the two databases (Fitch and Bankscope) used in our paper. We match banks by name and then employ a variable that measures the absolute difference in total assets (ADTA) to compare each match, where $ADTA = |BTA - FTA|/BTA$, BTA is the value of total assets of a given bank in Bankscope, and FTA is the value of total assets of the same bank in Fitch. Matches whose ADTA exceed 0.1 are excluded from our sample. Column (1) reports the number of banks whose ADTAs fall within each range bracket. Column (2) shows the percentage distribution of our sample across the different brackets. Due to missing data for several of our dependent and independent variables, the total number of observations reported here (11,881) decreases to 9,928 in Table 1.

Range of ADTA	(1)	(2)
	Frequency	Percentage
0	9,803	82.51
0 – 0.0000001	723	6.09
0.0000001 – 0.000001	273	2.30
0.000001 – 0.00001	19	0.16
0.00001 – 0.0001	33	0.28
0.0001 – 0.001	76	0.64
0.001 – 0.01	168	1.41
0.01 – 0.1	468	3.94
0.1 +	318	2.68
Total	11,881	100

Table 32: Correlation between matched banking variables from Fitch and Bankscope

This table examines the correlation between various variables reported by Fitch and Bankscope for the year in which the two databases overlap (year 2013). Column (1) reports the Pearson correlation coefficients between the variable values in Fitch and the corresponding values in Bankscope. Column (2) reports the same correlations, except that variables are trimmed at the 1% and 99% level. Column (3) reports the mean percentage difference between the paired variables. Difference ratios are calculated as (the value in Bankscope – the value in Fitch)/the value in Bankscope. The variables we use in our paper (i.e., variables which exhibit a maximum difference of 10%) are bolded and highlighted in grey.

	(1)	(2)	(3)
Variable Name	Correlation	Trimmed correlation	Percentage of difference ratio > 0.1
Total Liabilities & Equity	1	0.9999	0.00%
Total Assets	**1**	**0.9999**	**0.00%**
Net Interest Revenue	1	0.9999	4.21%
Number of Branches	1	0.9996	0.81%
Deposits & Short-term Funding	0.9999	0.9997	1.29%
Fixed Assets	0.9999	0.9997	4.13%
Gross Loans	0.9999	0.9999	1.78%
Net Loans	**0.9999**	**0.9999**	**1.71%**
Number of Employees	0.9998	0.9999	1.30%
Total Customer Deposits	**0.9998**	**0.9997**	**0.81%**
Net Income	**0.9998**	**0.9981**	**5.62%**
Tier 1 Capital	**0.9997**	**0.9990**	**1.23%**
Intangibles	0.9997	0.9999	6.97%
Profit before Tax	0.9996	0.9990	5.52%
Derivatives	0.9996	0.9978	2.91%
Reserves for Impaired Loans/NPLs	0.9995	0.9967	6.54%
Loan Loss Reserves	0.9995	0.9965	8.90%
Total Earning Assets	0.9994	0.9994	2.04%
Impaired Loans	0.9991	0.9959	9.34%
Net Fees and Commissions	0.9990	0.9891	5.96%
Equity	**0.9987**	**0.9985**	**4.39%**
Long term Funding	0.9981	0.9894	14.27%
Loan Loss Reserves/Gross Loans	**0.9979**	**0.9957**	**7.94%**
Equity/Net Loans	0.9976	0.9915	4.95%
Equity/Total Assets	**0.9976**	**0.9954**	**4.18%**
Equity/Liabilities	0.9969	0.9920	5.48%
Tier 1 Capital Ratio	**0.9963**	**0.9952**	**1.38%**
Equity/Customer & Short Term Funding	0.9959	0.9806	5.29%
Net Loans/Total Assets	0.9957	0.9951	0.80%
Trading Liabilities	0.9949	0.9853	2.96%
Tax	0.9948	0.9990	6.14%
Dividend Paid	0.9917	0.9803	13.46%

Subordinated Debts	0.9878	0.9574	4.36%
Impaired Loans/Gross Loans	0.9792	0.9865	7.94%
Net Loans/Deposits & ST Funding	0.9765	0.9933	1.90%
Net Interest Revenue/Average Assets	0.9762	0.9955	2.77%
Impaired Loans/Equity	0.9755	0.9750	11.90%
Net Charge-Offs	0.9683	0.9801	6.14%
Dividend Pay-Out	0.9571	0.9507	14.04%
Unreserved Impaired Loans/Equity	0.9487	0.9712	14.62%
Other Deposits and Short-term Borrowings	0.9484	0.9554	8.78%
Non Interest Expenses/Average Assets	0.9416	0.8846	51.47%
Net Interest Margin	0.8854	0.9637	34.14%
Other Operating Income/Average Assets	0.8801	0.5014	95.67%
Loan Loss Reserves/Impaired Loans	0.8612	0.9341	8.98%
Deposits from Banks	0.8459	0.8468	17.75%
Loans and Advances to Banks	0.8446	0.7786	17.12%
Liquid Assets	0.8369	0.7956	93.69%
Other Operating Income	0.6763	0.6308	95.42%
Return On Average Assets (ROAA)	0.6539	0.9895	8.30%
Return On Average Equity (ROAE)	0.6366	0.9812	10.27%
Other Securities	0.6242	0.4288	56.47%
Liquid Assets/Deposits & ST Funding	0.5550	0.4393	93.93%
Loan Loss Reserves	0.5016	0.4697	97.81%
Other Earning Assets	0.4416	0.3688	99.35%
NCO/Average Gross Loans	0.2672	0.9779	13.43%
Interbank Ratio	0.0548	0.1847	22.31%

Table 33: Definitions and descriptions of variables

Name	Description	Sources
Equity ratio	Equity/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Tier 1 capital ratio	Tier 1 capital/risk weighted assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Damage ratio	Total damages caused by natural disasters in a given country in year *t*, distributed across year *t* and year *t+1* following equation (2) and divided by the gross domestic product (GDP) of each country.	EM-DAT international disaster database
Log (total assets)	Natural log of total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Net loans ratio	Net loans/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Customer deposits ratio	Total customer deposits/total assets, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Net income to equity ratio	Net income/equity, winsorized at the 1.5% – 98.5% level	Bankscope & Fitch
Real GDP growth rate	Annual growth of the real GDP of a given country	World Bank
Growth rate of credit to private sector	Annual growth of domestic credit to the private sector (expressed as a percentage of GDP) in a given country, winsorized at the 1.5% – 98.5% level	World Bank
Log (real GDP per capita)	Natural log of real GDP per capita	World Bank
Year FE	Binary variables that take on a value of 1 if a given observation falls within a year from 2000 to 2017, 0 otherwise	Bankscope & Fitch
Country FE	Binary variables that take on a value of 1 if a bank operates in one of 149 countries, 0 otherwise	Bankscope & Fitch
Specialization FE	Binary variables that take on a value of 1 if a bank operates under one of seven business models/specializations (bank holding companies, commercial banks, cooperative banks, investment banks, Islamic banks, real estate and mortgage banks, and savings banks), 0 otherwise	Bankscope & Fitch
Accounting Standard FE	Binary variables that take on a value of 1 if a bank employs one of five accounting standards (IAS, IFRS, Local GAAP, Regulatory, and US GAAP) in a given year, 0 otherwise	Bankscope & Fitch

Table 34. Variable Definitions

Variables	Definition	Source
Natural disaster variables		
Damage ratio$_t$	Total damage of all natural disasters in a state divided by the annual state GDP in the prior fiscal year	SHELDUS Database
Huge disaster$_t$	Dummy variable that takes the value of 1 if there is one huge disaster happened in the state in a fiscal year, and 0 otherwise. Huge disaster is defined as a group of natural disasters causing more than $1 billion loss (in 2015 constant dollars) within 31 days (Barrot and Sauvagnat, 2015).	SHELDUS Database
Adjacent damage$_t$	For firms located in adjacent states of the states experiencing natural disasters, this variable equals the damage ratio of the disaster states in a fiscal year	SHELDUS Database
Innovation variables		
Patent value	Stock market value resulted from the patents owned by a public firm in a fiscal year	Kogan et al. (2017)
Ln (1+Patent)	The natural logarithm of one plus a firm's granted patent count in a fiscal year	National Bureau of Economic Research (NBER) Patent Database, http://www.patentsview.org
Ln (1+Citation)	The natural logarithm of one plus the truncation adjusted total citations of a firm's patents in a fiscal year	National Bureau of Economic Research (NBER) Patent Database, http://www.patentsview.org
Ln (1+Trademark)	The natural logarithm of one plus a firm's granted trademark count in a fiscal year	United States Patent and Trademark Office (USPTO)
Ln (1+Diversity)	The natural logarithm of one plus the number of different categories of granted trademarks of a firm in a fiscal year	United States Patent and Trademark Office (USPTO)
Ln (1+Exploitation)	The natural logarithm of one plus the number of a firm's exploitation trademarks in a fiscal year. An exploitation trademark is defined as trademarks that a firm has already registered at least one trademark in this trademark's class (assigned by the USPTO) over the last 10 years	United States Patent and Trademark Office (USPTO)
Ln (1+Exploratory)	The natural logarithm of one plus the number of a firm's exploratory trademarks in a fiscal year. An exploratory trademark is defined as that the firm has not registered any trademarks in this	United States Patent and Trademark Office (USPTO)

	trademark's class (assigned by the USPTO) over the last 10 years	
Ln (1+Marketing)	The natural logarithm of one plus a firm's marketing trademarks. Following Hsu et al. (2017), a trademark is defined as a marketing trademark if the trademark has no text (i.e., pure logos), or have text comprising four or more words (i.e., advertising slogans)	United States Patent and Trademark Office (USPTO)
Ln (1+Product)	The natural logarithm of one plus a firm's trademarks except its marketing trademarks	United States Patent and Trademark Office (USPTO)
Innovation component	The first PCA component of a firm's granted patent number and granted trademark number in a fiscal year	United States Patent and Trademark Office (USPTO)
Inventor comer	An inventor is a comer of firm j in year t if s/he generates at least one patent in firm k in year t-1 and generates at least one patent in firm j in year t+1	Patent Network Dataverse (Harvard Dataverse)
Inventor leaver	An inventor is a leaver of firm j in year t if s/he generates at least one patent in firm j in year t-1 and generates at least one patent in firm k in year t+1	Patent Network Dataverse (Harvard Dataverse)
Inventor NetComer	Inventor comer – Inventor leaver	Patent Network Dataverse (Harvard Dataverse)
Firm characteristics Variables		
Cash holdings	Cash and cash equivalents over total assets	Compustat
CEO vega	The change in the dollar value of the CEO wealth (in $thousands) for a one percentage change in the annualized standard deviation of stock returns in a fiscal year.	Dr. Lalitha Naveen's Web site (http://sites.temple.edu/lnaveen/data/)
Firm age	Number of years since a firm's first appearance in Compustat	Compustat
Firm size	Natural logarithm value of total assets in a fiscal year	Compustat
HHI	Sum of the squared market share of each firm's total sales in a 3-digit standard industrial classification (SIC) industry of a fiscal year	Compustat
Leverage	Total long-term debts over total assets in a fiscal year	Compustat
R&D ratio	Research and development expenses over total assets in a fiscal year	Compustat
R&D expense	Natural logarithm of research and development expenses	Compustat
ROA	Operating income over total assets in a fiscal year	Compustat
State GDP	The natural logarithm value of the annual GDP of a U.S. state	U.S. Census Bureau

State minimum wage	The minimum wage required by law in a U.S. state	U.S. Department of Labor
State population	Population of a U.S. state	U.S. Census Bureau
State unemployment	The average unemployment rate over a twelve-month period in a U.S. state	U.S. Census Bureau
Systematic risk	A Firm's systematic risk measured by industry segments	Armstrong and Vashishtha (2012)
Tobin's q	Market value of assets divided by the book value of assets. Market value of assets is calculated as: total assets – book value of equity + market value of equity. Market value of equity is calculated by the number of common shares outstanding multiplies the share price	Compustat
Unsystematic risk	A Firm's unsystematic risk measured by industry segments	Armstrong and Vashishtha (2012)

Table 35: Summary statistics

This table presents summary statistics of damages triggered by natural disasters, technological and product innovation, and firm specific characteristics for our main sample from 1990 to 2015. We report the number of observations, mean, median, standard deviation, 10% and 90% quantiles for all sample variables. Panel B presents the correlation matrix. Variable definitions are provided in Appendix (Table A1).

Variables	N	Mean	Median	SD	P10	P90
Damage ratio$_t$	99,521	0.0012	0.0003	0.0032	0.0000	0.0024
Huge disaster$_t$	99,521	0.1904	0.0000	0.3926	0.0000	1.0000
Adjacent damage$_t$	99,521	0.0070	0.0020	0.0148	0.0002	0.0162
Patent value	99,521	0.8598	0.0000	1.9311	0.0000	3.8190
Ln (1+Patent)	99,521	0.4309	0.0000	0.9828	0.0000	1.7918
Ln (1+Citation)	99,521	0.4526	0.0000	1.0731	0.0000	1.9940
Ln (1+Trademark)	99,521	0.3134	0.0000	0.6268	0.0000	1.3863
Ln (1+Diversity)	99,521	0.2275	0.0000	0.4277	0.0000	0.6931
Ln (1+Exploitation)	99,521	0.0496	0.0000	0.2028	0.0000	0.0000
Ln (1+Exploratory)	99,521	0.2908	0.0000	0.5951	0.0000	1.0986
Ln (1+Marketing)	99,521	0.0537	0.0000	0.1852	0.0000	0.0000
Ln (1+Product)	99,521	0.2752	0.0000	0.6024	0.0000	1.0986
Innovation component	99,521	0.1951	-0.5458	1.2683	-0.5458	1.9888
Inventor comer	46,868	0.0670	0.0000	0.5341	0.0000	0.0793
Inventor leaver	46,868	0.0574	0.0000	0.4716	0.0000	0.0648
Cash holdings	99,521	0.1265	0.0565	0.1692	0.0062	0.3427
CEO vega	34,812	120.5721	39.1253	278.0897	0.0000	302.9187
Firm age	99,521	17.0154	12.0000	13.5832	4.0000	39.0000
Firm size	99,521	5.5571	5.5667	2.2405	2.6237	8.4818
HHI	99,521	0.0613	0.0415	0.0591	0.0220	0.1145
Leverage	99,521	0.1720	0.0929	0.2117	0.0000	0.4545
R&D expense	99,521	1.0049	0.0000	1.6227	0.0000	3.5230
R&D ratio	99,521	0.0544	0.0000	0.1291	0.0000	0.1664
ROA	99,521	0.0120	0.0806	0.3227	-0.2149	0.2142
Systematic risk	89,230	0.0587	0.0483	0.0528	0.0209	0.1053
Tobin's q	99,521	2.4401	0.6598	4.8849	0.0353	6.2843
Unsystematic risk	89,230	0.0528	0.0458	0.0321	0.0240	0.0892

Table 36: Correlation matrix

This table reports the Pearson correlation matrix coefficients between explanatory variables. Variable definitions are provided in Appendix (Table A1).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Huge disaster$_t$	1																			
(2) Huge disaster$_{t-1}$	0.186	1																		
(3) Huge disaster$_{t-2}$	0.139	0.160	1																	
(4) Huge disaster$_{t-3}$	0.086	0.116	0.110	1																
(5) Damage ratio$_t$	0.375	0.035	-0.027	0.118	1															
(6) Damage ratio$_{t-1}$	0.160	0.384	0.019	-0.031	0.107	1														
(7) Damage ratio$_{t-2}$	-0.006	0.163	0.395	0.024	-0.061	0.085	1													
(8) Damage ratio$_{t-3}$	0.054	-0.003	0.165	0.412	0.080	-0.063	0.080	1												
(9) Adjacent damage$_t$	0.073	0.062	0.095	0.021	0.126	0.033	0.055	0.023	1											
(10) Adjacent damage$_{t-1}$	0.099	0.032	0.021	0.063	0.054	0.075	0.031	0.037	0.053	1										
(11) Adjacent damage$_{t-2}$	0.045	0.106	0.032	0.029	-0.018	0.044	0.067	0.032	0.004	0.032	1									
(12) Adjacent damage$_{t-3}$	0.182	0.044	0.108	0.041	0.104	-0.022	0.040	0.068	0.170	-0.008	0.031	1								
(13) Leverage	0.031	0.025	0.019	0.021	0.007	0.000	0.003	0.016	0.027	0.030	0.036	0.044	1							
(14) Tobin's q	-0.017	-0.026	-0.011	-0.012	-0.018	0.005	0.011	-0.004	-0.026	-0.024	-0.027	-0.024	-0.133	1						
(15) HHI	0.011	0.007	0.007	-0.004	0.023	0.024	0.018	0.011	0.033	0.038	0.040	0.036	0.058	-0.048	1					
(16) ROA	0.025	0.020	0.019	0.015	0.019	0.019	0.015	0.002	0.038	0.040	0.037	0.032	0.044	-0.120	0.085	1				
(17) Cash holdings	-0.024	-0.027	-0.021	-0.023	-0.026	-0.022	-0.016	-0.013	-0.040	-0.043	-0.045	-0.039	-0.232	0.318	-0.073	-0.310	1			
(18) Firm size	0.088	0.081	0.060	0.054	0.008	0.000	0.003	0.007	0.047	0.036	0.043	0.046	0.187	-0.069	-0.021	0.396	-0.334	1		
(19) Firm age	0.074	0.068	0.054	0.041	0.011	0.005	0.003	0.005	0.028	0.020	0.022	0.024	0.076	-0.123	0.024	0.162	-0.151	0.355	1	
(20) R&D ratio	-0.041	-0.034	-0.027	-0.017	-0.017	-0.019	-0.012	-0.003	-0.051	-0.051	-0.050	-0.048	-0.108	0.28	-0.156	-0.611	0.424	-0.336	-0.15	1

Table 37. The impact of natural disasters on corporate innovation (baseline results)

This table reports the results of the following pooled OLS regression:

$$Innovation_{jt} = \beta_1 \cdot Damage\ ratio_{it} + \beta_2 \cdot Controls_{jt} + Year\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}.$$

The pooled OLS regression is running at the firm-year level. The dependent variables are different proxies of corporate innovation at firm j in year t: *Ln (1+Patent), Ln (1+Trademark), and Innovation component*. The explanatory variable is *Damage ratio$_t$*, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included in Column (2), (4), and (6). We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) ***Ln (1+Patent)***	(2) ***Ln (1+Patent)***	(3) ***Ln (1+Trademark)***	(4) ***Ln (1+Trademark)***	(5) ***Innovation component***	(6) ***Innovation component***
Damage ratio$_t$	-1.700**	-3.951***	-2.699***	-0.916*	-4.840***	-4.513***
	(0.044)	(0.000)	(0.000)	(0.066)	(0.000)	(0.000)
L.Damage ratio$_t$	-2.569***	-4.093***	-1.530**	-0.897**	-3.926***	-4.443***
	(0.003)	(0.000)	(0.017)	(0.035)	(0.001)	(0.000)
L2.Damage ratio$_t$	-2.788***	-3.583***	-1.430**	-0.758	-4.090***	-3.952***
	(0.001)	(0.000)	(0.041)	(0.117)	(0.001)	(0.000)
L3.Damage ratio$_t$	-4.003***	-3.252***	-0.683	-0.890**	-4.064***	-3.751***
	(0.000)	(0.000)	(0.259)	(0.039)	(0.000)	(0.000)
Leverage	-0.159	-0.218***	-0.119	-0.168***	-0.267	-0.377***
	(0.293)	(0.000)	(0.107)	(0.000)	(0.194)	(0.000)
Tobin's q	0.028***	0.013***	0.012***	0.006***	0.037***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HHI	-0.778*	-0.142	-0.055	-0.230**	-0.707	-0.407*
	(0.091)	(0.537)	(0.807)	(0.028)	(0.240)	(0.073)
ROA	0.489***	0.071	0.155***	-0.007	0.595***	0.056
	(0.001)	(0.271)	(0.000)	(0.751)	(0.000)	(0.298)
Cash holdings	0.300***	0.135	0.106*	-0.012	0.379***	0.103
	(0.001)	(0.102)	(0.088)	(0.709)	(0.009)	(0.258)
Firm size	0.122***	0.210***	0.063***	0.099***	0.175***	0.289***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	0.012***	0.009***	0.006***	0.004***	0.016***	0.012***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D ratio	2.479***	0.930***	0.499***	0.106	2.646***	0.919***
	(0.000)	(0.000)	(0.006)	(0.444)	(0.000)	(0.000)
Constant	-0.569***	-0.572***	-0.160***	-0.334***	-1.182***	-1.390***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
Observations	99,521	99,521	99,521	99,521	99,521	99,521
Adj. R-squared	0.200	0.419	0.093	0.202	0.205	0.396

Table 38. The impact of natural disasters on corporate innovation (alternative innovation proxies)

This table reports the impact of natural disasters on corporate innovation among U.S. public firms located in disaster affected states between 1990 and 2015 using additional proxies for technological and product innovation. The dependent variables are additional proxies of corporate innovation at firm *j* in year *t*: *Patent value, Ln (1+Citation), Ln (1+Diversity), Ln (1+Exploitation), Ln (1+Exploratory), Ln (1+Marketing), and Ln (1+Product)* respectively from Column (1) to Column (7). The explanatory variable is *Damage ratio*$_t$, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included in Column (2), (4), and (6). We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Patent value	***Ln (1+Citation)***	***Ln (1+Diversity)***	***Ln (1+Exploitation)***	***Ln (1+Exploratory)***	***Ln (1+Marketing)***	***Ln (1+Product)***
Damage ratio$_t$	-7.586***	-3.729***	-0.857**	0.175	-1.037**	-0.373**	-0.635
	(0.000)	(0.000)	(0.019)	(0.328)	(0.025)	(0.049)	(0.196)
L.Damage ratio$_t$	-6.089***	-2.956***	-0.657**	-0.237	-0.822**	-0.426***	-0.486
	(0.000)	(0.002)	(0.029)	(0.205)	(0.031)	(0.009)	(0.251)
L2.Damage ratio$_t$	-7.384***	-3.761***	-0.390	-0.024	-0.696	0.171	-0.829*
	(0.000)	(0.001)	(0.232)	(0.874)	(0.140)	(0.334)	(0.069)
L3.Damage ratio$_t$	-7.272***	-3.538***	-0.476	-0.425**	-0.666*	-0.019	-1.046***
	(0.001)	(0.002)	(0.109)	(0.018)	(0.091)	(0.918)	(0.008)
Leverage	-0.397***	-0.238***	-0.113***	-0.029***	-0.159***	-0.020***	-0.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's q	0.055***	0.019***	0.004***	0.001***	0.006***	0.001***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HHI	-0.237	-0.117	-0.175**	-0.002	-0.219**	-0.009	-0.210**
	(0.649)	(0.631)	(0.017)	(0.937)	(0.024)	(0.686)	(0.042)
ROA	0.072	0.082	-0.006	-0.013***	-0.005	-0.007***	-0.003
	(0.551)	(0.257)	(0.663)	(0.001)	(0.832)	(0.004)	(0.910)
Cash holdings	0.239	0.139	-0.012	0.008	-0.016	0.002	-0.014
	(0.150)	(0.114)	(0.574)	(0.398)	(0.584)	(0.594)	(0.653)
Firm size	0.469***	0.226***	0.064***	0.022***	0.092***	0.011***	0.095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	0.019***	0.008***	0.003***	0.001***	0.004***	0.000***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

R&D ratio	1.291***	1.006***	0.063	0.012	0.102	-0.006	0.114
	(0.000)	(0.000)	(0.456)	(0.589)	(0.438)	(0.481)	(0.420)
Constant	-7.586***	-3.729***	-0.857**	0.175	-1.037**	-0.373**	-0.635
	(0.000)	(0.000)	(0.019)	(0.328)	(0.025)	(0.049)	(0.196)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,521	99,521	99,521	99,521	99,521	99,521	99,521
Adj. R-squared	0.457	0.394	0.193	0.089	0.200	0.037	0.202

Table 39: The impact of natural disasters on corporate innovation (Robustness tests)

The table reports the results of several robustness tests for the impact of natural disasters on corporate innovation. In Column (1)-(3), we exclude the potential outliers of five states being most frequently hit by natural disasters. Those states are Alabama, Florida, Georgia, Louisiana, and Mississippi. In Column (4)-(6), we redefine the damage caused by natural disasters with a dummy variable that only captures the huge disasters. *Huge disaster$_t$* takes the value of 1 if there is one huge disaster (see Table A1 for detailed definition) happened in the state in a fiscal year, and 0 otherwise. The dependent variables are different proxies of corporate innovation at firm j in year t (the natural disaster year) and the three years following the disaster year: *Ln (1+Patent), Ln (1+Trademark)*, and *Innovation component*. All variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) ***Ln (1+Patent)***	(2) ***Ln (1+Trademark)***	(3) ***Innovation component***	(4) ***Ln (1+Patent)***	(5) ***Ln (1+Trademark)***	(6) ***Innovation component***
Damage ratio$_t$	-5.453***	-0.483	-5.287***			
	(0.000)	(0.363)	(0.000)			
L.Damage ratio$_t$	-6.156***	-1.062*	-6.291***			
	(0.000)	(0.052)	(0.000)			
L2.Damage ratio$_t$	-5.663***	-1.084*	-6.055***			
	(0.000)	(0.065)	(0.000)			
L3.Damage ratio$_t$	-5.653***	-0.878	-5.697***			
	(0.000)	(0.117)	(0.000)			
Huge disaster$_t$				-0.043***	-0.012***	-0.052***
				(0.000)	(0.006)	(0.000)
L. Huge disaster$_t$				-0.035***	-0.015***	-0.046***
				(0.000)	(0.009)	(0.000)
L2.Huge disaster$_t$				-0.052***	-0.015***	-0.061***
				(0.000)	(0.002)	(0.000)
L3. Huge disaster$_t$				-0.033***	-0.015***	-0.044***
				(0.000)	(0.007)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,943	92,943	92,943	99,521	99,521	99,521
Adj. R-squared	0.423	0.206	0.401	0.413	0.201	0.392

Table 40. The impact of natural disasters on corporate innovation (PSM-DID)

This table reports the results for the impact of natural disasters on corporate innovation using a difference-in-differences analysis based on propensity score matching routine (PSM-DID). We match firms in the states hit by natural disasters with firms in the states that are not affected by disasters on a vector of firm characteristics using one-to-one nearest neighbor matching each year, without replacement. To perform the post-matching DID analysis, the sample consists of corporate innovation output three years before and three years after the natural disaster year. We estimate the OLS regressions as follows:

$$Innovation_{jt} = \beta_1 \cdot Treat_{it} * Post_{it} + \beta_2 \cdot Treat_{it} + \beta_3 \cdot Post_{it} + \beta_4 \cdot Controls_{jt} + Year\ FE + Industry\ FE + State\ FE + \varepsilon_{jt}.$$

The pooled OLS regression is running at the firm-year level. The dependent variables are different proxies of corporate innovation at firm j in year t (the natural disaster year) and the three years following the disaster year: *Ln (1+Patent), Ln (1+Trademark), and Innovation component*. *Treat* is a dummy variable that takes the value of 1 for firms that locate in the states hit by natural disasters, and 0 for matched firms that locate in the states are not hit by natural disasters. *Post* is a dummy variable that takes the value of 1 for innovation output that is produced within 3 years after the natural disasters, and the value of 0 if the innovation output that is produced within 3 years prior to the disaster. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) ***Ln (1+Patent)***	**(2)** ***Ln (1+Trademark)***	**(3)** ***Innovation component***
*Treat*Post*	-0.032***	-0.015**	-0.045***
	(0.001)	(0.046)	(0.001)
Treat	0.008	-0.009*	-0.003
	(0.293)	(0.092)	(0.772)
Post	0.016**	0.019**	0.038***
	(0.035)	(0.012)	(0.002)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	65,939	65,939	65,939
Adj. R-squared	0.448	0.221	0.424

Table 41. The spillover effect of natural disasters on neighbors' innovation

This table reports the empirical results on how natural disasters could affect corporate innovation for the firms located in the adjacent states of disaster states. The dependent variables are different proxies of corporate innovation at firm j in year t (the natural disaster year) and the three years following the disaster year: *Ln (1+Patent), Ln (1+Trademark),* and *Innovation component*. The explanatory variable is *Adjacent Damage$_t$*, which is the total damage of all natural disasters in adjacent states that experiencing natural disasters scaled by relevant states' annual GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included in Column (2), (4), and (6). We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) *Ln (1+Patent)*	(2) *Ln (1+Patent)*	(3) *Ln (1+Trademark)*	(4) *Ln (1+Trademark)*	(5) *Innovation component*	(6) *Innovation component*
Damage ratio$_t$	-1.093	-3.948***	-2.708***	-0.977*	-4.351***	-4.585***
	(0.210)	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)
L.Damage ratio$_t$	-2.413***	-4.164***	-1.400**	-0.807*	-3.655***	-4.418***
	(0.002)	(0.000)	(0.028)	(0.066)	(0.001)	(0.000)
L2.Damage ratio$_t$	-1.983**	-3.593***	-1.328**	-0.661	-3.296***	-3.833***
	(0.019)	(0.000)	(0.049)	(0.196)	(0.003)	(0.000)
L3.Damage ratio$_t$	-3.102***	-3.376***	-0.659	-0.801*	-3.304***	-3.751***
	(0.000)	(0.000)	(0.275)	(0.066)	(0.002)	(0.000)
Adjacent damage$_t$	-1.349***	-0.017	-0.053	0.074	-1.185**	0.077
	(0.009)	(0.936)	(0.820)	(0.599)	(0.033)	(0.771)
L. Adjacent damage$_t$	-0.414	0.126	-0.165	-0.121	-0.519	-0.010
	(0.288)	(0.551)	(0.404)	(0.329)	(0.254)	(0.966)
L2. Adjacent damage$_t$	-0.852**	-0.010	-0.158	-0.178	-0.902*	-0.233
	(0.034)	(0.954)	(0.420)	(0.161)	(0.053)	(0.275)
L3. Adjacent damage$_t$	-1.449***	0.137	-0.033	-0.124	-1.218**	-0.033
	(0.002)	(0.442)	(0.857)	(0.312)	(0.015)	(0.889)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
Observations	99,262	99,262	99,262	99,262	99,262	99,262
Adj. R-squared	0.201	0.419	0.093	0.202	0.207	0.396

Table 42. The impact of natural disaster on disaster-related innovation

The table reports the results on how natural disasters affect disaster-related technological innovation in public firms. The dependent variables are different proxies of technological innovation at firm j in year t (the natural disaster year) and the three years following the disaster year: *Patent value*, *Ln (1+Patent), Ln (1+Citation)*. The explanatory variable is *Damage ratio$_t$*, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) *Patent value*	(2) *Ln (1+Patent)*	(3) *Ln (1+Citation)*
Damage ratio$_t$	-46.693	-0.217	-0.497
	(0.543)	(0.503)	(0.692)
L.Damage ratio$_t$	11.601	0.022	0.058
	(0.872)	(0.952)	(0.967)
L2.Damage ratio$_t$	-33.147	-0.440	-1.549
	(0.626)	(0.244)	(0.277)
L3.Damage ratio$_t$	-43.270	-0.495*	-1.668*
	(0.550)	(0.086)	(0.073)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	99,521	99,521	99,521
Adj. R-squared	0.007	0.032	0.006

Table 43. Corporate research and development spending after natural disasters

This table reports the change on corporate research and development spending among the firms in the states after being hit by natural disasters. Research and development spending is measured with the logarithm value of research and development expenses (*R&D expense*). The explanatory variable is *Damage ratio*$_t$, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) *R&D expense*	(2) *R&D expense*
Damage ratio$_t$	-7.288***	-3.518***
	(0.000)	(0.009)
L.Damage ratio$_t$	-7.007***	-4.240***
	(0.000)	(0.001)
L2.Damage ratio$_t$	-7.758***	-4.195***
	(0.000)	(0.000)
L3.Damage ratio$_t$	-5.662***	-4.097***
	(0.000)	(0.000)
Controls	Yes	Yes
Year FE	No	Yes
Industry FE	No	Yes
State FE	No	Yes
Observations	99,521	99,521
Adj. R-squared	0.356	0.633

Table 44. Inventor mobility after natural disasters

This table provides the influence of natural disasters on inventors' mobility. Panel A reports the inventor mobility at firm-level (*Inventor comer, Inventor leaver* and *Inventor netcomer*) among the firms in the states after being hit by natural disasters. The explanatory variable is *Damage ratio$_t$*, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. Panel B reports the inventor mobility at state-level (*Inventor comer, Inventor leaver* and *Inventor netcomer*) in the states after being hit by natural disasters. The explanatory variable is Disaster (t-3, t), which is an indicator variable that takes the value of 1 for the year hit by natural disasters and three years thereafter in the disaster states, and 0 for the years before natural disasters in disaster states, as well as all the years in the states has never been hit by any natural disasters. Year, and state fixed effects are included in Column (2), (4) and (6). We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Firm-level

	(1)	(2)	(3)	(4)	(5)	(6)
	Inventor comer	*Inventor comer*	*Inventor leaver*	*Inventor leaver*	*Inventor NetComer*	*Inventor NetComer*
Damage ratio$_t$	-5.045***	-4.734***	-0.520	-1.754*	-4.525***	-2.980***
	(0.000)	(0.001)	(0.685)	(0.095)	(0.000)	(0.002)
L.Damage ratio$_t$	-0.766	-1.308	-0.278	-2.706***	-0.489	1.398**
	(0.511)	(0.148)	(0.777)	(0.000)	(0.436)	(0.011)
L2.Damage ratio$_t$	-0.786	-2.230**	1.503	-1.400	-2.289***	-0.830
	(0.479)	(0.032)	(0.230)	(0.157)	(0.001)	(0.140)
L3.Damage ratio$_t$	0.984	-2.332***	0.234	-2.397***	0.750	0.065
	(0.335)	(0.003)	(0.821)	(0.003)	(0.269)	(0.922)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
Observations	44205	44204	44205	44204	44205	44204
Adj. R-squared	0.108	0.269	0.098	0.259	0.002	0.095

Panel B: State-level

	(1)	(2)	(3)	(4)	(5)	(6)
	Inventor comer	*Inventor comer*	*Inventor leaver*	*Inventor leaver*	*Inventor NetComer*	*Inventor NetComer*
Disaster$_{(t-3,\ t)}$	-33.928***	-16.069**	-24.305***	-8.607	-9.624*	-7.462
	(0.000)	(0.036)	(0.001)	(0.221)	(0.092)	(0.110)
State unemployment	0.387	-3.539	-4.338**	-8.859**	4.725***	5.320
	(0.864)	(0.382)	(0.035)	(0.017)	(0.005)	(0.171)
State population	5.382	40.038	2.491	124.834***	2.890	-84.795*
	(0.723)	(0.434)	(0.857)	(0.008)	(0.796)	(0.084)
State minimum wage	-5.428	30.839***	-7.017*	34.437***	1.588	-3.598
	(0.204)	(0.000)	(0.070)	(0.000)	(0.613)	(0.646)
State GDP	53.055***	80.106*	50.978***	58.008	2.077	22.097
	(0.000)	(0.088)	(0.000)	(0.178)	(0.851)	(0.623)
Constant	-101.192	-380.754	71.487	-718.722	-81.589	1024.138*
	(0.560)	(0.550)	(0.576)	(0.238)	(0.519)	(0.088)
Year FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
Observations	1173	1173	1173	1173	1173	1173
Adj. R-squared	0.175	0.538	0.171	0.524	0.014	0.061

Table 45. Corporate risk-taking after natural disasters

This table reports the corporate risk-taking change among the firms in the states after being hit by natural disasters. CEO risk-taking behavior is measured by *CEO vega*. We also examine the changes in systematic risk (*Systematic risk*) and firm specific risk (*Unsystematic risk*) among the firms in the state after being hit by natural disasters. The explanatory variable is *Damage ratio*$_t$, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) *CEO vega*	(2) *CEO vega*	(3) *Systematic risk*	(4) *Systematic risk*	(5) *Unsystematic risk*	(6) *Unsystematic risk*
Damage ratio$_t$	0.288	-0.258	0.011	0.046	0.016	0.017
	(0.133)	(0.340)	(0.843)	(0.331)	(0.726)	(0.705)
L.Damage ratio$_t$	-0.099	-0.341	0.048	0.095*	0.001	0.007
	(0.559)	(0.182)	(0.335)	(0.099)	(0.972)	(0.850)
L2.Damage ratio$_t$	0.074	-0.081	0.004	0.036	-0.030	-0.025
	(0.650)	(0.752)	(0.944)	(0.394)	(0.419)	(0.406)
L3.Damage ratio$_t$	0.121	0.286	0.050	0.071	-0.030	-0.034
	(0.477)	(0.273)	(0.414)	(0.137)	(0.388)	(0.387)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
Observations	33,122	33,122	78,474	78,474	78,474	78,474
Adj. R-squared	0.178	0.263	0.017	0.161	0.037	0.363

Table 46. The influence of natural disasters on corporate cash holdings

This table reports the corporate cash holdings changes following natural disasters. The explanatory variable is *Damage ratio*$_t$, which is the total damage of all natural disasters in state i divided by the annual state GDP in year t-1. All other independent variables are defined in Appendix (Table A1). All firm characteristic variables are as of the end of the prior year. Year, industry, and state fixed effects are included. We report coefficient estimates with *p-values* in parentheses below. *p-values* are calculated using clustered standard errors at industry level according to 3-digit SIC code. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels, respectively.

	(1) *Cash holdings*	(2) *Cash holdings*
Damage ratio$_t$	-0.446***	-0.139
	(0.000)	(0.147)
L.Damage ratio$_t$	-0.343***	-0.095
	(0.003)	(0.264)
L2.Damage ratio$_t$	-0.309***	-0.119*
	(0.000)	(0.094)
L3.Damage ratio$_t$	-0.360**	-0.169*
	(0.010)	(0.090)
Controls	Yes	Yes
Year FE	No	Yes
Industry FE	No	Yes
State FE	No	Yes
Observations	99,521	99,521
Adj. R-squared	0.635	0.643