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Tornado activity, house prices, and stock returns

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ABSTRACT

In this paper we investigate the effects of tornado activity on house prices and stock returns in the US. First, using geo-referenced and metropolitan statistical area (MSA)-level data, we find tornado activity to be responsible for a significant drop in house prices. Spillover tornado effects between adjacent MSAs are also detected. Furthermore, our granular analysis provides evidence of tornadoes having a negative impact on stock returns. However, only two sectors seem to contribute to such a negative effect (i.e., consumer discretionary and telecommunications). In a macro-analysis, which relies on aggregate data for the South, West, Midwest and Northeast US regions, we then show that tornado activity generates a significant drop in house prices only in the South and Midwest. In these regions, tornadoes are also responsible for a drop in income. Tornado activity is finally found to positively (negatively) affect stock returns in the Midwest (South). If different sectors are examined, a more heterogeneous picture emerges.

"*Tornadoes are among the most destructive natural events and occur most frequently in the United States.*" Long, Stoy, and Gerken (2018).

1. Introduction

Rising global temperature levels has led to an intensification of natural disasters. According to the 2018 World Economic Forum Report, natural disasters represent one of the global risks that is most likely to occur and cause severe damages on properties and infrastructures as well as loss of human life, especially due to geophysical disasters (e.g., earthquakes, volcanic activity, landslides, tsunamis, or geomagnetic storms). Lacking climate-change mitigation/adaptation strategies contributed significantly to the intensification of natural disasters (Tol, 2009; Donadelli, Jüppner, Paradiso, & Schlag, 2019). Such evidence have thus stimulated empirical and theoretical research on the economic and social impacts of global warming and natural disasters. Since the establishment of the IPCC (Intergovernmental Panel on Climate Change) in November 1988, global warming has been seen as the most important driver of climate change. For this reason, global warming has attracted most of the academic, policy and media attention. However, the increasing frequency and higher intensity of natural disasters have induced scientists to turn their attention also to the macroeconomic effects of extreme weather events like floods, storms, hurricanes/typhoons and tornadoes. Intuitively, motivated by the devastating nature of phenomena like Katrina, Harvey, Sandy, and Irma, scholars have primarily focused on hurricanes (see,

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among others, Murphy & Strobl, 2010; Strobl, 2011, 2012). In particular, recent studies have been interested in examining the effects of hurricane strikes on income and property values. Very few, however, have focused on tornadoes.[1] With this paper we aim to fill this gap by providing novel results on the macroeconomic and financial effects of tornado activity.

Actually, hurricanes and tornadoes are very different. Perhaps the only similarity between tornadoes and hurricanes is that they both contain strong rotating winds causing severe damages. In general, hurricanes form over warm water in the tropical oceans (far away from the jet stream) whereas tornadoes form over land (and in particular within storms very close to the jet stream). In fact, the most intense hurricanes over the history have formed in the Caribbean Sea or Gulf of Mexico generating sizable damages in the south-east and east coasts of the United States (US). Noteworthy, of the 36 hurricanes recorded and classified by the National Hurricane Center, 11 have directly hit Florida and only seven (six) have directly hit North Carolina (Texas). Needless to say, this has pushed forward research on the economic impacts of hurricanes either on the US coastal cities/counties or the Caribbeans while leaving behind analyses on the effects of more granular natural phenomena like tornadoes. Tornadoes are instead well known to form in different geographical areas and touch several US states. In particular, they have been found to occur most frequently (in particular during spring times) in the so-called "Great Plains" region, which embraces the entirety of Kansas, Nebraska, North Dakota, and South Dakota and parts of Oklahoma and Texas. This is also clear from Fig. 1, which shows the average number of tornadoes occurred in each US state over the period 1991–2015. With an average number of 146.7, 92.4 and 65.4 the first three states most affected by tornadoes are Texas, Kansas and Oklahoma. Whereas the Great Plains have the most tornado occurrences, a region in the "Southeastern" US encompassing Arkansas, the northern and central portions of Louisiana, Mississippi, and Alabama, as well as portions of western Tennessee has the highest tornado risk and the greatest concentration of tornado fatalities.[2] So, even if small in size, tornadoes manifest more frequently and can be more powerful than hurricanes or typhoons.[3] Thus, both tornadoes and hurricanes can be responsible for the destruction of physical and human capital. But the most important difference between a tornado and any other natural disaster (e.g., hurricane or flood) is that the former cannot be easily predicted (see, among others, Murphy, Falkinerb, McBeanc, Doland, & Kovacse, 2005; Cao & Cai, 2008; Kunkel et al., 2013). This difference is key once it comes the time to examine the implications of tornadoes for asset prices and risk perception.

Motivated by this evidence and the lack of research focusing on the macroeconomic and financial implications of tornadoes, in this empirical work we investigate the impact of tornado activity on house prices and stock returns in the US. To this end, a two-step analysis is carried out. First, we perform a granular analysis by relying on geo-referenced (metropolitan statistical area [MSA]-level) data on tornadoes (house prices) at a monthly frequency in order to examine the "local" impact of tornado activity. In this analysis, we account also for potential tornado spillover effects across adjacent MSAs. Second, we conduct an analysis at the regional level aimed at capturing the implications of tornado activity for house prices and stock returns in the following US regions: South (S), Midwest (MW), West (W) and Northeast (NE). This macro-analysis is performed by using annual data on tornadoes retrieved from the National Oceanic and Atmospheric Administration (NOAA) database, which measures tornadoes in terms of size, intensity, and loss.[4] Annual regional house prices are from the US Census Bureau database.

In the micro-level analysis, results from panel regressions show that tornadoes have a significant (lagged) negative impact on house prices. Importantly, we find evidence of a both contemporaneous and lagged spillover effect between adjacent MSA real estate property values. Moreover, tornadoes are found to have a negative (lagged) impact on stock returns. By classifying firms by sector, we further show that only a couple of sectors (i.e., consumer discretionary and telecommunications) are responsible for the observed negative effect on equity valuations.

In the macro-analysis, for each region, we first employ standard VAR models to examine the impact of a tornado size shock on house prices and income, and then perform panel regressions to check whether regional firms' returns are exposed to tornado activity. VAR investigations show that a tornado size shock generates a significant drop in real house prices in those regions that are most frequently affected by tornadoes (i.e., S and MW). Moreover, in these regions tornado size shocks explain a non-negligible fraction of fluctuations in house prices. Tornado size represents thus a significant driver of house prices in the S and MW. By contrast, tornado activity does not seem to influence average real estate property values in the NE and W. Tornadoes are instead found to marginally affect regional stock market returns. Actually, we find only a mild (and apparently counterintuitive) positive exposure in the MW. Of course, there can be several factors supporting the observed positive effect of tornado activity on stock returns in the MW, i.e., (*i*) the majority of companies located in the MW develop their business outside the region; (*ii*) most firms in the MW are fully insured against any natural disasters; (*iii*) investors might account for the fact that MW firms are willing to introduce new technologies to mitigate the adverse effects of natural disasters. At the sector level, we observe that tornadoes have a negative significant impact on the financials and healthcare sectors in the S and on four different sectors in the NE (i.e., consumer goods, healthcare, industrials and technology).[5]

[1] Few exceptions exist but rely on a single specific city, county or state (Ewing, Kruse, & Thompson, 2003; Ewing, Kruse, & Thompson, 2005).

[2] Note that the recent tornado that hit Alabama on March 3, 2019 is the proof that earthquakes, tsunamis and hurricanes are not the only natural disasters having devastating effects. The Alabama's 2019 tornado is actually guilty of more than 20 deaths and billions of dollars of damages. Interestingly (and not surprisingly), while writing this paper on May 20, 2019 we became aware that a total of 14 tornadoes were confirmed in central Oklahoma and western Texas, carrying warnings and considerable damage to real estate properties, businesses and vehicles and the possibility of complete destruction. According to the National Weather Service, two of them have been classified as large and extremely dangerous. A week later (on May 26, 2019), in Oklahoma City a tornado made two victims after having completely destroyed a residence.

[3] The strongest tornadoes – those in categories 4 and 5 – have estimated winds of 210 mph and higher, while the strongest hurricanes – those of 4 and 5 rating – have winds of 131 mph and higher.

[4] Note that we use tornado size as a main indicator of tornado activity in each region. This choice is also motivated by several climate studies pointing out that the size of a tornado is best related to its intensity and damage power (see, among others, McCarthy, 2003; Brooks, 2004).

[5] Using temperature as a proxy for climate change, Colacito, Hoffmann, and Phan (2019) also observe that climate-change related phenomena affect

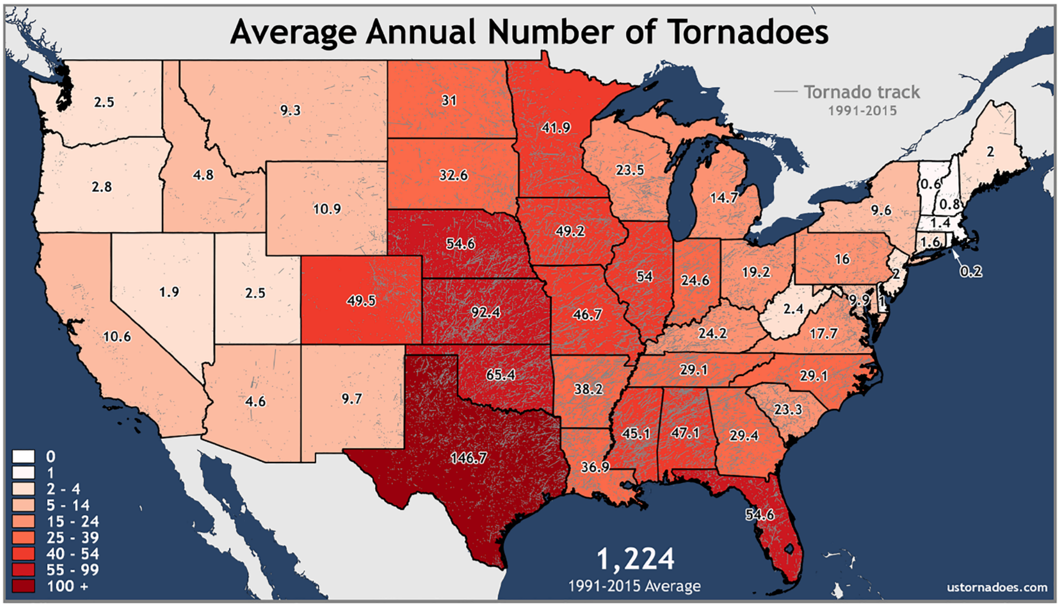

Fig. 1. US States and Average Tornadoes Number. *Source:* http://www.ustornadoes.com/2016/04/06/annual-and-monthly-tornado-averages-across-the-united-states/.

The rest of the paper is organized as follows. In Section 2 we discuss conceptual issues involved in our study, relating first to the difference between tornadoes and other climate disasters (2.1) and then to the expected effect of tornadoes on house (2.2) and stock prices (2.3), and review the most closely related literature (2.4). Section 3 describes data, methodology, and results of the micro-level (3.1) and macro-level (3.2) analysis. Section 4 concludes.

2. Conceptual issues

2.1. Hurricanes, tornadoes and other natural disasters

Before moving to the discussion on the impacts of natural disasters (including tornadoes) on house prices and stock market returns, we would like to turn our attention once again to the difference between hurricanes (and other natural disasters) and tornadoes. This point is of first order importance to understand the related real macro effects generated by these natural phenomena. Let us first remark that hurricanes and tornadoes are different. Both produce powerful and rotating wind causing severe damages. However, the two natural phenomena have different size and intensity as well as form differently. Tornadoes can be violent and come with winds above 200mph. On average, tornadoes cover a smaller surface but are by far more frequent than hurricanes. Moreover, tornadoes do not generate additional natural disasters whereas hurricanes come with severe floods. Given the high frequency of tornadoes, preventive alarms play a crucial role in reducing both fatalities and injuries (Simmons & Sutter, 2008). For instance, in 2008, approximately 75% of tornado warnings issued by the National Weather Service (NWS) were false alarms (Brotzge, Erickson, & Brooks, 2011) while between 2000 and 2004 26% of all reported tornadoes across the US occurred without any NWS warning (Brotzge & Erickson, 2010).[6] A challenge in the predictability of tornadoes thus arises from their physical nature (see also Murphy et al., 2005; Cao & Cai, 2008; Cao & Cai, 2011). While hurricanes impact only coastal locations, tornadoes occurs in any part of the US. Tornadoes originate in a variety of storm types where each of them exhibits a unique climatology. This makes challenging the development of a unique process through which scientists can detect different tornadoes and thus set reliable warnings. Ellis, Burow, Gassert, Mason, and Porter (2019) do not find any evidence of a significant relationship between tornado-genesis and the probability of a warning success. It is thus evident that predicting hurricanes and tropical storms is not as challenging as predicting tornadoes (or anticipating their direction). Over the last 30 years, for instance, thanks to improvements in weather forecast models and satellite observations, the three-day track error for tropical storms and hurricanes in the Atlantic Ocean, Caribbean Sea, and Gulf of Mexico has been reduced by more than 90%.[7] Moreover, Hansen, Kruschke, Greatbatch, and Weisheimer (2019) have recently developed a new methodology able to predict up to 97% of all storms. Not surprisingly, the discussed differences are also reflected in a poor degree of co-movement between tornadoes and other natural disasters (see Table 1). In the next section we discuss how the unpredictable nature of tornadoes can influence the channels through which they affect house and equity prices.

(*footnote continued*)
different sector non-homogeneously. For instance, production in the mining and utilities sectors is positively affected by rising temperature levels.

[6] See Fig. 3 of Brotzge et al. (2011) for the dynamics of the false tornado alarms at the beginning of the 2000s.

[7] Source:http://arstechnica.com/science/2019/08/hurricane-forecasters-may-be-reaching-the-limits-of-predictability/.

Table 1
Tornadoes vs. Hurricanes and Floods.

Correlation (t-Stat)	US: 1954–2016			US: 1975–2016		
	Tornado	Hurricane	Flood	Tornado	Hurricane	Flood
Tornado	1			1		
Hurricane	0.141 (1.106)	1		−0.080 (−0.499)	1	
Flood	−0.869 (−0.680)	−0.031 (−0.246)	1	0.116 (0.731)	0.037 (0.229)	1

Notes: Tornado:= number of tornadoes classified as F3+; Hurricane:= the number of hurricanes; Flood:= precipitation anomaly (measured in inches). All variables have been retrieved from NOAA database. T-Statistics are reported in parentheses.

2.2. Natural disasters and house prices

Naturally, house price levels are driven by demand and supply dynamics. A branch of the natural hazards literature considers climate disasters as unexpected shocks affecting both the housing demand and the housing supply (see, for example, Ewing, Kruse, & Wang, 2007; Murphy & Strobl, 2010). According to this view, a tornado strike may damage or destroy parts of existing building and core infrastructures (e.g., roads, railways, electrical and Wi-Fi stations). One should then observe a shortage in both housing supply and demand with the latter being caused by a slow-down in local economic activity due to properties' destruction and wealth losses. On the one side, natural disasters reduce housing supply affecting positively house price levels. On the other side, the drop in housing demand causes house price levels to decrease. The overall impact on property values is thus ambiguous. Existing studies argue that the demand side of housing market generally accounts for much of the movement in real estate property prices (Dipasquale & Wheaton, 1996; Malpezzi, 1999; Leung, 2014). According to this view, the effect of tornadoes or other natural disasters on average house price levels is expected to be negative (Ewing et al., 2007).

A different literature stream, conceptualizes the relationship between house prices and climate-change related events using the so-called hedonic theory (see, for example, MacDonald, Murdoch, & White, 1987; Donovan, Champ, & Butry, 2007; Bin, Kruse, & Landry, 2008; Kiel & Matheson, 2018).[8] The main characteristic of this theory is that the equilibrium price function results from sellers maximizing profits and buyers maximizing utility. In such a framework, it is usually assumed that all agents are (fully) rational. The rationality implies that buyers are able to perfectly measure the expected loss from natural disasters and, then, to capitalize this (negative) premium into house price levels. As a consequence, the presence of rational expectations in the hedonic approach implies no variations in house prices following a natural disaster.

Troy and Romm (2004) and Pryce, Chen, and Galster (2011) remove the rational expectations hypothesis and assume agents to be driven by myopia and amnesia once it comes to evaluate the impact of climate shocks on real estate property values. The idea here is that the observed house price could diverge from the fully risk-adjusted price especially if a long period passed by since the last natural shock. In this respect, Pryce et al. (2011) argues that, for the same house quality level, the risk perceived by household living in frequent risky areas (*FR*) is higher than the risk perceived by households living in low frequent risky area (*IR*). This means that the fully risk-adjusted price in frequent risky regions (P_{RA}^{FR}) is lower than the fully risk-adjusted price in infrequent risky regions (P_{RA}^{IR}). In frequent risky areas, even if the distance between P_{RA}^{FR} and P_{ZR} (zero risk house price) is very large due to rising climate risk, the actual or observed price (P_{A}^{FR}) rarely deviate significantly from P_{RA}^{FR}. This because the frequent occurrence of natural disasters makes agents more aware of the related risk (Fig. 2, Panel b). Differently, in areas where natural disasters occur less frequently the actual price (P_{A}^{IR}) deviates strongly from P_{RA}^{IR} (Fig. 2, Panel a). Actually, in the presence of infrequent natural disasters, agents encounter more difficulties in mapping the true level of risk. It turns out that house price levels tend to drop more in those areas that are less frequently affected by natural disasters. Getting a complete climate change-related risk profile requires often the solution of complex climate models. Human attention is a limited resource (DellaVigna, 2009) and, for this reason, people may prefer to avoid advanced calculus. As aforementioned, predicting tornadoes represents a serious challenge. This, in turn, makes the understanding of the tornadoes-induced risk (in particular for households) a very tough task. Therefore, households tend to avoid to account for tornadoes risk (i.e., risk negligent agents). In this respect, there have been conducted surveys indicating that households living in hazard-prone areas decide to buy a property ignoring completely the embedded natural disaster-induced risk (see, for example, Burningham, Fielding, & Thrush, 2008; Willis, Natalier, & Revie, 2011). In this scenario, when investigating the effect of climate shocks, we simply look at the determinants of the supply and demand of house prices.

One final aspect worthy to be discussed refer to the size of these natural phenomena. How far do tornadoes travel once they touch the ground? And what about the size of the damage they caused? As aforementioned, tornadoes are local events hitting relatively small geographical areas. However, the total damage caused by a tornado or series of local tornadoes can be pretty severe having thus an impact also on neighboring areas. In this respect, one should expect powerful tornadoes touching a specific geographic area to

[8] The hedonic theory, originally developed by Rosen (1974), is a standard model of supply and demand for a commodity with different attributes.

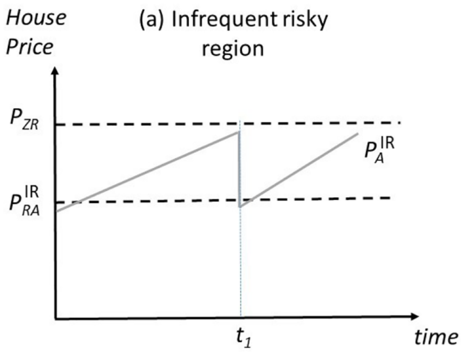

Fig. 2. House prices with myopia and amnesia: the case of infrequent (*IR*) and frequent (*FR*) natural disaster. *Source:* Adapted from Pryce et al. (2011).

have a spillover effect on adjacent areas. Of course, spillover effects can lead to direct damages as well as to indirect ones. Indirect impacts are of psychological nature, i.e., households living "close" to areas struck by a natural disaster believe that the phenomenon could potentially affect also their own district (Pommeranz & Steininger, 2018).

Let us stress that if house prices across different MSAs are (historically) highly interconnected, then tornado spillover effects amplify. Intuitively, this suggests that local (but powerful) natural disasters like tornadoes can have adverse implications also on aggregate house prices i.e., average house price levels of the state or region most frequently hit by tornadoes. Using MSA-level data on house prices, we perform a standard analysis to examine the dynamic interconnectedness across house prices belonging to the same state/region. We first extract the first principal component from the MSA house prices within each state. For the majority of the US states the first principal component is found to account for more than 85% of the cross-MSA house price variations (see Table B.1). This indicates that the house price levels of different metropolitan areas belonging to the same state follow a common pattern. We next follow the geographical classification in Fig. C.1 and use the extracted state-level principal components to build four regional spillover indexes. These – obtained employing the methodology proposed by Diebold and Yilmaz (2009, 2012) – are depicted in Fig. B.1 and show an increasingly and highly integrated housing market, especially in the S. It is thus reasonable to examine the impact of tornadoes also on aggregate regional house price levels with the ultimate goal of detecting whether in the regions, which are most frequently affected by tornadoes, the real estate sector suffers more.[9]

2.3. Natural disasters, stock returns and risk

What about the effects on natural disasters on stock returns? Actually, in the literature there is no a general consensus on what are the implications for firm equity valuations of natural disasters. For instance, Wang and Kutan (2013) report no change in US equity returns, but only a small change in volatility, following a natural disaster. Leiter, Oberhofer, and Raschky (2009) suggest that investors may interpret damages as short-run phenomena, expecting an increase in the productivity over long-run. In this way, the effect of an adverse weather-related disaster on asset returns of a company may be positive. More recently, Lanfear, Lioui, and Siebert (2019) find that extreme natural events can have a negative impact on US equity returns.

In general, hurricanes have a lead-time of three days. Given this, a hurricane warning represents an additional info that agents can account for. The large hurricane lead-time has a major impact on firms' plan. Unlike hurricanes, the lead-time of tornadoes is rather small (less than 24 hours). In addition, it is also difficult to predict in which direction a tornado will evolve. For this, it is very hard for investors to anticipate and quantify the effects of tornadoes on firms' marginal profitability. Ex-ante, it is thus rather challenging for investors to account for the risk associated to tornadoes.

Another important aspect is related to the effect of tornadoes on the risk perception of the representative investors. Most of the literature focusing on studying the impact of extreme events on the financial risk behaviour makes use of the so-called 'Prospect' and 'Risk as feeling' theories. 'Prospect theory', firstly introduced by Kahneman and Tversky (1979), describes the decision making process under uncertainty and in presence of risky options (i.e., the typical situation that an investor faces when he decides to buy a stock). One of the main characteristic of the prospect theory is that losses are over-valued against gains due to loss aversion. The high level of investor's loss aversion towards infrequent natural events should result in high risk premium. This, in particular, should happen if investors have a short-investment horizon (Benartzi & Thaler, 1995; Brekke & Johansson-Stenman, 2008).[10] The 'Risk as feeling' theory, firstly introduced by Loewenstein, Weber, Hsee, and Welch (2001), emphasizes the role of emotions in evaluating

[9] The choice of performing a macro-analysis using aggregate regional data (see Section 4.2) is also motivated by the presence of strong spillover effects across MSA house prices.

[10] In a similar fashion, research has suggested that catastrophe bond investors tend to overweight small probabilities of losses and require to be compensated for this extra risk (Bantwal & Kunreuther, 2000).

risky decisions. According to this theory, emotions (e.g., excitement, worry and anxiety) develop as a consequence of the decision making process, influencing cognitive evaluations about the (rational) assessment of potential outcomes. Kuhnen and Knutson (2011) find that positive emotions lead investors to take riskier choices, whereas in presence of negative emotions investors are more risk-adverse. These theories aimed at capturing investors' risk profile, however, do not account for a key characteristic of tornadoes, i.e., they are very hard to predict. This might induce investors to naively underestimate the phenomenon an thus not insure themselves properly. As indicated by Barahona, Driessen, and Frehen (2018), in 'the extreme case where risk exposures are unpredictable, then there should be no demand associated to these risk exposures and they should be not priced'.

One final aspect we would like to discuss relates to the heterogeneous nature of the effects (in particular on equity valuations) induced by local natural phenomena like tornadoes. Also for firm stock returns, a tornado touching one MSA can have an impact on the performance of a firm located in a nearby area. This because tornadoes cause substantial damages to roads, railways, bridges, power plants, Wi-Fi networks, etc. In this respect, tornado activity can affect the business activity of firms belonging to different sectors non-homogeneously. For instance, one sector can truly suffer whereas another one can be completely immune. Of course, there can be firms more exposed to international business or having a larger fraction of their activities in areas unaffected by natural disaster than others. Intuitively, these firms can be perceived as less risky by investors and thus only marginally undermined.

2.4. Related literature

Over the last two decades, a non-negligible number of empirical studies have examined the macroeconomic implications of natural disasters. Most of them have focused on the effects of natural disasters on macroeconomic aggregates (see Table A.1) and house prices (see Table A.2). Little research has instead been devoted to the stock price implications of natural disasters (see Table A.3).

Our work is most closely related to Hallstrom and Smith (2005), Beracha and Prati (2008) and Murphy and Strobl (2010) who investigate the effects of hurricanes on the US house prices. However, we differ from them under several dimensions. First, we focus on tornadoes. As aforementioned, tornadoes and hurricanes exhibit several physical differences. Moreover, tornadoes' macroeconomic implications have been barely studied as indicated in Tables A.1, A.2 and A.3. Hallstrom and Smith (2005), Beracha and Prati (2008) and Murphy and Strobl (2010) focus on the US coastal counties/cities and the Central American and Caribbean regions, i.e., areas most frequently hit by hurricanes. Differently, we examine the effects of tornadoes on both house and equity prices not only in the US as a whole (via a micro-analysis) but also in four US regions (via a macro-analysis).

Most broadly, our work is also related to the recent macro-finance literature focusing on the implications of temperature-shifts (and other climate change-related variables) on the business cycles and equity valuations (see, among others, Bansal, Kiku, & Ochoa, 2016; Donadelli, Jüppner, Riedel, & Schlag, 2017; Balvers, Du, & Zhao, 2017; Khan, Metaxoglou, Knittel, & Papineau, 2019; Colacito et al., 2019). In particular these studies have focused on the effects of rising temperatures on consumption, productivity and aggregate stock market returns. Differently, we turn our attention also to the implications for house prices. Moreover, in the spirit of Colacito et al. (2019) we exploit US regional rather than aggregate country effects.

3. Empirical strategy

In this section we describe the data and the methodologies employed in our micro (Section 4.1) and macro (Section 4.2) analysis. As previously mentioned, the granular analysis relies on geo-referenced data on tornadoes and MSA-level data on house prices at monthly frequency. Here, tornadoes in each MSA are captured by means of dummies. Differently, the macro-analysis makes use of annual data aggregated at the regional level and employ (for each region) a tornado size index as a benchmark measure of tornado activity.[11]

3.1. A granular analysis

3.1.1. Data

- **Tornadoes:** Geo-referenced data on individual tornadoes are obtained from the Storm Events Database of the National Oceanic and Atmospheric Administration (NOAA). Information on the location of extreme events include identifiers for the state and the county (FIPS code). We first aggregate individual tornado data at the county level by determining whether a tornado hits the respective county in a given month of a year. In the next step, we aggregate the county level data to MSAs by using the delineation file from the US Office of Management and Budget (OMB). This allows us to generate a time series dummy variable for each MSA, which equals one when a tornado happens in that area at a given point in time and zero otherwise. To analyze possible spillover effects from tornadoes to house prices and equity returns in neighboring areas, we check at each point in time for each MSA whether there are tornadoes happening in neighboring MSAs. To identify these MSAs, we use the county adjacency files from the Census Bureau.[12]

[11] The choice of focusing also on a macro-level analysis is motivated by the fact that tornado effects may take time to spillover across different areas. In this respect, Downton and Pielke (2005) while investigating the accuracy of natural disasters data argue that only 'estimates aggregated over large areas or long time periods appear to be reasonably reliable'.

[12] By doing so, we ignore tornadoes in neighboring counties that do not belong to an MSA. However, since MSAs are regions with high degree of social and economic integration, we expect spillover effects to be generally larger between these areas and that neglecting non-metropolitan areas does not have a significant impact on our results.

- **House prices:** Monthly data on seasonally adjusted house prices at the metropolitan level are from the FreddyMac House Price Index (FMHPI) database. The FMHPI database comprises data for 382 MSAs in the US. Nominal house prices are deflated using the aggregate seasonally adjusted consumer price index (CPI) for all urban consumers (all items less shelter), available from US Bureau of Labour Statistics. House price growth is calculated as the first difference of the log of the real house price index. To construct the monthly panel on MSA house prices and tornado information, matching is done on the Core-based statistical area (CBSA) code.
- **Stock market returns:** Monthly averages of firm return indexes (RI) come from Refinitv Datastream. Excess returns are computed by subtracting the 3-month T-bill rate, also obtained from Datastream, from the annualized first difference of the log of the average return index multiplied by 100. Information on the firm location including ZIP codes are obtained from Worldscope database, also available from Datastream. We perform the same data cleaning procedure as for the analysis on the regional level. For our analysis on the effects of tornadoes on equity returns, we need to match NOAA data with firm level data from Datastream. This procedure is not straightforward, since the location identifier for firms is the postal ZIP code, which is differently defined compared to the FIPS code used in NOAA database. First, mapping counties to ZIP codes is incomplete, since not all ZIP codes are included in the US Zip codes to county FIPS crosswalks available online. Also, there is no unique mapping, since a ZIP area may touch different counties. To simplify our analysis, we consider again the tornado information on the MSA level used in the house price analysis and match firms' ZIP codes to metropolitan area CBSA codes where possible. To this end, we only keep firms whose ZIP codes can be uniquely matched to the CBSA codes of MSAs. Hence, for constructing the panel, we combine information on the excess return of a firm with information on tornadoes that happen in the MSA where the firm is located.

All data here are monthly and run from January 1975 to May 2019.

3.1.2. Methodology

House price returns: Panel analysis (MSA-level). To analyze local and spillover effects of tornadoes on house prices in MSAs, we estimate the following equation

$$\Delta log(RHPI_{i,t}) = c_i + \rho\Delta log(RHPI_{i,t-1}) + \beta_0 TD_{i,t} + \beta_1 TD_{i,t-1} + \gamma_0 TD_{i,t}^{SP} + \gamma_1 TD_{i,t-1}^{SP} + \nu_t + \varepsilon_{i,t}, \tag{1}$$

where $RHPI_{i,t}$ is the real house price index of the MSA i at time t, $TD_{i,t}$ is a dummy that equals one if a tornado hits MSA i at time t and zero otherwise, and $TD_{i,t}^{SP}$ is a dummy that equals one if a tornado hits an adjacent MSA of MSA i at time t. We estimate a standard fixed effects model with cross-section and time fixed effects (to control for aggregate effects) at monthly frequency over the sample period January 1975 to May 2019.[13]

Stock price returns: Panel analysis (MSA-level). We also investigate the local and spillover effects of tornadoes aggregated at the MSA-level on individual firms' equity returns, estimating the equation

$$ExR_{i,t}^{j} = c_i + \rho ExR_{i,t-1}^{j} + \beta_0 TD_{j,t} + \beta_1 TD_{j,t-1} + \gamma_0 TD_{j,t}^{SP} + \gamma_1 TD_{j,t-1}^{SP} + \nu_t + \varepsilon_{i,t}, \tag{2}$$

where $ExR_{i,t}^{j}$ is the excess equity return from firm i, located in MSA j, at time t, $TD_{j,t}$ is a dummy that equals one if a tornado hits MSA j at time t and zero otherwise, and $TD_{j,t}^{SP}$ is a dummy that equals one if a tornado hits an adjacent MSA of MSA j at time t.[14] We estimate a standard fixed effects model with cross-section and time fixed effects at monthly frequency over the sample period January 1975 to May 2019.[15] In a first step, we perform the regression over the whole set of firms. Afterwards, we estimate Eq. (2) separately for 11 different sectors.[16]

3.1.3. Results

House prices. Results reported in Table 2 show that local tornadoes affect house price growth only with a lag of one month. This evidence is in line with Downton and Pielke (2005) who argue that it takes time to have an accurate measure of the damage of a natural distaster and that the initial estimate of the damage is usually biased. This coud help to explain why the impact of tornadoes on house prices evolves overtime. Moreover, entries in Table 2 show that tornadoes hitting neighboring MSAs have also a negative and significant impact on house prices (both contemporary and with a lag of one month).[17] This corroborates our discussion on the importance of spillover effects in the housing market.[18]

Stock price. Table 3 shows the results of the effects of tornadoes on excess returns of all firms and for the firms belonging to the same sector. For the total of firms (MKT), results suggest that these effects are negative, lagged and local. This result seems to be in line with the explanation that in general it takes time to estimate precisely the impact of natural disasters (Downton & Pielke, 2005).

[13] We do not account for the Nickell bias because of the large time dimension, which means that the bias is likely to be small.

[14] Note that in this case, we do not control for the market excess return. Since the tornado regressors are not cross-section invariant in this analysis, we can control for aggregate effects using time fixed effects.

[15] As in the analysis for house price returns, we do not account for the Nickell bias because of the large time dimension.

[16] Note that there have been changes in the sector classification in Datastream while revising this paper.

[17] The significant coefficient for contemporaneous spillover effects of tornadoes may seem surprising. Since closing on a home may take several weeks after a home buyer's offer is accepted, pricing of tornado risk happens with a delay. It could however be that a tornado occurs over the first week of the month, so it may still be possible that prices are settled at the end of the month. The coefficient for contemporaneous local tornado effect being insignificant could however be due the fact that neighboring MSAs together usually span a wider area, so that it is more likely that a tornado hits the area at the beginning of a month.

[18] See also Pommeranz and Steininger (2018) on this point.

Table 2
Tornadoes in MSAs and house prices: 1975m1–2019m5.

$\Delta log(RHPI(-1))$	0.82808***
	(0.00599)
TD	−0.00005
	(0.00004)
$TD(-1)$	−0.00011**
	(0.00004)
TD^{SP}	−0.00007***
	(0.00002)
$TD^{SP}(-1)$	−0.00007***
	(0.00003)
MSA fixed effects	YES
Month fixed effects	YES
N	181,071

Notes: This table reports estimations results from a fixed effects regression of log-differences of MSA house price on its lag, the local tornado dummy (contemporaneous and with one lag), and the tornado dummy for adjacent MSAs (contemporaneous and with one lag) using cross-section and time fixed effects. Robust standard errors are computed by clustering standard errors at the MSA level and are reported in parenthesis. *N* denotes the number of observations. The sample spans the period from January 1975 to May 2019. *** and ** denote significance at the 1% and the 5% level, respectively.

Table 3
Tornado Activity vs. Sectoral Stock Returns.

	MKT	BS	CD	CS	E	FIN	HC	IND	RE	TECH	TEL	UT
$\Delta Exr(-1)$	0.136***	0.124***	0.134***	0.133***	0.135***	0.121***	0.143***	0.127***	0.120***	0.140***	0.138***	0.098***
	(0.002)	(0.008)	(0.004)	(0.010)	(0.007)	(0.004)	(0.005)	(0.005)	(0.014)	(0.004)	(0.007)	(0.012)
TD	0.244	−3.6	1.316	−0.649	3.895**	0.4	−0.458	0.114	−0.226	0.802	−7.600***	1.323
	(0.429)	(2.379)	(1.044)	(2.137)	(1.575)	(0.970)	(1.477)	(0.976)	(1.693)	(1.471)	(2.537)	(1.880)
$TD(-1)$	−1.230***	−3.135	−1.800*	−2.105	0.088	−0.226	−1.045	0.164	−1.102	−1.959	−1.332	0.363
	(0.428)	(2.014)	(1.037)	(2.061)	(1.575)	(1.007)	(1.411)	(0.970)	(1.771)	(1.517)	(2.930)	(1.862)
TD^{SP}	0.364	2.656	−0.941	−0.405	−2.471	−0.284	0.526	0.787	0.632	0.834	2.606	1.025
	(0.394)	(2.050)	(1.019)	(1.952)	(1.841)	(0.860)	(1.189)	(0.895)	(1.511)	(1.266)	(2.433)	(1.561)
$TD^{SP}(-1)$	0.07	−1.431	−0.948	−3.082	1.381	−0.322	−0.266	2.478***	1.642	−0.471	0.406	−3.657*
	(0.405)	(1.882)	(1.042)	(1.935)	(1.873)	(0.905)	(1.298)	(0.901)	(1.484)	(1.318)	(2.241)	(1.933)
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2,793,108	121,330	458,623	119,046	170,258	525,546	314,462	457,416	88,534	336,027	108,915	86,679

Notes: This table reports estimations results from a fixed effects regression of firms excess return on its lag, the local MSA tornado dummy (contemporaneous and with one lag), and the tornado dummy for adjacent MSAs (contemporaneous and with one lag) using cross-section and time fixed effects. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parenthesis. *N* denotes the number of observations. BS:= Basic Materials, CD:= Consumer Discretionary, CS:= Consumer Staples, E:= Energy, FIN:= Financials, HC:= Healthcare, IND:= Industrials, RE:= Real Estate, TECH:= Technology, TEL:= Telecommunications, UT:= Utilities. The sample spans the period from January 1975 to May 2019. ***, **, and * denote significance at the 1% the 5%, and the 10% level, respectively.

This could explain why the market needs time to fully understand the impact of a torndado. Tornadoes from neighboring MSAs do not significantly affect firms' equity returns. A more heterogeneous picture appears if the analysis is conducted at the sectoral level. We find negative local effects for the consumer discretionary (lagged effect) and telecommunication (contemporaneous) sectors. Excess returns for the energy sector are instead positively affected (without lag) by tornadoes. Finally, lagged spillover effects are observed in the industrial (positive) and utility (negative) sectors.

Taken together, entries in Table 3 suggest the presence of sectors directly affected by tornado damages (e.g., energy and telecommunications) and sectors indirectly affected by tornadoes (e.g., industrials and utilities). Tornadoes occurrence tend to induce the energy sector to invest in R&D for adaptation purposes increasing thus its marginal profitability whereas it generates non-negligible economic costs for the telecommunications sector due to the destruction of key business lines. Evidence of a negative spillover effect are found only in the utilities sector. This could happen because utilities firm are responsible for supplying water, sewage services, electricity, natural gas in several areas. It seems then that tornado activity is beneficial for companies in the industrial sector operating in the nearby area not hit by a tornado. Potentially, these unaffected firms intercept a large part of the extra demand coming from damaged companies in adjacent MSAs.

3.2. A macro analysis

3.2.1. Data

Tornadoes, House Prices and Stock Returns

- **Tornadoes.** Tornado indexes for the four US regions have been built by using state-level tornadoes data from the NOAA Center (https://www.spc.noaa.gov/wcm/). As a main indicator of tornado activity we rely on a *Tornado Size Index*, i.e., total surface covered by a tornado in a year.[19] Annual regional tornado size indexes – expressed in log (2009 = 100) – are plotted in Fig. 3.
- **Real house prices**. Data on nominal house price indexes for the four US regions are from the US Census Bureau database (https://www.census.gov/construction/nrs/historical_data/index.html). The four geographic regions (i.e., S, MW, NE and W) are identified according to the classification provided by the US Census Bureau (see Fig. C.1). All regional nominal house prices are scaled by the CPI (all items less shelter).
- **Stock market returns**. Annual averages of firm total return indexes (RI) are obtained from *Refinitiv Datastream*. Excess returns are computed by subtracting the annual average 3-month T-bill rate, also obtained from *Datastream*, from the growth rate of firms' average return indexes. As market rate we choose the annual growth rate of the average S&P 500 price index (source: *Datastream*). Information of firms' locations (address nation and state of headquarters) are obtained from Worldscope database (variables WC06026 WC06024), also available by *Datastream*. We download firm data for all available Worldscope constituent lists for the US (WSUS1-WSUS24). Duplicates are removed from the firm panel. We also drop firms which are wrongly classified as US firms by checking firms' ISINs and the regional information from Worldscope. Finally, we only include securities that are classified as common equity (TYPE = EQ) and have a major quotation (MAJOR = Y). To reduce the effect of possibly spurious outliers, firm returns are winsorized each year at the bottom 1% and top 99% levels.

Additional variables

- **Real GDP per capita**. Following Boarini, Johansson, and d'Ercole (2006), we use real GDP per capita as a proxy of income per capita.[20] State-level data on nominal GDP have been retrieved from the Christopher Chantrill's website (https://www.usgovernmentspending.com/download_multi_year). The regional GDP is obtained by using a two-steps procedure. First, we sum up nominal GDPs of all states belonging to the same region. The obtained regional nominal GDP is then deflated by using the related regional GDP deflator. The real regional GDP is then divided by total population to get the regional real GDP per capita. Regional data on population is obtained summing up the population of all states belonging to the same region.
- **Homeowner vacancy rates**. Homeowner vacancy rate is defined as the proportion of the homeowner housing inventory which is vacant for sale. Source: US Census Bureau (https://www.census.gov/housing/hvs/data/histtabs.html).
- **Opportunity cost of capital**. The opportunity cost of capital is calculated as follows (see, for example, Dröes & van de Minne, 2016): $occ_t = (i_t - E[infl_t]) + 2\%$,[21] where i_t is the 10-year T-bond rate (source: FRED,http://fred.stlouisfed.org/series/GS10) and $infl_t$ the inflation rate (calculated as the log difference of regional deflators). The expected inflation rate is obtained by using a simple (7-year) moving average filter (see Dröes & van de Minne, 2016).
- **Population density**. Population density for each region is computed as the ratio between the regional population and the total area of the region measured in squared miles. Data on regional surfaces are from the U.S. Census Bureau (2016).

All data span the period 1963–2017, except for stock market returns that run from 1974 to 2017.

3.2.2. Methodology

House price returns: VAR Investigations (Regional-Level). We examine the macroeconomic implications of tornadoes by means of regional VAR models. We first focus on the effects on output and house prices by estimating a trivariate VAR for each of the four US regions. The reduced-from VAR reads as follows

$$\Omega_t^j = \Pi(L)\Omega_t^j + \nu_t^j \quad \nu_t \sim N(0, \Xi) \tag{3}$$

where $\Omega_t^j = [ti_t^j, y_t^j, hpi_t^j]$ represent the set of endogenous variables (i.e., tornado size index, income per capita and house price index),[22] Π denotes the VAR coefficients matrix and ν_t is the vector of reduced-form residuals having zero mean and var-cov matrix Ξ, and j identifies the US region (i.e., S, W, MW, NE).

For the sake of completeness and robustness, in a second test we estimate a VAR-X where the following macro and financial

[19] For the sake of completeness other tornado indexes have been constructed. These are (i) *Tornado Intensity Index*, i.e., damage generated by a tornado over man-made structures and (ii) *Tornado Loss Index*, i.e., value (on an ordinal scale) capturing the property loss of a tornado. Full details on the construction of the regional tornado indexes for the US are provided in Appendix C.

[20] Note that throughout the paper we use the terms GDP per capita and income per capita interchangeable. Actually, in our VAR analysis, the GDP per capita serves as proxy for income per capita.

[21] According to this interpretation, the opportunity cost of capital is an interest rate-based variable, i.e., a variable in which the interest rate is at the center of its modelling.

[22] The choice of focusing on these variables is consistent with the theoretical literature considering disposable income as the main determinant of house prices (see, for example, Malpezzi, 1999; Leung, 2014).

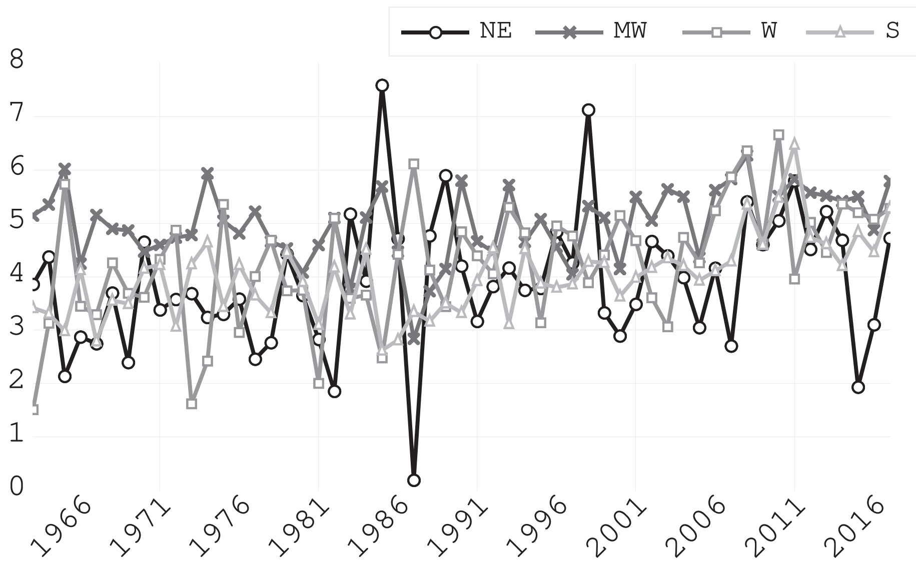

Fig. 3. US Regional Tornado Size Indexes (1963–2017).

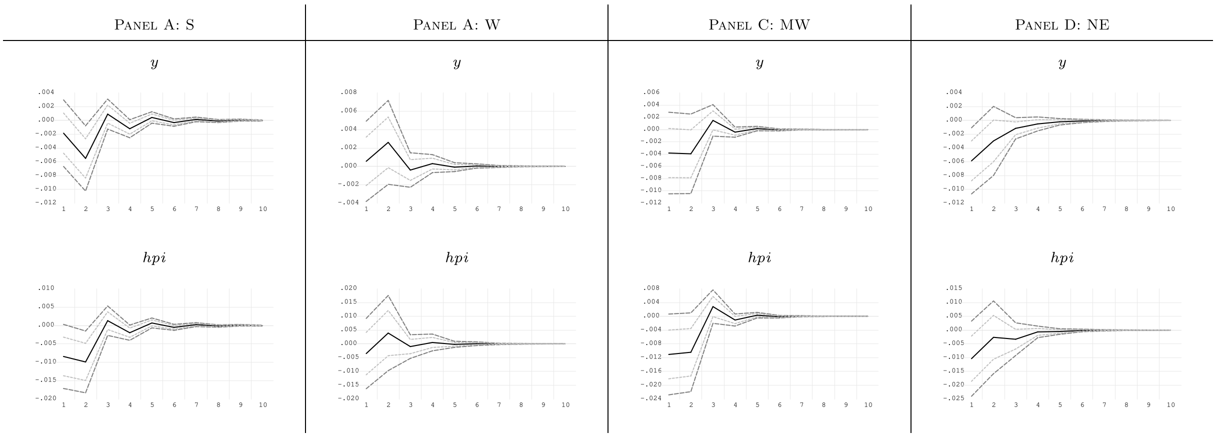

Fig. 4. Impulse-responses to a "tornado size index" shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a "tornado size index" (ti_{size}) shock in the South (Panel A), West (Panel B), Midwest (Panel C) and Northeast (Panel D) US regions. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands. Sample: 1963–2015..

variables are added to the original vector Ω_t^j: population density (pop), homeowner vacancy rate (hvr), and opportunity cost of capital (occ). The oil price (oil) is instead used as pure exogenous variable. The reduced-form VAR-X reads as follows

$$\Omega_t^j = C(L)X_t + \Pi(L)\Omega_t^j + \nu_t^j \quad \nu_t \sim N(0, \Xi), \tag{4}$$

where $C(L)$ and $\Pi(L)$ are matrix polynomials; $\Omega_t^j = [ti_t^j, pop_t^j, hvr_t^j, y_t^j, hpi_t^j, occ_t^j]'$ is the new 6×1 vector of endogenous variables (in this order); and X_t is the 1×1 vector of exogenous variables (i.e., oil price).[23] In the spirit of recent climate change studies, we assume tornado indexes to be orthogonal to the other stochastic elements in the econometric framework. Therefore, tornado indexes are

[23] The choice of including these variable in our VAR analysis is in line with the empirical literature aimed at capturing the economic drivers of house prices. Real GDP per capita is a proxy for economic activity and/or income (Englund & Ioannides, 1997). Population density is a variable capturing the demand pressure on house prices (Clark & Herrin, 2000; Song & Knaap, 2003). The opportunity cost of capital can be viewed both as a demand and a supply factor (Dröes & van de Minne, 2016). The vacancy rate is an indicator of supply–demand imbalances (Caplin & Leahy, 2011). Oil price is a variable proxying for construction and building costs (Breitenfellner, Cuaresma, & Mayer, 2015; Antonakakis, Gupta, & Mwamba, 2016). In addition, the oil price dynamics is to a large extent determined by international exogenous factors. For this reason, a large part of literature investigating the effects of oil price changes on US economy over the post World War II periods treats oil price as exogenous (see, for example, Hamilton, 1983; Lee, Ni, & Ratti, 1995; Bernanke, Gertler, Watson, Sims, & Friedman, 1997).

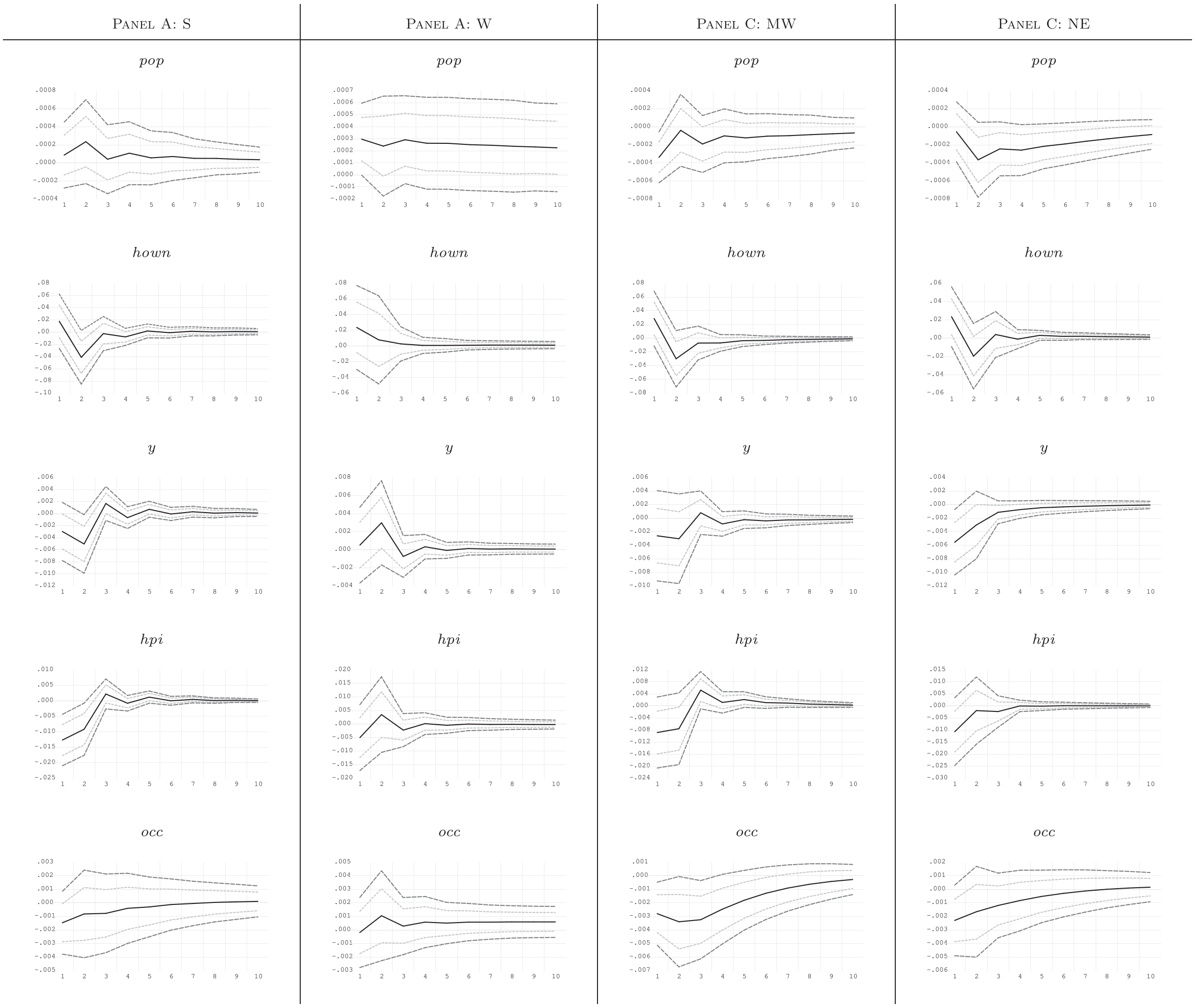

Fig. 5. Impulse-responses to a "tornado size index" shock. *Notes:* This figure depicts impulse responses of population density (*pop*), homeowner vacancy rate (*hown*), income per capita (*y*), house market prices (*hpi*) and opportunity cost of capital (*occ*) to a "tornado size index" (ti_{size}) shock in the South (Panel A), West (Panel B), Midwest (Panel C) and Northeast (Panel D) US regions. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands. Sample: 1963–2015. .

ordered first in a Cholesky-decomposition.[24] Both in the VAR and VAR-X, all variables are expressed as first-differences, except for the opportunity cost of capital, which is expressed in level.

Stock market returns: Panel analysis (Regional-Level). To test whether tornado size risk affects firms' returns, we run (for each region *j*) the following panel regression

$$ExR_{i,t}^{j} = c_i + \sum_{s=1}^{p} \rho_s ExR_{i,t-s}^{j} + \beta ti_t^{j} + \mathbb{X}_t^{j} + \varepsilon_{i,t}^{j}, \quad \forall\ i. \tag{5}$$

where firms' excess returns are regressed on their lagged values ($ExR_{i,t-s}^{j}$), firm-fixed effects, regional tornado size index (ti_t^{j}), and

[24] Note that this ordering is based on the assumption that *occ* responds instantly to innovations of other variables since inflation expectations and interest rates are quite sensitive to changes in economic system, whereas other variables (i.e., *pop*, *hvr*, *y*, and *hpi*) react with one lag to a shock in the opportunity cost. The lag-response of income, vacancy rate and population density to a shock in *occ* follows the assumption that these variables are traditionally viewed as "slow moving" variables and ordered before interest rate-based variables (such as *occ*) and asset-prices variables (such as *hpi*) (see, for example, Gilchrist & Zakrajšek, 2012; Walentin, 2014). Let us stress that generalized impulse responses lead to very similar implications. Results are available upon request.

other control variables ($\mathbb{X}_t^j$). As controls, we add the aggregate market excess return, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008) and a linear time trend.[25]

3.2.3. Results

VAR Results (House Prices). Fig. 4 depicts the estimated dynamic responses of income per capita and house prices to a shock to our newly developed tornado size index for the four US regions.[26] As recently documented, natural disaster shocks (e.g., hurricane strikes) might affect both the demand and the supply of real estate properties (see, for example, Murphy & Strobl, 2010). On the one hand, the destructive power of hurricanes (or other natural disasters) has a first order negative effect on housing supply due to a relative low number of available properties (i.e., excess demand). As a results, one observes a rise in properties' value. On the other hand, natural disasters undermine production by reducing income levels and thus the demand of durable goods (including houses), implying a drop in house prices. Of course, the net effect is a priori unknown. In our analysis, the demand effect seems to dominate the supply effect in those US regions more frequently affected by tornadoes (i.e., MW and S). In fact, impulse responses depicted in Fig. 4 suggest that in these regions tornado activity produces an adverse effect on income and house prices.[27] Our results are robust to (*i*) using the small sample bias adjustment bootstrap procedure suggested by Kilian (1998) (see Fig. D.2) and (*ii*) controlling for the 2008–2009 financial crisis (see Fig. D.3). Impulse responses estimated from the extended VAR-X are plotted in Fig. 5. The previously observed significant house price drop remains unaffected. This is particularly true for the S where the negative effect is amplified and tornado size shocks are found to account for 15.20% (14.61%) of the variations in house price levels at two (five) years horizon (see Table 4). According to our VAR-X investigations, a tornado size shock is also a significant driver of income in the S. In fact, it explains a non-negligible fraction of variations in income per capita (i.e., 6.51% at five years horizon). Actually, our results are in line with several empirical studies documenting a negative effect of natural disasters on property values (see Table A.2) and output (see Table A.1) in the southern US states.[28]

Broadly, our macro-analysis seems to corroborate the granular-based results presented in Section 4.1.3. Spillover effects are found to be important in the housing market and stronger in those regions that are most frequently affected by tornadoes because of the drop in housing demand (see Fig. B.1).

Panel Results (Stock Returns). We begin our panel analysis by estimating Eq. (5) separately for each region. Regression results are reported in Table 5 and indicate that tornadoes have a significant (at 10% level) positive effect only in the MW. This results may come as a surprise. However, it can be explained by the fact that investors are aware that firms are (on average) fully insured by natural disasters (including tornadoes). Moreover, it might be also the case that many of the firms with headquarter in the MW are large enough to develop their business in other US and non-US regions, and for this reason their profitability is marginally damaged by local tornadoes. It may also be the case that agents expect companies in the MW investing in new technologies aimed at mitigating the economic cost of tornadoes. This would lead to higher efficiency (i.e., profits). Note that by using the tornado intensity index and the tornado loss index as alternative tornado activity proxies one obtains very similar effects. (see Appendix E, Table E.1). It is worth noting that tornado intensity has a significant positive (negative) effect on stock returns in the MW (S).

Potentially, tornado-related effects may come as a good news for some sectors and as a bad news for other sectors. To capture whether tornado size effects are heterogeneous across sectoral returns, we estimate Eq. (5) for ten different sectors (see Table 6). To fully understand these results let us remark that our estimates here rely on annual regional data. As previously discussed, this allows us to capture spillover effects showing up over a longer horizon due to lacking information on the true damage induced by tornadoes. Therefore, at this frequency, slightly different implications for stock market returns can be observed.

As expected, there is evidence of significant heterogeneity in the sectoral effects of tornado activity. Cross-sectoral differences in tornadoes-induced effects could be explained by the different economic structure contributing to aggregate output in each region. For example, there is evidence of a strong positive significant effects on the technology sector in the W where innovation represents the main driver of firms' profitability. This result is in line with Leiter et al. (2009)'s findings. Actually, tornado risk in this region could trigger technological innovations such as early warning systems for natural disasters. In other words, firms are willing to further invest in technology for adaptation purposes. The NE focuses on finance and banking, which may explain why we observe the largest significant effects on the financial sector in this region. Noteworthy, the effect is positive suggesting that insurance and banking companies due to the intensification of tornadoes and thus the increasing demand of insurance contracts for protection against natural disasters boost their total turnover. Differently, in the S the effect on the financials sector is negative.[29]

[25] Note that we cannot include a full set of time dummies as the regional tornado index is a cross-section invariant regressor. In order to control for aggregate effects, we instead include the market excess return and GDP growth. Selected time dummies, as for the financial crisis in our case, can be included as well. Real GDP growth is computed from aggregate US real GDP retrieved from the Bureau of Economic Analysis.

[26] Our results are robust to using (*i*) variable in log-levels and (*ii*) different tornado indexes, namely tornado intensity and tornado loss. All these checks are documented in Appendix D.

[27] Our results are in line with Colacito et al. (2019) who observe that climate change – as measured by temperature shifts – have significant adverse effects mainly in the South of the US.

[28] Few exceptions are Murphy and Strobl (2010); Aqeel (2011); Liao and Panassié (2019) and Skidmore and Toya (2002); Berlemann and Wenzel (2018) who find instead positive effects of natural disasters on house prices and income in the Southern US.

[29] Note that this evidence is in line with the negative exposure of financial sector returns to tornado activity observed in our previous granular analysis (see Table 3). However, coefficients in the granular analysis are not statistically significant.

Table 4
Forecast Error Variance Decomposition.

S (*Shock*: ν_t^{ti})

Horizon	*pop*	*hown*	*y*	*hpi*	*occ*
1	0.29	0.83	1.95	**11.39**	2.05
2	1.37	4.65	6.41	**15.20**	1.30
5	1.00	4.47	6.51	**14.61**	0.89

MW (*Shock*: ν_t^{ti})

Horizon	*pop*	*hown*	*y*	*hpi*	*occ*
1	6.78	2.66	0.79	**2.86**	7.28
2	3.72	5.02	1.81	**4.69**	8.59
5	3.19	5.16	1.94	**5.59**	9.42

W (*Shock*: ν_t^{ti})

Horizon	*pop*	*hown*	*y*	*hpi*	*occ*
1	5.18	1.02	0.08	**0.89**	0.03
2	4.15	0.99	2.09	**0.96**	0.52
5	4.09	0.95	2.00	**0.97**	0.54

NE (*Shock*: ν_t^{ti})

Horizon	*pop*	*hown*	*y*	*hpi*	*occ*
1	0.14	2.67	6.64	**2.95**	3.93
2	3.71	3.43	7.36	**2.78**	3.44
5	4.89	3.39	7.36	**2.86**	2.67

Notes: Forecast error variance decomposition of macroeconomic variables and prices due to Tornado Size Index shocks in the US Regions. All figures refer to the point estimates of the VARX model defined in Eq. 4.

Healthcare effects are generally found to be negative across regions.[30] This could indicate that the healthcare system in the US may still not be sufficiently prepared for such disasters or simply underestimate the real impact of tornadoes. The positive effect on consumer services in the NE may reflect increasing precautionary purchases of consumers due to tornado risk, leading to increasing sales of food and drug retailers and other retailers. The negative sign for consumer goods and industrials instead may reflect adverse tornado effects on infrastructure used by producers. Finally, the utility sector in the MW being positively affected may be surprising as well. We suspect that this could reflect efforts to make utilities more resilient to natural disasters.

For the sake of robustness, we have replicated the sectoral analysis by using also the tornado intensity and loss indexes. The main sectoral tornadoes-induced effects reported in Table 6 remain unaltered (see Tables E.2 and E.3).

Table 5
Tornado Size and US Firm Excess Returns: System GMM Panel Estimates by Region.

1974–2017	NE	MW	S	W
Size	−0.009	0.005*	−0.001	0.03
	(0.006)	(0.003)	(0.001)	(0.035)
N	50970	34614	57552	48621

Notes: This table reports estimation results from Arellano-Bover/Blundell-Bond system GMM regressions for each region of firm excess return on its lags and the regional tornado index, controlling for the aggregate market rate, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008), and a linear time trend. For the lagged dependent variable, we choose a lag length of 3 to eliminate autocorrelation in the error term. We report only estimates for the tornado index using the two-step estimator available in STATA. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parentheses. For the other estimation options, we choose the default specifications from STATA. *N* denotes the number of observations. The sample is 1974–2017. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

[30] Evidence of a negative impact of tornadoes in the healthcare sector is observed also in the granular analysis (see Table 3).

Table 6
Tornado Size and US Firm Excess Returns: System GMM Panel Estimates by Region and Sector.

		NE	MW	S	W
BM	*Size*	0.005	0.001	0.013	0.213
		(0.021)	(0.011)	(0.305)	(0.225)
	N	2192	1942	2198	2772
CG	*Size*	−0.039**	0.006	−0.004	−0.073
		(0.016)	(0.007)	(0.003)	(0.122)
	N	4754	4880	5356	3773
CS	*Size*	0.066***	0.003	0.002	−0.05
		(0.021)	(0.010)	(0.003)	(0.104)
	N	5780	3720	6860	6313
FIN	*Size*	0.044***	0.027***	−0.005***	−0.137
		(0.010)	(0.005)	(0.001)	(0.084)
	N	12287	8477	13613	8779
HC	*Size*	−0.100***	0.001	−0.007***	−0.001
		(0.015)	(0.016)	(0.002)	(0.075)
	N	6727	2198	4416	6149
IND	*Size*	−0.043***	−0.002	−0.002	0.026
		(0.010)	(0.006)	(0.002)	(0.084)
	N	10657	8806	10307	8118
O&G	*Size*	−0.155	−0.012	0.002	0.003
		(1.920)	(0.240)	(0.002)	(0.198)
	N	703	472	7114	2106
TECH	*Size*	−0.135***	−0.038	0.001	0.274***
		(0.025)	(0.024)	(0.002)	(0.093)
	N	5375	2296	5393	9016
TEL	*Size*	−0.041	−0.031	−0.005	−0.497
		(0.392)	(0.094)	(0.021)	(1.385)
	N	716	344	847	585
UT	*Size*	0.088	0.033***	−0.001	0.083
		(0.146)	(0.009)	(0.007)	(0.296)
	N	1644	1382	1362	978

Notes: This table reports estimation results from Arellano-Bover/Blundell-Bond system GMM regressions for each region and by sector of firm excess return on its lags and the regional tornado index, controlling for the aggregate market rate, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008), and a linear time trend. For the lagged dependent variable, we choose a lag length of 3 to eliminate autocorrelation in the error term. We report only estimates for the tornado index using the two-step estimator available in STATA. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parentheses. For the other estimation options, we choose the default specifications from STATA. *N* denotes the number of observations. BM:= Basic Materials, CG:= Consumer Goods, CS:= Consumer Services, FIN:= Financials, HC:= Healthcare, IND:= Industrials, O&G:= Oil&Gas, TECH:= Technology, TEL:= Telecommunications, UT:= Utilities. The sample is 1974–2017. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

4. Concluding Remarks

In this paper, we have examined the implications of tornado activity for the dynamics of house prices and stock returns in the US. Geo-referenced data on tornadoes from the Storm Events Database of the National Oceanic and Atmospheric Administration (NOAA) and MSA-level data on house prices are first employed to perform a micro-level analysis. Tornado activity is observed to undermine real estate property values. Importantly, a tornado hitting a specific metropolitan area is found to have adverse effects on the housing market of the adjacent MSA, suggesting thus the presence of significant spillover effects. Our micro-analysis provides also evidence of tornadoes having a lagged negative effect on stock returns. However, only a couple of sectors seem to be responsible for this negative impact. A macro-analysis using aggregate annual data for the South, Midwest, Northeast and West US regions is also conducted. Here a regional tornado size index is constructed to capture tornado activity in each US region. VAR investigations show that a tornado size shock is responsible for a drop in house prices as well as in income in those regions most frequently affected by tornadoes (i.e., South and Midwest). Regional aggregate returns are instead weakly affected by tornadoes. We observe tornado activity to have a negative impact only on the financials and healthcare (consumer goods, industrials, healthcare, technology) sectors in the South (Northeast).

Our work represents a first attempt to examine the implications of tornadoes on real and financial assets. It is worth pointing out that there are several dimensions under which this work can be fruitfully extended. First, it would be interesting to examine whether the impacts of tornado activity in low- and middle-income countries on property values is stronger due to the presence of poorly integrated and developed financial markets. Second, our results could be potentially rationalized in a two-sector production economy with durable and non-durable goods embedding also tornado risk. These extensions are left for future research.

Appendix A. Related literature: a summary

Table A.1
Empirical studies on the effects of natural disasters on US economic variables.

Reference	Natural Disaster	Analysis	Area (Sample)	Economic Variable Effect (sign)
Skidmore and Toya (2002)	*C*	Cross-section	88 countries + US (1960 − −1990)$^{\pm}$	*hc* (−), *TFP* (+), *y* (+)
Ewing et al. (2003)	*T*	Time series	Texas (1980–2002)	*N* (−/+)$^{\mp}$
Sarmiento (2007)	*F*	Micro panel	US municipalities (1997–1999)	*N* (−)
Belasen and Polachek (2008)	*H*	Micro panel	Florida (1988–2005)	*N* (−), *W* (+)
Strobl (2011)	*H*	Macro panel	East & Southeast coast (1970–2005)	*y* (−)†
Hsiang and Jina (2014)	*H*	Macro panel	109 countries + US (1950–2008)	*y* (−)
Boustan et al. (2017)	*ND*	Micro panel	US counties (1930–2000)‡	*PR* (+)
Deryugina (2017)	*H*	Macro panel	US counties (1979–2002)	*N* (−), *TR* (+)
Berlemann and Wenzel (2018)	*H*	Macro panel	170 countries + US (1960–2006)	*y* (+)*

Notes: *H* = Hurricane; *F* = Flood; *W* = Wind; *T* = Tornado; *C* = Climate disaster index (floods, hurricanes, and tornadoes); *ND* = Natural Disaster (floods, storms, tornadoes, earthquakes, droughts, extreme temperatures and landslides). *hc* = Human capital investment; *TFP* = Total Factor Productivity; *y* = Per capita GDP; *N* = Employment; *W* = Employment income; *PR* = Poverty rate; *TR* = Government transfers received by individuals. $^{\pm}$ Data are expressed as average over the period 1960–1990. $^{\mp}$ Results depend on the industrial sector. † The effect is significant only in the short-run. ‡ The unit of analysis is county/decade. * The sign refers to developed countries.

Table A.2
Empirical studies on the effects of natural disasters on US house prices.

Reference	Climate Disaster	Analysis	Area (Sample)	House Price Effect (sign)
Speyrer and Ragas (1991)	*H*	Micro panel	Louisiana (1971–1986)	(−)
Rinehart and Pompe (1994)	*H*	Micro panel	South Carolina (1983–1990)	(−)
Bin and Polasky (2004)	*F*	Micro panel	North Carolina (1992–2002)	(−)
Hallstrom and Smith (2005)	*H*	Micro panel	Florida (1980–2000)	(−)
Bin and Kruse (2006)	*F*	Micro panel	North Carolina (2000–2004)	(−)
Ewing et al. (2007)	*W*, *H*, *T*	Time series	Texas (1981–2002)	(−)
			Tennessee (1979–2002)	(−)
			Oklahoma (1977–2002)	(−)
			Florida (1976–2002)	(−)
			North Carolina (1985–2002)	(−)
Graham et al. (2007)	*H*	Micro panel	North Carolina (1996–1999)	(−/+)$^{\pm}$
Bin et al. (2008)	*F*	Micro panel	North Carolina (2000–2004)	(−)
Beracha and Prati (2008)	*F*	Micro panel	US zip codes impacted by Hurricanes (2004–2005)	(−/+)$^{\mp}$
McKenzie and Levendis (2010)	*F*	Micro panel	Louisiana (2004–2006)	(−)
Murphy and Strobl (2010)	*H*	Macro panel	East & Southeast coast (1988–2005)	(+)
Aqeel (2011)	*H*	Micro panel	Selected Southern regions (2000–2008)	(+)
Saginor and Ge (2017)	*H*	Micro panel	North Carolina (1984–2007)	(−)
Boustan et al. (2017)	*ND*	Micro panel	US counties (1930–2000)†	(−)
Gibson et al. (2018)	*F*	Micro panel	New York (2003–2017)	(−)
Liao and Panassié (2019)	*H*	Micro panel	Florida (2000–2016)	(+)

Notes: *H* = Hurricane; *F* = Flood; *W* = Wind; *T* = Tornado; *ND* = Natural Disaster (floods, storms, tornadoes, earthquakes, droughts, extreme temperatures and landslides). † The unit of analysis is county/decade. $^{\pm}$ The effect of hurricane on house prices depends on its intensity and damages. $^{\mp}$ The authors find a drop in the short-run and a positive effect in the long-run.

Table A.3
Empirical studies on the effects of natural disasters on US financial markets.

Reference	Natural Disaster	Analysis	Area (Sample)	Financial Variable Effect (sign)
Wang and Kutan (2013)	H	Time series	US + Japan (1989–2011)	$h\,(+)$
Bourdeau-Brien and Kryzanowski (2017)	F, H, W	Time series$^{\pm}$	US states (1990–2014)	$Ret\,(+)^{\mp}$, $h\,(+)$
Lanfear et al. (2019)	H	Time series$^{\pm}$	US (1990–2017)	$Ret\,(-)$

Notes: H = Hurricane; F = Flood; W = Wind. Ret = Stock price returns; h = Conditional volatility of stock returns. $^{\pm}$ Event-study. $^{\mp}$ This result is valid for firms located in the disaster state.

Appendix B. PCA and spillover effects

In what follows we discuss (i) the methodology employed to capture potential spillover effects across MSA-level house prices and (ii) the result on the degree of interconnectedness between MSA-level house prices within states first and regions afterwards.

As indicated in Section 4.1.1, we use MSA data on house prices for the period 1975:M1-2019:M6. All house price real growth rates belonging to the same state are used to extract state-level principal components.[31] The first principal component is then used to capture (for each state) an average common trend across the different MSA house prices. The percentage of variance explained by the first principal component is reported in Table B.1. The state-level principal components are then employed to compute four regional house price spillover indexes. For each region, the spillover index is extracted using the procedure of Diebold and Yilmaz (2009, 2012). First, a VAR model with three lags is estimated.[32] Second, we use the generalized 5-step-ahead forecast error variance decomposition. Finally, the spillover index is built dynamically in a rolling-window fashion using a window of 120 months. Regional house price spillover indexes are plotted in Fig. B.1.

Table B.1
Percentage of variance explained by the 1st PC.

West	% explained by 1st PC	**Midwest**	% explained by 1st PC	**South**	% explained by 1st PC	**Northeast**	% explained by 1st PC
Alaska	0.983	Illinois	0.803	Alabama	0.867	Connecticut	0.887
Arizona	0.910	Indiana	0.799	Arkansas	0.776	Maine	0.908
California	0.881	Iowa	0.860	Delaware	0.851	Massachusetts	0.900
Colorado	0.851	Kansas	0.771	District of Columbia	NA	New Hampshire	0.927
Hawaii	0.967	Michigan	0.928	Florida	0.918	New Jersey	0.808
Idaho	0.826	Minnesota	0.736	Georgia	0.869	New York	0.833
Montana	0.930	Missouri	0.934	Kentucky	0.754	Pennsylvania	0.816
Nevada	0.949	Nebraska	0.852	Lousiana	0.888	Rhode Island	NA
New Mexico	0.900	North Dakota	0.935	Maryland	0.818	Vermont	NA
Oregon	0.900	Ohio	0.877	Mississippi	0.823	Average	
Utah	0.908	South Dakota	0.837	North Carolina	0.830		
Washington	0.833	Wisconsin	0.790	Oklahoma	0.810		
Wyoming	0.859			South Carolina	0.826		
				Tennessee	0.884		
				Texas	0.876		
				Virginia	0.864		
				West Virginia	0.689		
Average	0.900		0.844		0.834		0.868

Source: 'NA' indicates that the calculation of the 1st PC is not available. The States with the label 'NA' are composed only by one metropolitan area.

[31] For those states with only one MSA (like for the District of Columbia), we use the house price growth rate of the single metropolitan area.
[32] Bayesian Information Criterion (BIC) is used for choosing the optimal lag-length.

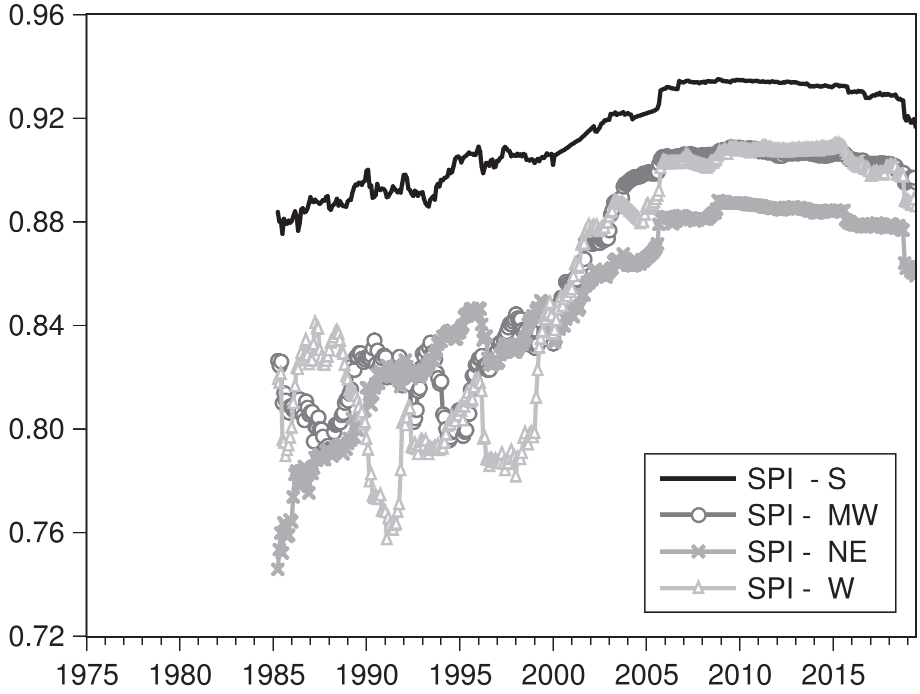

Fig. B.1. Dynamic Spillover Index (SPI) for US Regions, 1985m4-2019m6.

Appendix C. Macro data

C.1. US regional tornado indexes

In what follows we provide a more detailed description of the construction of the four US regional tornado indexes employed in our macro-analysis (Section 4.2). Data on tornadoes have been retrieved from the NOAA Storm Prediction Center (NOAASPC). NOAASPC Tornado database contains information about 616539 tornadoes in the US from 1950 to 2018. Each observation has a label indicating the State in which the calamity happened. Observations from Puerto Rico have been dropped. The following regional labels are subsequently created: South, West, Midwest, Northeast. The regional aggregation follows the states classification defined in Fig. C.1.

- **Tornado Size Index**: Tornado size measures the aggregate surface covered by tornadoes in a year. For every tornado in the NOAASPC, data on the length (in miles) and the diameter (in yards) are available. After converting diameter values in miles, the surface/size of a tornado is captured by multiplying diameter with length. The regional tornado size index is then expressed as follows:

$$TornadoSize_t^j = \sum_{i=1}^{I} \sum_{n=1}^{N} Size_{njt} \tag{6}$$

where $Size_{njt}$ measures the total surface covered by tornado n in State i of Region j in year t.

- **Tornado Intensity Index**: Tornado Intensity Index accounts for the aggregate magnitude of tornadoes of a Region in a year. For every tornado in the database, the magnitude is expressed with a value ranging from 0 to 5.

$$TornadoIntensity_t^j = \sum_{i=1}^{I} \sum_{n=1}^{N} Magnitude_{nit} \tag{7}$$

where $Magnitude_{nit}$ is the magnitude of tornado n in State i of Region j in year t.

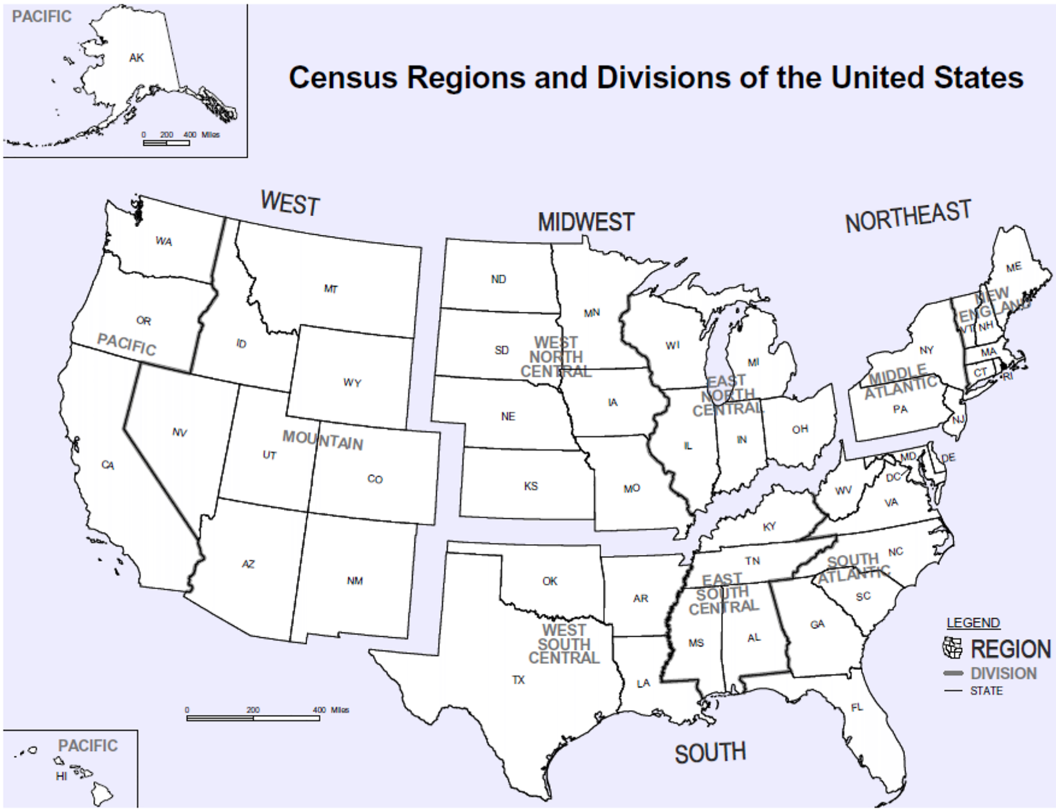

Fig. C.1. US Regions (by CENSUS).

Note that a value of -9 indicates a missing value. We fixed this issue by replacing the -9 with the average regional tornado magnitude. Only 105 of 616539 tornadoes (less than 0.01%) in the database have a missing magnitude.

- **Tornado Loss Index**: Tornado Loss estimates the total damage tornadoes caused to properties in a year. This variable is computed by adding all Tornado Losses in a given year in the NOAASPC. Prior to 1996, Property Loss is expressed on an ordinal scale with values ranging from 1 to 9. A value of 0 is assigned to missing data. From 1996, the damage to properties is measured either in US dollars or in US million dollars. In these periods, the fraction of missing data is unbalanced, as in the second period it drastically increases. This happens probably due to the more precise estimations required in the second period, that makes easier to collect missing values. We solved this discrepancies in two steps. First, we converted all the available data in the ordered 1–9 scale. Then, for eachrRegion, the mean of the tornado loss was assigned to missing data. 24668 of 616539 tornadoes (about 4.00%) in the database have a missing Loss. The tornado loss index is then computed as follows:

$$TornadoLoss_t^j = \sum_{i=1}^{I} \sum_{n=1}^{N} Loss_{nit} \tag{8}$$

where $Loss_{nit}$ measures the damage (in a 1–9 scale) of tornado n in State i belonging to Region j in year t.

Appendix D. Robustness Test: VAR analysis

D.1. Level

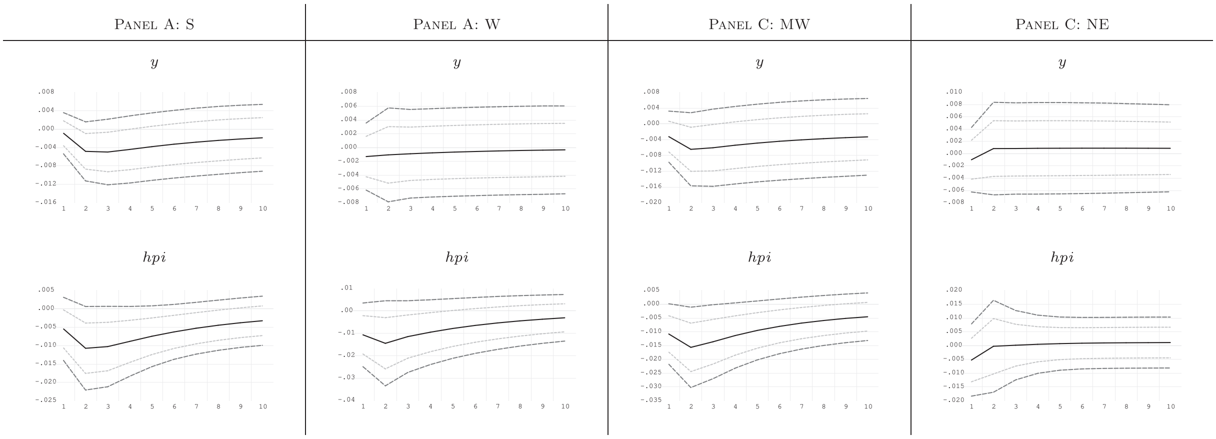

Fig. D.1. Impulse-responses to a "tornado size index" shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a "tornado size index" (ti_{size}) shock in the South (Panel A), West (Panel B), Mid-West (Panel C) and North-East (Panel D) US regions. All variables are expressed in log-levels. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands. Sample: 1963–2015..

D.2. Kilian (1998)'s Bootstraped adjustment

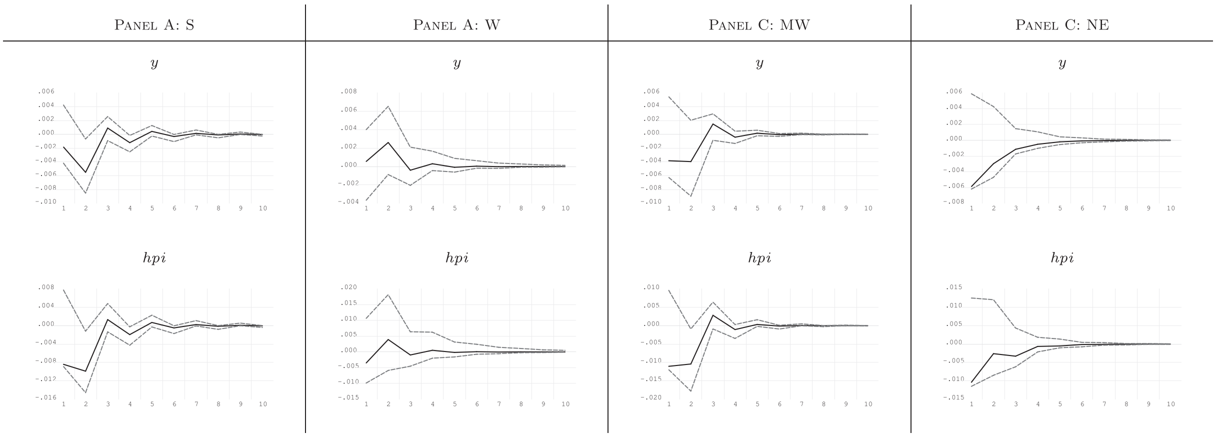

Fig. D.2. Impulse-responses to a "tornado size index" shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a "tornado size index" (ti_{size}) shock in the South (Panel A), West (Panel B), Mid-West (Panel C) and North-East (Panel D) US regions. All variables are expressed in log-levels. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands obtained using Kilian (1998)'s bootstrap procedure adjustment for small sample. Sample: 1963–2015..

D.3. Financial crisis

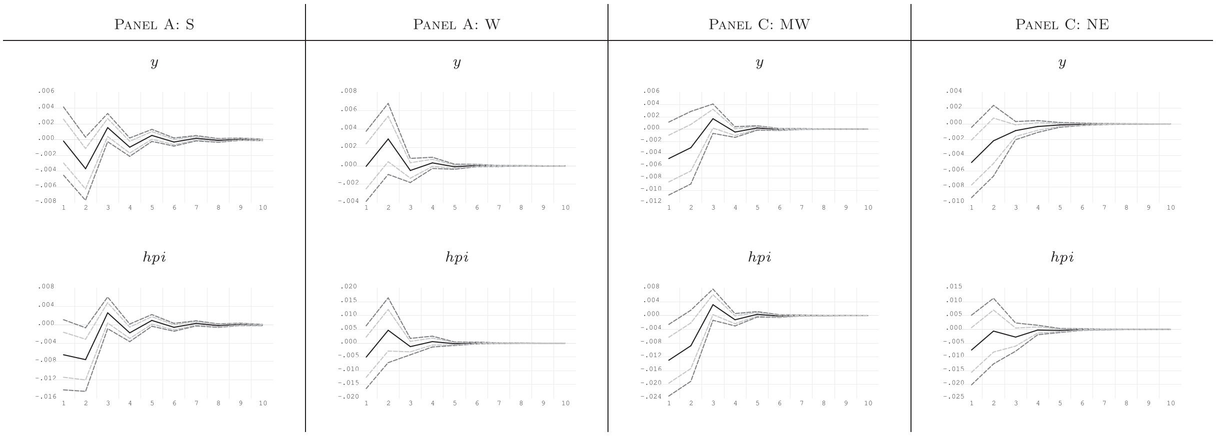

Fig. D.3. Impulse-responses to a “tornado size index” shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a “tornado size index” (ti_{size}) shock in the South (Panel A), West (Panel B), Mid-West (Panel C) and North-East (Panel D) US regions. All variables are expressed in log-levels. VAR estimations include a constant and a dummy variable for 2008–2009 financial crisis. Horizontal axis units represent years after the shock. Solid “black” lines: IRFs. Dashed “dark grey” line: 90% confidence bands. Dashed “light grey” line: 68% confidence bands. Sample: 1963–2015..

D.4. Different tornado indexes

Tornado Intensity

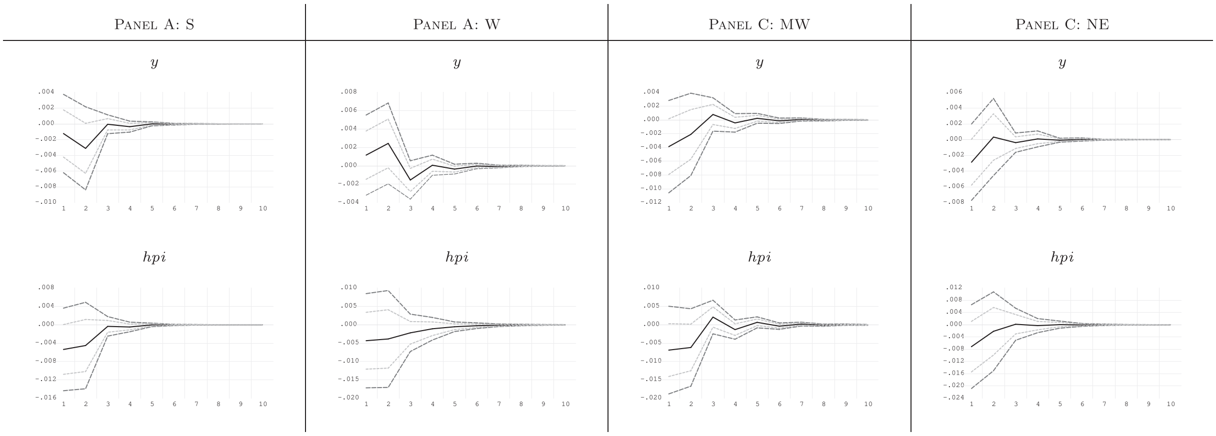

Fig. D.4. Impulse-responses to a “tornado intensity index” shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a “tornado intensity index” (ti_{int}) shock in the South (Panel A), West (Panel B), Mid-West (Panel C) and North-East (Panel D) US regions. All variables are expressed as percentage deviations from their steady state. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid “black” lines: IRFs. Dashed “dark grey” line: 90% confidence bands. Dashed “light grey” line: 68% confidence bands. Sample: 1963–2015..

Tornado Loss

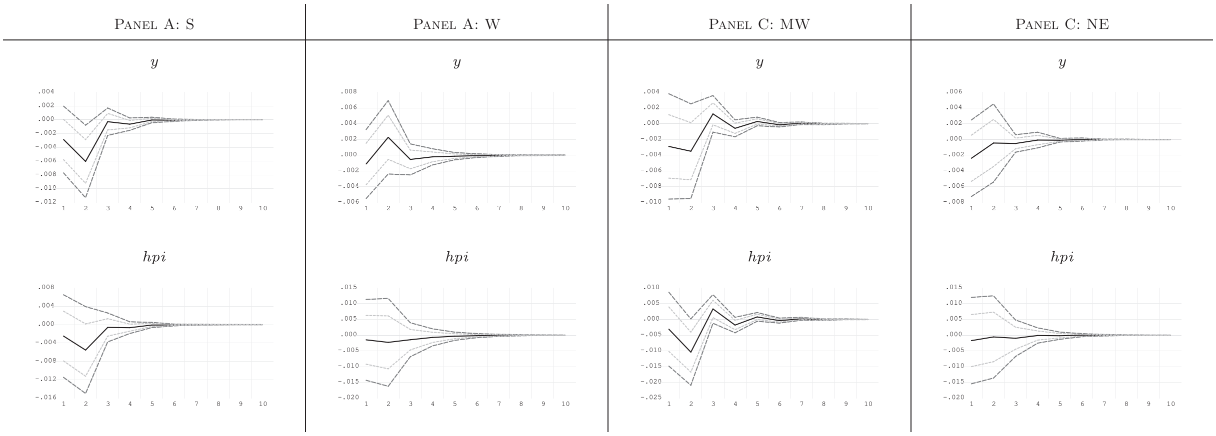

Fig. D.5. Impulse-responses to a "tornado loss index" shock. *Notes:* This figure depicts impulse responses of income per capita (y) and house market prices (hpi) to a "tornado loss index" (ti_{loss}) shock in the South (Panel A), West (Panel B), Mid-West (Panel C) and North-East (Panel D) US regions. All variables are expressed as percentage deviations from their steady state. VAR estimations include a constant. Horizontal axis units represent years after the shock. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands. Sample: 1963–2015..

Appendix E. Robustness test: panel analysis

Table E.1
Tornadoes Intensity, Tornadoes Loss and US Firm Excess Returns: System GMM Panel Estimates by Region (1974–2017)

Tornado Index	NE	MW	S	W
Intensity	0.021	0.010***	−0.009***	−0.192***
	(0.014)	(0.004)	(0.002)	(0.028)
N	50970	34614	57552	48621
Loss	0.006	0.001	−0.001	0.007
	(0.006)	(0.001)	(0.001)	(0.006)
N	50970	34614	57552	48621

Notes: This table reports estimation results from Arellano-Bover/Blundell-Bond system GMM regressions for each region of firm excess return on its lags and the respective regional tornado index, controlling for the aggregate market rate, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008), and a linear time trend. For the lagged dependent variable, we choose a lag length of 3 to eliminate autocorrelation in the error term. We report only estimates for the respective tornado index (i.e., Intensity and Loss) using the two-step estimator available in STATA. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parentheses. For the other estimation options, we choose the default specifications from STATA. *N* denotes the number of observations. The sample is 1974–2017. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table E.2
Tornado Intensity and US Firm Excess Returns: System GMM Panel Estimates by Region and Sector.

		NE	MW	S	W
BM	*Intensity*	0.096*	0.051***	0.033	−0.322***
		(0.054)	(0.015)	(0.402)	(0.120)
	N	2192	1942	2198	2772
CG	*Intensity*	0.001	0.007	−0.022**	−0.204**
		(0.036)	(0.010)	(0.009)	(0.102)
	N	4754	4880	5356	3773
CS	*Intensity*	0.187***	−0.004	−0.006	−0.101
		(0.053)	(0.011)	(0.009)	(0.079)
	N	5780	3720	6860	6313
FIN	*Intensity*	0.132***	0.013	−0.021***	−0.230***
		(0.024)	(0.008)	(0.005)	(0.064)
	N	12287	8477	13613	8779
HC	*Intensity*	−0.207***	0.018	−0.026***	−0.267***
		(0.034)	(0.020)	(0.010)	(0.091)
	N	6727	2198	4416	6149
IND	*Intensity*	−0.016	0.009	−0.006	−0.201***
		(0.025)	(0.008)	(0.006)	(0.058)
	N	10657	8806	10307	8118
O&G	*Intensity*	−0.063	−0.007	−0.003	−0.51
		(5.469)	(0.478)	(0.008)	(2.569)
	N	703	472	7114	2106
TECH	*Intensity*	−0.214***	0.013	0	−0.234***
		(0.060)	(0.022)	(0.009)	(0.079)
	N	5375	2296	5393	9016
TEL	*Intensity*	−0.101	−0.043	−0.011	−0.408
		(0.286)	(0.763)	(0.051)	(0.936)
	N	716	344	847	585
UT	*Intensity*	0.145	0.048*	−0.006	0.175
		(0.620)	(0.025)	(0.012)	(0.123)
	N	1644	1382	1362	978

Notes: This table reports estimation results from Arellano-Bover/Blundell-Bond system GMM regressions for each region and by sector of firm excess return on its lags and the regional tornado index, controlling for the aggregate market rate, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008), and a linear time trend. For the lagged dependent variable, we choose a lag length of 3 to eliminate autocorrelation in the error term. We report only estimates for the tornado index using the twostep estimator available in STATA. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parentheses. For the other estimation options, we choose the default specifications from STATA. *N* denotes the number of observations. BM:= Basic Materials, CG:= Consumer Goods, CS:= Consumer Services, FIN:= Financials, HC:= Healthcare, IND:= Industrials, O&G:= Oil&Gas, TECH:= Technology, TEL:= Telecommunications, UT:= Utilities. The sample is 1974–2017. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table E.3
Tornado Loss and US Firm Excess Returns: System GMM Panel Estimates by Region and Sector.

		NE	MW	S	W
BM	*Loss*	0.038**	0.017***	0.013	−0.002
		(0.017)	(0.004)	(0.163)	(0.024)
	N	2192	1942	2198	2772
CG	*Loss*	0.025	0.001	−0.001	−0.014
		(0.016)	(0.003)	(0.002)	(0.019)
	N	4754	4880	5356	3773
CS	*Loss*	0.021	−0.005	0	0.016
		(0.018)	(0.003)	(0.002)	(0.016)
	N	5780	3720	6860	6313
FIN	*Loss*	0.040***	0.005***	−0.004***	−0.038***
		(0.012)	(0.002)	(0.001)	(0.014)
	N	12287	8477	13613	8779
HC	*Loss*	−0.081***	0.002	−0.001	0.031*
		(0.014)	(0.006)	(0.005)	(0.017)
	N	6727	2198	4416	6149
IND	*Loss*	−0.015	0	0.001	0.014
		(0.012)	(0.003)	(0.002)	(0.014)
	N	10657	8806	10307	8118
O&G	*Loss*	−0.033	0.001	−0.006**	0.044
		(0.406)	(0.113)	(0.003)	(0.031)
	N	703	472	7114	2106
TECH	*Loss*	−0.058**	0.004	0.007**	0.008
		(0.027)	(0.006)	(0.003)	(0.018)
	N	5375	2296	5393	9016
TEL	*Loss*	−0.023	0.002	0.008	0.007
		(0.522)	(0.101)	(0.016)	(0.211)
	N	716	344	847	585
UT	*Loss*	0.026	0.009	−0.003	−0.026
		(0.064)	(0.015)	(0.003)	(0.063)
	N	1644	1382	1362	978

Notes: This table reports estimation results from Arellano-Bover/Blundell-Bond system GMM regressions for each region and by sector of firm excess return on its lags and the regional tornado index, controlling for the aggregate market rate, real GDP growth, two year dummies capturing the effects from the global financial crisis (2007 and 2008), and a linear time trend. For the lagged dependent variable, we choose a lag length of 3 to eliminate autocorrelation in the error term. We report only estimates for the tornado index using the twostep estimator available in STATA. Robust standard errors are computed by clustering standard errors at the firm level and are reported in parentheses. For the other estimation options, we choose the default specifications from STATA. *N* denotes the number of observations. BM:= Basic Materials, CG:= Consumer Goods, CS:= Consumer Services, FIN:= Financials, HC:= Healthcare, IND:= Industrials, O&G:= Oil&Gas, TECH:= Technology, TEL:= Telecommunications, UT:= Utilities. The sample is 1974–2017. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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