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Extreme weather and corporate fixed asset policies: leasing as alternative finance

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Abstract

This paper investigates how weather-affected firms make decisions on fixed asset purchases and financing choices for fixed asset acquisition. Utilizing a unique dataset comprising over 26,000 firms across 40 countries, we find that weather-affected firms are more prone to purchase fixed assets, increasing investments in machinery, equipment, and real estate. These purchases are primarily financed through equity, bank loans, and government grants. Particularly, we find leasing is a vital fallback financing source for firms experiencing losses due to extreme weather. Firms that exclusively rely on leasing rather than other financial sources are more likely the ones that face significant external financing barriers, including complex loan procedures, high collateral requirements, and increased loan rejection rates. Interestingly, weather-affected firms who have successfully obtained non-leasing finance for fixed asset purchases, have a higher tendency to also engage in leasing, underscoring that such firms adopt flexible strategies for fixed asset acquisition.

Keywords: extreme weather; firm-level climate losses; fixed assets; financing decisions; leasing; financial obstacles

JEL Classification: E44; F33; G15; L72; Q31

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1. Introduction

Natural hazards have become more frequent and intense,[1] affecting the globe significantly, with developing countries suffering 90% of the impacts.[2] These warning effects of extreme weather have touched all walks of life, including individuals, businesses, and governments. Natural disasters have damaged public infrastructure, residential properties, and business factories (Hallegatte et al., 2019). Despite these adverse impacts, there is a lack of understanding in literature regarding how extreme weather influences firm fixed asset decisions.

The first research gap refers to decisions on fixed asset acquisition, which is one of the most crucial asset management strategies for firms to carry on their business (Mitchell et al., 2002; Mitchell and Carlson, 2001), especially under extreme weather. There is little empirical evidence on whether disaster-affected firms purchase fixed assets after they experience losses. Furthermore, literature has not explored the specific types of fixed assets that firms prioritize in the aftermath of disasters. Such firms may adjust spending based on the types of assets involved, such as machinery, vehicles, land, plants, and buildings. Existing studies primarily focus on overall investments, by which total investments in capital expenditures (i.e., properties and plants) are often used as a proxy (Correa *et al.*, 2023). This approach overlooks the nuanced impacts of natural disasters on various types of fixed assets. The lack of detailed exploration may be attributed to the difficulty in gathering granular data on firms' diverse fixed asset types under the impact of extreme weather. Significantly, there appears to be scarce study on whether firms acquire fixed assets in the wake of weather-related losses especially in less developed countries, where disaster-related losses account for 90%.[3]

The second research gap is related to financial sources that disaster-affected firms use for fixed asset acquisition. In response to the heightened operating costs, insolvency issues, and liquidity risks faced by these firms, banks often become more cautious, reducing lending or imposing stricter terms such as higher interest rates and increased collateral requirements (Huang et al., 2022; Huynh et al., 2020; Javadi and Al Masum, 2021). Therefore, these firms struggle to access traditional finance (e.g., bank loans) (Baltas et al., 2022). Nonetheless, the literature

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[1] Global natural disasters reported by type between 1970 and 2023 (https://ourworldindata.org/grapher/natural-disasters-by-type) and Centre for Research on the Epidemiology of Disasters (https://emdat.be/) provide the number of reported natural disasters from 1990 to 2023.

[2] A World Meteorological Organization (WMO) report highlights that from 1970 to 2021, around 12,000 disasters occurred, resulting in over 2 million fatalities and US$4.3 trillion in economic losses (https://public.wmo.int/en/resources/atlas-of-mortality).

[3] Also, this oversight is critical as Small and Medium Enterprises (SMEs) account for over 50% of employment, 40% of GDP in developing countries (https://www.worldbank.org/en/topic/smefinance), and The 2016 World Trade Report examines the participation of SMEs (https://www.wto.org/english/res_e/publications_e/wtr16_e.htm).

lacks investigation on these alternative financial sources in the context of fixed asset acquisition for weather-affected firms. This gap is particularly crucial given that financial access barriers are more pronounced for small- and medium-sized enterprises (SMEs) compared to larger firms (Beck and Demirguc-Kunt, 2006; Hanedar et al., 2014). Understanding the financial strategies of firms of all sizes in the aftermath of natural disasters is essential for formulating supportive policies that can aid these firms in their resilience-building efforts.

Another gap involves an underexplored role of leasing as an alternative strategy for fixed asset acquisition, especially under extreme weather conditions. While leasing is recognized as a key external financing source (Cook et al., 2021; Devos and Rahman, 2014; Sharpe and Nguyen, 1995), its use in disaster scenarios remains under-researched. Only recently Wang (2023) examines leasing in the context of natural disasters, but does not study the interrelation between leasing and purchasing fixed assets. As leasing decisions are not made in isolation from purchasing choices (Johnson and Lewellen, 1972; Ofer, 1976), in many cases firms may adopt a flexible approach, combining both strategies. This interrelation between leasing and purchasing is crucial to understand, as it provides a more comprehensive view of how firms adapt their asset management strategies in response to natural disasters. Wang (2023) studies only U.S. listed firms and explores only the collateral channel as a main reason for firms opting to lease fixed assets. It overlooks other potential barriers that firms face in accessing external finance in less developed countries, where financial markets are not well-regulated.

We explore the following research questions to address the above literature gaps: i) the likelihood of disaster-affected firms purchasing fixed assets; and the types of fixed assets invested (i.e., machinery or real estate); ii) the financial sources used, from internal funds to external sources; iii) the likelihood of these firms to lease assets. To further examine the interrelation between leasing and purchasing, we look at two distinct groups: i) those that have secured non-leasing finance (e.g., bank loans, supplier trade credit and government grants) and have indeed purchased fixed assets, and ii) those that are unable to raise any non-leasing finance to purchase fixed assets (so-called *completely leasing*).

To address the above research questions, we use a large data set provided by the sixth BEEPS (Business Environment and Enterprise Performance Survey), a joint initiative of the European Bank for Reconstruction and Development (EBRD) and the World Bank. This dataset covers more than 26,000 enterprises (both large firms and SMEs) in 40 countries (mostly in developing economies) between 2018 and 2020. This data set includes information about firm-level weather-related losses, fixed asset purchases, purchases of fixed asset types, leasing, and financial sources.[4]

We find that weather-affected firms opt to increase fixed asset investments, specifically in machinery, equipment, and real estate. They primarily finance these purchases through equity, bank loans, trade credit, and government grants, rather than internal or informal sources. Additionally, these firms tend to lease assets, especially if they cannot secure non-leasing finance for their fixed asset purchases (e.g., bank loans, trade credit and government grants). Interestingly, even among firms that have successfully obtained non-leasing finance to proceed to purchase fixed assets also show a higher tendency to lease, indicating that a flexible approach to asset management after disasters is employed by disaster-affected firms. Our results are robust through a coefficient stability test (Oster, 2019), a propensity score matching, and a 2SLS (two-stage least squares estimation with an instrument variable).

We further investigate mechanisms by which disaster-affected firms opt for leasing rather than non-leasing finance for asset purchases. We find that these firms lean towards leasing mainly due to obstacles in accessing finance (i.e., bank loan rejections, higher collateral demands, and complex loan procedures. This finding suggests that the firms are not always able to access credit from traditional finance such as banks as they pose considerable hurdles for these firms in the post-disaster events.

Our study makes several contributions. First, we join the growing literature on the impact of weather/climate change on firm strategies. Prior research has focused on how firms affected by adverse weather adapt R&D (research and development) investment strategies (Blanford, 2009; Le *et al.*, 2023), manage cash (Huynh et al., 2020; Javadi et al., 2020), carbon performance (Orazalin et al., 2023), CEO compensation design (Hossain et al., 2023), and engage in corporate social responsibility activities (Ozkan et al., 2022). We extend this literature by delving into how weather-affected firms make decisions on fixed assets, particularly in terms of acquisition and the types of assets procured. Second, our study adds new insights into the selection of financial sources for the fixed assets amidst weather-related losses. We find that disaster-affected firms seek alternative financial sources, including equity, bank loans, government grants, and supplier trade credit. Notably, our findings highlight the vital role of leasing as a strategic financial tool for these firms, enabling them to acquire necessary fixed assets to sustain and advance their business operations in the face of climatic adversities. Moreover, literature on firm leasing deserves more empirical study (Chu, 2020;

[4] We provide justifications for why we use the sixth BEEPS, and data sample in Section 3.1.

Eisfeldt and Rampini, 2009). To our best knowledge, only the work of Wang (2023) studies natural disasters and firm leasing. However, Wang (2023) does not examine the interrelation between leasing and purchasing fixed assets. Our results suggest that weather-impacted firms do not necessarily tradeoff between leasing and purchasing, they can instead adopt flexible strategies for both. Unlike Wang (2023) who finds only one channel (i.e., collateral) that drives leasing decisions, we document various mechanisms that induce disaster-affected firms to lease fixed assets such as discouragement from credit application (i.e., complex application procedures, high collateral requirements and higher rejection). Finally, our study provides insights on the impact of extreme weather on firm fixed asset policies with international evidence, specifically for firms in less developed countries.

The remainder of our study is structured as follows. We discuss relevant literature and develop hypotheses in Section 2. Section 3 illustrates our methodology and data sample. We present, interpret, and discuss our results in Section 4. Section 5 concludes and discusses the implications of our research.

2. Literature review and hypothesis development

Natural disasters wreak havoc on infrastructure, real estate, and industrial assets, including facilities, machines, and factories (Hallegatte et al., 2019). The aftermath often involves significant operational disruptions, production halts, and supply chain breakdowns, leading to a marked decrease in production flexibility (Reinartz and Schmid, 2016). In the face of such devastation, disaster-affected firms are compelled to either restore their destroyed physical assets or re-equip their production chains to continue business operations. However, empirical research on how firms manage their fixed assets in the context of extreme weather is limited. Correa et al. (2023) suggest that firms are generally less inclined to increase overall capital expenditures (on properties and plants), following such events. Using only the overall capital expenditures overlooks the strategies of different asset types that firms acquire. Our paper thus extends this strand of research to understand whether disaster-affected firms increase fixed assets and what types of assets they purchase.

Drawing from Competitive Advantage theory (Porter, 1992; Porter and Kramer, 1985), which advocates for the continual maintenance, improvement, and innovation of fixed assets to foster competitive advantages, our study situates itself within the realm of fixed asset management. The existing literature, particularly from the resource-based and physical-resource-based perspectives, suggests that during crises, such as the 2008/2009 financial crisis or the Covid-19 pandemic, firms often adopt retrenchment strategies (Morrow Jr et al., 2004) by discarding less productive assets (Lim et al., 2013; Morrow Jr et al., 2004) or seizing the opportunity to acquire additional assets when adequately funded (Lim et al., 2020). In line with the Competitive Advantage theory, we posit that disaster-affected firms must actively work to recover from the damage by restoring physical assets. This restoration is not just about resuming business operations, but it is also about maintaining competitiveness with firms unaffected by natural disasters. Furthermore, in line with the resource-based perspective, we suggest that these firms might also replace damaged physical assets with new ones, contingent upon having sufficient financial resources.

Another theoretical angle is the Real Options theory (Myers, 1977), which provides a framework for valuing the flexibility inherent in investment opportunities, particularly in an uncertain environment. Firms under high uncertainty consider investment opportunities as financial options, by which firms can delay, expand, modify, or abandon investments. Therefore, “opportunities to purchase real assets” are viewed as real options. Firms consider “purchasing real assets” based on a variety of scenarios, ranging from adjustment costs and market power to different inefficiencies present in product or resource markets (Trigeorgis and Reuer, 2017). Chakrabarti (2015) highlights that firms reconfiguring assets in crisis situations, such as financial downturns, encounter increased risks. Applied to extreme weather scenarios, this suggests that disaster-affected firms might postpone or forego fixed asset investments due to heightened uncertainties. We argue that making a strategic decision to acquire “real assets” remains a crucial move for firms aiming to uphold their competitive advantage and sustain business operations in challenging times. Owing to the distinctive nature of our dataset, we are able to scrutinize firms' strategic choices by examining the specific monetary amounts they allocate for acquiring various categories of fixed assets. Based on these above arguments, we develop our first three hypotheses as follows.

H1a: Disaster-affected firms (as compared to non-disaster-affected firms) are more likely to purchase fixed assets.

H1b: Disaster-affected firms (as compared to non-disaster-affected firms) are more likely to purchase machinery, vehicles, and equipment.

H1c: Disaster-affected firms (as compared to non-disaster-affected firms) are more likely to purchase real estate such as land and buildings.

Extreme weather puts firms under difficult situations such as slower sales growth (Barrot and Sauvagnat, 2016), lower earnings (Addoum et al., 2020; Hugon and Law, 2019) and more volatile cash flows (Huang et al., 2018). Weather-affected firms encounter greater costs of capital (Ginglinger and Moreau, 2023; Huynh et al., 2020), and reduce overall leverage and short-term debt (Ginglinger and Moreau, 2023; Huang et al., 2018). Baltas *et al.* (2022) highlight how such firms adapt to limited access to traditional finance such as bank loans, often turning to alternatives such as private equity, crowdfunding, and venture capital. These sources are typically used for general operational needs. Our study extends this research by examining both internal (retained earnings) and external financial sources (equity, bank and non-bank loans, trade credit, government grants, and informal sources). This approach aims to clarify whether these firms utilize such alternative financial sources specifically for purchasing fixed assets post-disaster.

Applying the pecking order theory (Myers and Majluf, 1984) in the context of climate change risks, we posit that disaster-affected firms may find it more difficult to raise external funds. External sources are often perceived as costlier, making them a less preferred option. Furthermore, the static trade-off theory (Fischer et al., 1989; Flannery and Rangan, 2006) suggests that firms restructure their capital based on anticipated distress costs. These costs could be exacerbated for firms suffering from climate-related losses, affecting their financial strategies and decisions regarding capital structure adjustments. Conversely, Trigeorgis and Reuer (2017) employ the "*real options theory*" to argue that firms should integrate greater flexibility into their strategic utilization of external resources. While this strategy proves effective under normal circumstances, the advent of climate change shocks could diminish a firm's strength and current standing, potentially hindering its ability to leverage external sources, including bank loans, credit applications, and more. Based on these above arguments, our next hypothesis is as follows.

H2. Disaster-affected firms (as compared to non-disaster-affected firms) are more likely to raise more internal funds, rather than external funds to purchase fixed assets.

Acquiring fixed assets can be in various forms, including purchasing and leasing them (Johnson and Lewellen, 1972; Ofer, 1976). Under a leasing contract, the lessee pledges the leased assets to the lessor, and the leased assets are considered as collateral. The lessee can use the leased assets without committing any additional collateral, making leasing financing possibly more attractive for financially constrained firms. According to a collateralization pecking order perspective (Rampini and Viswanathan, 2013), the most financially constrained firms often lease assets, while less financially constrained firms tend to raise secured/unsecured debt. As disaster-affected firms face both issues of collateral (i.e., due to damage of properties) and financial distress (Huynh et al., 2020), we argue that they tend to make more leasing decisions.

Drawing from Real Options theory, we propose a nuanced interrelation between leasing and purchasing fixed assets in the context of extreme weather. This perspective suggests that disaster-affected firms might delay asset investments, opting to lease as a flexible interim solution. This approach contributes to existing literature on asset acquisition decisions (Johnson and Lewellen, 1972; Ofer, 1976) by focusing specifically on extreme weather scenarios. Additionally, incorporating the Risk Premium perspective (Li and Tsou, 2019), financially constrained firms might balance their purchase-versus-lease decisions based on the risk premium between leased and purchased capital. Therefore, in such contexts, firms may not strictly choose one over the other but could consider a combination of both purchasing and leasing as part of their strategic response to disaster challenges. Based on these above arguments, we develop our last hypotheses as follows.

H3a: Disaster-affected firms (as compared to non-disaster-affected firms) are more likely to lease fixed assets.

H3b: Disaster-affected firms who could not raise any financial sources for their fixed assets purchases (i.e., non-leasing sources such as bank loans) tend to lease fixed assets.

H3c: By contrast, disaster-affected firms who have secured non-leasing financial sources to purchase fixed assets (i.e., non-leasing sources such as bank loans) tend to lease fixed assets.

3. Data and Methodology

3.1. Data sample

Our study uses a large cross-sectional data set from BEEPS (Business Environment and Enterprise Performance Survey) – a joint initiative of the European Bank for Reconstruction and Development (EBRD) and the World Bank. There are different rounds of BEEPS, including the surveys in 1999–2000, 2002, 2005, 2008–2009, 2011–2016 and 2018–2020).[5]

We use the sixth round of BEEPS that is the most recent version and covers almost 28,000 enterprises (both large firms and SMEs) in 41 countries between 2018 and 2020.

[5] The EBRD-EIB-WB Enterprise Surveys 2018-2020 (Accessed at https://www.beeps-ebrd.com/wp-content/uploads/2020/04/beeps_vi_es_r_oct20.pdf).

Importantly, only in the sixth round, BEEPS includes a green economy module which contains various questions regarding firm green management practices, and weather-related information. Therefore, we obtain almost all information of firm-level fixed asset decisions, financial sources, employment, imports, exports, ownership, and weather-related losses from BEEPS VI.

We collect data of currency exchange rates from the World Bank Indicators to convert the local-currency monetary amounts of fixed asset purchases to U.S. dollars to ensure the consistencies of all estimations. Furthermore, we also control the GDP (Gross Domestic Product) per capita as the control variable for country heterogeneity. In the robustness tests, data for our instrument variable is about forest coverage (country forest area scaled by population density) are also collected from the World Bank Indicators. In the data merging process among the data sources, we lose observations for West Bank and Gaza due to missing data of currency exchange rates. Our final sample includes 26,898 observations in 40 countries between 2018 and 2020.[6]

3.2. Variables

3.2.1. Dependent variables

Regarding firm fixed asset decisions, our first variable is tangible assets based on the following BEEPS question: "In fiscal year, did this establishment purchase any new or used fixed assets, such as machinery, vehicles, equipment, land or buildings, including expansion and renovations of existing structures?". The tangible assets are a dummy variable that equals one if the answer is "Yes," and zero if the answer is "No."

Our continuous dependent variables for fixed asset purchases are based on the question: "In fiscal year, how much did this establishment spend on purchases of: i) new or used machinery, vehicles, and equipment, and ii) land and buildings, including expansion and renovations of existing structures." Accordingly, we take the natural logarithm of one plus the amount of purchases and name the variables as machine/equip and land buildings. Obtaining detailed data on expenses for specific asset types is difficult in the literature, but using this BEEPS question helps us illuminate the types of firm fixed assets.

We rely on the question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"

[6] As BEEPS VI provides cross-sectional data, the number of firms is also 26,898. However, the number of observations may be different across the regressions, depending on the maximum likelihood iteration and missing information of other variables. Details of the observations of each variable are provided in Table 1.

to construct our financial source dependent variables: internal funds (internal funds or retained earnings), owners/equity (Owners' contribution or issued new equity shares), banks (borrowed from banks: private and state-owned), non-banks fin (borrowed from non-bank financial institutions, which include microfinance institutions, credit cooperatives, credit unions, or finance companies), suppliers/customers (purchases on credit from suppliers and advances from customers), gov grant (government grants), and friends/others (moneylenders, friends, relatives).[7]

We construct our leasing dependent variable based on this BEEPS question: "In fiscal year, did this establishment use any assets, such as machinery, vehicles, equipment, land or buildings, under leasing?". Our leasing variable is a dummy that equals one if the answer is "Yes," and zero if the answer is "No."

3.2.2. Main independent variables

Our independent variable is to gauge the impact of extreme weather at firm level; therefore, we use the following BEEPs question: "Over the last three years, did this establishment experience monetary losses due to extreme weather events (such as storms, floods, droughts, or landslides)?". We construct a dummy variable named loss weather that equals one if the answer is "Yes," and zero if the answer is "No."

3.2.3. Control variables

Following the literature (Baltas et al., 2022; Chu, 2020; Johnson and Lewellen, 1972; Wang, 2023), we include several commonly-used control variables. We include firm size, which is the natural logarithm of permanent and full-time workers. BEEPS defines firm size based on the number of employees, where firms are small-sized (5–19 employees), medium-sized (20–99 employees), and large-sized (above 100 employees). Large firms are more likely to invest more and easily obtain external funds (Beck and Demirguc-Kunt, 2006; Huang et al., 2022). We include firm age (the year that the firm participated in the BEEPS minus its establishment year) to capture firm operating experience that affects investment and financing decisions (Duong et al., 2021; Hanedar et al., 2014). Firms under a high market competition tend to display higher investment levels (Akdoğu and MacKay, 2008; Röller and Tombak, 1993); therefore, we construct a variable named competitor, which is the natural logarithm of

[7] Firms also answered that they issued bonds, but there are only 25 observations with non-zero and non-missing values. Our regressions drop the test on this bond issuance due to little variation in this variable.

one plus the number of competitors for the firms' main product. As offshore activities (exports) also affect firms' financing and investments (Hoberg and Moon, 2017; Moon and Phillips, 2021), we construct direct ex and indirect ex to capture the percentage of sales from direct and indirect exports of the firms. Lastly, we include ownership-related variables, including foreign own (percentage of foreign ownership), family own (percentage of the firm is owned by the same family) and female own (a dummy variable that equals one if amongst the owners of the firm, there are females, and zero otherwise), as ownership types can determine finance source choices and investments (Anderson et al., 2012; Anderson and Reeb, 2003; Chaudhuri et al., 2020).

3.3. Model specifications

To test our hypotheses with the dummy dependent variables (including tangible assets and leasing variables), we employ the following logistic regression model (Eq.1).

$$\Pr\left(Y_{i,j,c} = 1|X_{i,j,c}\right) = F(\beta_0 + \beta_1 loss\ weather_{i,j,c} + \beta' X_{i,j,c} + Industry_j + Year_t + Country_c + \varepsilon_{i,j,c})$$

$$= \frac{1}{1+e^{-(\beta_0+\beta_1 loss\ weather_{i,j,c}+\beta' X_{i,j,c}+Industry_j+Year_t+Country_c+\varepsilon_{i,j,c})}} \quad \text{(Eq.1)}$$

We use an OLS (Ordinary Least Squares) regression model (Eq.2) to test the hypotheses for continuous dependent variables, including machine/equip, land buildings, internal funds, owners/equity, banks, non-banks fin, suppliers/customers, gov grant, and friends/others, which are the external sources if the firms need to raise.

$$Y_{i,j,c} = \beta_0 + \beta_1 loss\ weather_{i,j,c} + \beta' X_{i,j,c} + Industry_j + Year_t + Country_c + \varepsilon_{i,j,c} \quad \text{(Eq.2)}$$

Where $Y_{i,j,c}$ represents a dependent variable for firm i in industry j and in country c. Our main independent variable of interest is loss weather. $X_{i,j,c}$ demonstrates our control variables, including firm size, firm age, competitor, indirect ex, direct ex, foreign own, family own, and female own. Industry, year, and country fixed effects are included to control for time-varying and omitted variables specific to a given year, industry, and country. The robust standard errors are clustered at firm-industry-country level to account for heteroscedasticity.

Importantly, Oster (2019) proves that merely including observed controls in regression analyses — a common practice to eliminate concerns about omitted variable bias — may not be entirely reliable. This is especially true when the observed confounding variables do not precisely represent the actual covariates that are missing from the analysis. Therefore, we employ coefficient stability tests devised by Oster (2019) to assess the scale of selection bias from unobservable factors for all regressions with continuous dependent variables.

4. Results and discussions

4.1. Sample distributions

Table 1 presents our sample distribution by country, in which Egypt accounts for almost all the sample, approximately 11.40%, while Montenegro accounted for the least minority of the sample, about 0.55%. However, regarding loss weather (i.e., losses due to extreme weather) by country in Table 1, on average Greece and Malta display the largest proportions of firms suffering from weather-related losses, with 18.7% and 18.2% of firms in the two countries, respectively. Our BEEPS sample is unique as it covers firms of all sizes, largely in less developed countries, and especially firm-level actual weather-related losses.[8]

[INSERT TABLE 1 HERE]

[INSERT TABLE 2 HERE]

Sample distribution by industry is presented in Table 2, where retail and services account for almost all our samples. The industry sectors in which the largest proportions of firms experience weather-related losses are manufacturing, wholesale, hotels, and services, roughly 11% or 12%. The industry that has least disaster-affected firms is the services of motor vehicles, wholesale, and retail,[9] accounting for 0.5% of the total firms in this industry.

4.2. Descriptive statistics and correlations

In Table 3, regarding loss weather, on average 8% of the total firms in our sample suffered from monetary losses due to extreme weather over the last three years. There are, on

[8] The firm-level climate risk data of Sautner et al. (2023) is not comparable as it captures only listed firms, mostly in more developed economies, and does not directly gauge firm-level losses (i.e., only captures the climate risk-related words in firms' earnings call transcripts).

[9] This industry category emphasizes the 'services' that facilitates the motor vehicles, wholesale and retail. In other words, 'wholesale' and 'retail' are not their main business.

average, roughly 36.7% of the total firms purchasing fixed assets, where the purchases of machine/equip are about 2.28 million U.S. dollars and the purchases of land buildings are about 0.539 million U.S. dollars. Regarding the financial sources that fund the fixed asset purchases, on average the internal funds accounted for 73.44%, banks accounted for 15.41%, while the other sources are minimal. The mean of leasing is .184, indicating that 18.4% of the total firms leasing their fixed assets.

Also in Table 3, firms have an average of 150 employees, ranging from the minimum number of one employee to the maximum number of roughly 1.6 million employees. The average years of establishment is 20 years, while the average number of competitors of the main products/services is 110. Direct exports account for 10.33%, while indirect exports account for 3.72% in the mean values. There are 6.22%, 44.54% and 29.6% respectively of the total firms in our sample demonstrating foreign ownership, family ownership and female ownership.

[INSERT TABLE 3 HERE]

In Table 4, loss weather is positively and significantly correlated with tangible assets, owners/equity, banks, suppliers/customers, and leasing, but negatively and significantly correlated with internal funds. These correlations may imply that weather-affected firms suffer a lack of internal funds and seek external funds to finance their fixed assets purchases. Table 4 also shows that losses due to extreme weather are positively correlated with firm size, firm age, export activities and all types of ownership. Overall, the correlation coefficients are not significant large in magnitude, possibly mitigating multicollinearity concerns.

[INSERT TABLE 4 HERE]

4.3. Extreme weather and fixed asset policies

Table 5 shows the results for our first three hypotheses regarding fixed asset purchases. Column 1 presents the result of a logistic regression for H1a, where the dependent variable is a dummy variable - tangible assets. The estimated coefficient of loss weather ($\beta = 0.5639$) is positive and significant at 1% level, indicating that weather-affected firms have more tendency to purchase new or used fixed assets, such as machinery, vehicles, equipment, land, or buildings, including expansion and renovations of existing structures, in contrast with Correa et al. (2023). In terms of the economic significance, as β = 0.5639 in the log-odds scale, we calculate the marginal effect by taking the first derivative of tangible assets corresponding to change in loss weather to interpret it in probability. We find that the marginal effect of loss weather on tangible assets is 0.1087, meaning that there is 10.87% higher probability for weather-affected firms to purchase fixed assets after the disasters.

[INSERT TABLE 5 HERE]

In Columns 2 and 3 in Table 5, we present the results for H1b and H1c, respectively. The dependent variables of H1a and H1b are based on the BEEPS question: "In fiscal year, how much did this establishment spend on purchases of i) new or used machinery, vehicles, and equipment, and ii) land and buildings, including expansion and renovations of existing structures." We find that the estimated coefficients of loss weather (β = 0.2313 and β = 0.6479, respectively) are positive and significant at 1%. Compared to non-weather-affected firms, on average weather-affected firms are more likely to increase purchases of machine/equip by 2.24% or roughly 51 thousand U.S. dollars. The average increase in purchases of land buildings is also economically significant, with an increase by 23.79% or roughly 128 thousand U.S. dollars.[10] These results confirm again the impact of extreme weather on corporate fixed asset management, by which weather-affected firms tend to restore fixed assets by purchasing them after the extreme weather attacks. Two additional tests by Oster (2019) have been validated the coefficients with δ value exceeding 1. Concomitantly, in two scenarios, the intervals established between β* and the baseline coefficient consistently exclude zero. This suggests that the coefficients are robust and indicates a higher likelihood of firms, which have experienced extreme weather losses, opting to purchase tangible assets. Additionally, it is worth noting that the magnitude of land and buildings is three times larger than that of machinery and equipment.

[10] As the high skewness in machine/equip and land buildings shown in descriptive statistics, we use natural logarithm form in our regressions. The mean of the natural logarithm form of machine/equip and land buildings are 10.3284 and 2.7238, respectively. Therefore, an increase by 2.24% in purchases of machine/equip is calculated as 0.2313/10.3284, and 2.24%*2.276 million $ (the mean of machine/equip in money terms) is roughly 51 thousand $. Similarly, 23.79% is calculated as 0.6479/2.7238, and 23.79*0.539 million $ (the mean of land buildings in money terms) is about 128 thousand $.

Our results on the choices of fixed asset types seemingly supports the Competitive Advantage theory (Porter, 1992; Porter and Kramer, 1985) as more than ever, weather-affected firms need to continuously replace and innovate their fixed assets to compete with counterparts without being affected by extreme weather. Moreover, weather-affected firms may need to consider "real options" to integrate greater flexibility into their strategic utilization of external resources (Trigeorgis and Reuer, 2017).

4.4. Fixed asset purchases and financial sources under extreme weather

We address our H2 hypotheses to understand which financial sources weather-affected firms raise for fixed asset purchases. The dependent variables of H2 are based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:" internal funds, owners/equity, banks, non-banks fin, suppliers/customers, gov grant, and friends/others. We present the results in Table 6 and Figure 1.

The estimated coefficients of loss weather are positive and significant in the models of owners/equity (Column 2, β = 1.4163, significant at 5%), banks (Column 3, β = 2.1325, significant at 5%), suppliers/customers (Column 5, β = 1.5436, significant at 1%) and gov grant (Column 6, β = 0.3515, significant at 10%), while it is negative and significant in the model of internal funds (Column 1, β = –4.8722, significant at 1%). These results imply that extreme weather experience has induced firms to seek alternative external funds, rather than internal funds. We also find that weather-affected firms are less likely to raise funds from friends/others (e.g., moneylenders, friends, relatives) (Column 7). The results are economically significant. For example, on average firms experiencing losses due to extreme weather are more likely to increase funds from owners/equity by 35.77% (1.4163/3.959), banks by 13.84% (2.1325/15.410), suppliers/customers by 40.98% (1.5436/3.767) and gov grant by 47.05% (0.3515/0.747). The average decline in funds from internal funds by 6.63% (–4.8722/73.443) and friends/others by 49.52% (–0.3011/0.608).

[INSERT TABLE 6 HERE]

[INSERT FIGURE 1 HERE]

In line with Oster's (2019) recommendations, a δ value exceeding 1 indicates that our results are less likely to be swayed by selection bias due to unobservable factors. We developed the bias-adjusted coefficient (β*), designed to accurately reflect the influence of loss weather on each financial source, considering the potential presence of all unobserved confounders in the regression analysis. The intervals formed between β* and the baseline coefficient do not encompass zero in any instance. These findings strengthen the assertion that our results are robust and not merely a product of unobserved confounding factors, lending greater validity to the conclusions drawn from the study.

Our results support Baltas et al. (2022) but in the context of the extreme weather impact. However, different from Baltas et al. (2022), we find that disaster-affected firms appear to maximize all possible finance access sources (Trigeorgis and Reuer, 2017), rather than following the pecking order (Myers and Majluf, 1984). Obviously, firms affected by extreme weather face a higher internal cash flow volatility and reduction in sales (Ginglinger and Moreau, 2023; Huang et al., 2018), it is more difficult for them to raise funds internally (i.e., retained earnings).

4.5. Extreme weather and leasing decisions

Regarding firm leasing decisions (H3a, H3b, and H3c hypotheses), the results are reported in Table 7. In Column 1, we use the full sample and find that on average disaster-affected firms are more likely to lease fixed assets, with a positive and significant coefficient of loss weather (β = 0.5086, significant at 1%). As β = 0.5086 is in log-odds ratio, it is translated to the marginal effect as 0.0638, indicating that there is 6.38% more probability that disaster-affected firms lease fixed assets.

In Column 2, we restrict our sample to a subsample where disaster-affected firms have raised financial funds (i.e., non-leasing finance, including internal funds, owners/equity, banks, non-bank fin, suppliers/customers, gov grant and friends/others) and purchased fixed assets. We find a positive and significant coefficient of loss weather (β = 0.4466, significant at 1%), indicating that there is 8.26% more probability (in marginal effect) that disaster-affected firms still go for leasing even if they have raised other financial sources for their fixed asset purchases.

In Column 3, we look at a subsample where disaster-affected firms could not raise any non-leasing finance and did not purchase any fixed assets. We again find that weather-related losses are more likely to lease fixed assets. This result (β = 0.4791, significant at 1%) indicates that disaster-affected firms demonstrate 3.96% more probability that completely lease fixed assets due to access restrictions to other finance.

Our results in Table 7 contribute to the literature, specifically we argue that disaster-affected firms do not necessarily choose either purchase or lease fixed assets (Johnson and

Lewellen, 1972; Ofer, 1976). Instead, they can make financing decisions on both purchasing and leasing. Moreover, our leasing results show that it is not easy for disaster-affected firms to raise financial funds after natural disasters (Ginglinger and Moreau, 2023; Huynh et al., 2020) to buy fixed assets (as shown in our H2 and H3), so they choose to leasing financing instead.

[INSERT TABLE 7 HERE]

4.6.Robustness and endogeneity tests

Our baseline results may be driven by omitted variables and other possible endogeneity issues. First, it is arguable that firm-level monetary losses due to extreme weather may not be exogenous; instead, firm-specific characteristics may affect whether firms experience losses under natural disaster attacks. Thus, our first robustness test employs a propensity score matching method (PSM) to deal with this endogeneity issue. In this PSM method, firms that suffer from weather-related losses are in the treatment group, while firms that do not experience weather-related losses are in the control group. In Panel A of Table 8, we employ logistic regressions, where the dependent variable is loss weather, to estimate the probabilities (propensity scores) of how likely firms experience disaster-impacted losses based on firm-specific characteristics (i.e., all control variables). The results of logistic regressions for estimating propensity scores are shown in *Pre-Match* models (Columns 1, 3, 5 and 7), where each *Pre-Match* column estimates propensity scores for different outcomes (i.e., tangible assets, machine/equip, land buildings, financial sources and leasing).[11] The *Pre-Match* results demonstrate that firm-specific characteristics such as firm age, competitor and foreign own are more likely to boost the probabilities of firm-level weather-related losses, while direct ex (direct exports) have less probability to affect firm-level disaster-related losses. These *Pre-Match* results prove that weather-related losses at firm level are not random. Next, we proceed with the matching method by employing the nearest neighbor method with replacement between firms in treatment group and the ones in control group. As we aim to match firms between the two groups that are similar in terms of firm-level characteristics (i.e., similar propensity scores), we also require firms to be in the same country, industry, and year (i.e., the year when firms participated in BEEPS). After matching firms, to prove our successful matching, we re-run our logistic regressions that we have conducted in *Pre-Match* models and

[11] Although there are seven different dependent variables proxying for financial sources in our baseline regressions, for simplicity we conduct one PSM Pre-Match for all the financial sources.

present the results in *Post-Match* models (Columns 2, 4, 6 and 8). All the *Post-Match* models show insignificant coefficients, and smaller Pseudo R-squared values, suggesting no distinguishable differences in the observable firm-level characteristics between the two groups. The results of *Post-Match* models prove that PSM has successfully removed all observable differences other than the difference in the impact of weather-related losses. We next use the matched samples to re-test our baseline regressions and report the results in Panel B of Table 8. Our baseline results mostly remain.[12]

[INSERT TABLE 8 HERE]

Second, the causal impact of weather-related losses on firm fixed assets and financing choices may not be completely exogenous. To establish and prove the causality, we employ a 2SLS (two-state least squared) estimation with an instrument. Our instrument variable is *forest cover*, which is the natural logarithm of one plus the country-level forest area (in kilometers) divided by country population density (population per square kilometers). Apparently, *forest cover* does not directly affect firm-level fixed asset and financing decisions, but directly affects firm-level weather-related losses. Increased forest coverage can help mitigate the impacts of floods, droughts, and other extreme weather conditions. Our choice is grounded in the findings of Gauthier et al. (2015), which clearly demonstrate the advantages of forest cover in reducing losses associated with climate change. As expected, in the first-stage estimations (Panel A of Table 9), the more country-level forest cover is, the lower probabilities firms suffer from weather-related losses (e.g., in Column 1, $\beta = -0.0051$, significant at 1%). In the first-stage estimations, as *forest cover* is at country level, we do not include country fixed effects; instead, to mitigate any country-level omitted factor, we include country-level GDP per capita. Panel A of Table 9 shows that our models do not suffer from weak identification, with significant Kleibergen-Paap F statistics ($p = 0.000$ or 0.001). Panel B of Table 9 shows the results of our 2SLS approach, where we find our baseline results largely hold, except for suppliers/customers, so we should be conservative to claim the causality in the model of suppliers/customers.

[INSERT TABLE 9 HERE]

[12] As we put more conditions (firms in the same industry, country, and year), the observation numbers significantly drop with many conditions. The estimated coefficients of owners/equity, banks and friends/others remain the same signs as in the baseline results, but not significant, possibly due to smaller observations.

4.7. Why do weather-affected firms choose to lease fixed assets?

The results in H3a, H3b, and H3c show that weather-affected firms that could not raise funds for fixed asset purchases are more likely to choose leasing financing. Such results are based on our subsamples where we restrict the observations to firms that have/have not raised financial funds. However, we still do not know what drives the choices of firm financing decisions. Therefore, in this section, we further shed light on what the reasons for firms not to raise funds for fixed asset purchases. To do so, we look at a subsample where firms have not raised non-leasing financial funds to purchase fixed assets but choose leasing. We use the following BEEPS question to examine firm finance obstacles: *"What was the main reason why this establishment did not apply for any line of credit or loan?"*. The answers to this question includes *suff capital* (No need for a loan - establishment had sufficient capital), *complexity* (Application procedures were complex), *unfav interest* (Interest rates were not favorable), *high collateral* (Collateral requirements were too high), *insuff loans* (Size of loan and maturity were insufficient), and *unapproved* (Did not think it would be approved), *rejected* (Application was rejected/withdrawn).

We find that weather-affected firms who could not raise any non-leasing funds are more likely to suffer from a lack of capital, more complex loan application procedures, a high collateral requirement and a high loan application rejection). Our results are presented in Figure 2 and Table 10 from Columns 1-7. In terms of economic magnitude, for example, there is (β = 0.3690, significant at 5%) 1.29% more probability that weather-affected firms face complex loan application procedures, (β = 0.4115, significant at 5%) 1.74% more chances that weather-affected firms are required greater collateral, and (β = 0.5232, significant at 5%) 6.19% more chances that weather-affected firms are rejected their loan applications.[13] The results in Columns 1-7 are based on only credit or loan applications, so we further investigate the overall finance obstacles of the firms in Column 8, based on the BEEPS question as follows: *"To what degree is Access to Finance an obstacle to the current operations of this establishment?"*. Our dependent variable in Column 8 is *fin obstacles* (a dummy variable that equals one if firms rank the finance access obstacle equivalent or above two out of four scales). The result in Column 8 again confirms the finance access issue that incentivizes weather-affected firms to choose leasing.

[13] The coefficients of complexity, high collateral and rejected in Table 10 are translated into probabilities by being converted from log-odds ratios to probabilities by calculating the marginal effects.

Our results in Table 10 are important to understand that not all weather-affected firms are able to raise funds (e.g., banks, suppliers/customers, owners/equity) because they are significantly hindered from those sources and ultimately choose to lease fixed assets. Our study does not only support the work of Wang (2023) that finds weather-affected firms choose leasing due to the high collateral requirement rationale, but also points out other channels, including complexity in loan application procedures and rejection likelihood.

[INSERT TABLE 10 HERE]

[INSERT FIGURE 2 HERE]

5. Conclusions

Our paper shows a higher tendency among weather-affected firms to increase fixed asset investments and engage in asset leasing, highlighting a significant reliance on alternative financing options. Our findings suggest that not all disaster-impacted firms can secure traditional finance (such as bank loans or equity issuance) or other sources (government grants or trade credit) to support their fixed asset purchases. More importantly, our paper provide notable evidence that firms experiencing weather-related losses adapt flexible financing choices, by utilizing maximal financial sources that they manage to raise (i.e., both borrow to purchase and lease fixed assets).

Such extensive impacts of extreme weather on firms, particularly those in less developed countries, necessitate a comprehensive and tailored policy response. This underscores the need for enhanced access to capital through mechanisms such as specialized disaster relief funds (government grants) or favorable loan programs, which governments and financial institutions should collaboratively establish. The bureaucratic complexity and stringent collateral demand of loan applications hinder the recovery of weather-affected firms. Therefore, streamlining these processes and reducing collateral requirements is essential for faster access to funds. Additionally, encouraging leasing options through tax incentives or benefits is vital to align with the financial strategies of these firms.

Encouraging firms, particularly those in high-risk industries, to diversify their operations and revenue streams is paramount. This strategy would serve as a buffer, mitigating the financial strain imposed by extreme weather events. Firms should invest in resilient infrastructure and technologies, coupled with comprehensive risk management strategies inclusive of weather-related insurance products, would further fortify firms against the ravages of extreme weather.

Although our paper documents the important role of leasing, with the limitation of further information about leasing, we cannot study whether firms continue to lease assets in a long run. Our findings, however, at least show that firms who just experienced losses due to extreme weather need to recover immediately by utilizing all possible finance. Future research may need to have more information to observe firms' long-run strategies for fixed asset acquisition post-disasters.

Finally, we wish to highlight a significant secondary finding regarding forest coverage. In the first stage of the 2SLS analysis, we discovered significant effects of forest coverage on weather-related losses, underscoring the crucial role that maintaining and expanding forest areas play an important role in mitigating the impacts of climate change.

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Appendix A. Variable construction and definitions.

Variables	Description	Sources
loss weather	A dummy variable named that equals one if the answer is 'Yes', and zero if the answer is 'No' to the BEEPS question: "Over the last three years, did this establishment experience monetary losses due to extreme weather events (such as storms, floods, droughts, or landslides)?".	BEEPS
tangible assets	A dummy variable named that equals one if the answer is 'Yes', and zero if the answer is 'No' to the BEEPS question: "In fiscal year, did this establishment purchase any new or used fixed assets, such as machinery, vehicles, equipment, land or buildings, including expansion and renovations of existing structures?".	BEEPS
machine/equip	The natural logarithm of one plus the amount of purchases of new or used machinery, vehicles, and equipment. This is based on the BEEPS question: "In fiscal year, how much did this establishment spend on purchases of: i) new or used machinery, vehicles, and equipment, and ii) land and buildings, including expansion and renovations of existing structures."	BEEPS
land buildings	The natural logarithm of one plus the amount of purchases of land and buildings, including expansion and renovations of existing structures. This is based on the BEEPS question: "In fiscal year, how much did this establishment spend on purchases of: (i) new or used machinery, vehicles, and equipment, and (ii) land and buildings, including expansion and renovations of existing structures."	BEEPS
internal funds	Percentage of internal funds or retained earnings over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
owners/equity	Percentage of owners' contribution or issued new equity shares over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
banks	Percentage of funds borrowed from banks: private and state-owned over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
non-bank fin	Percentage of funds borrowed from non-bank financial institutions, which include microfinance institutions, credit cooperatives, credit unions, or finance companies over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
suppliers/customers	Percentage of Purchases on credit from suppliers and advances from customers over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
gov grant	Percentage of government grants over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
friends/others	Percentage of moneylenders, friends, relatives, etc. over total purchases of fixed assets. This is based on the BEEPS question: "Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:"	BEEPS
leasing	A dummy variable named that equals one if the answer is 'Yes', and zero if the answer is 'No' to the BEEPS question: "In fiscal year, did	BEEPS

	this establishment use any assets, such as machinery, vehicles, equipment, land or buildings, under leasing?”	
firm size	The natural logarithm of permanent, full-time workers	BEEPS
firm age	The year that the firm participated in the BEEPS minus the establishment year	BEEPS
competitor	The natural logarithm of one plus the number of competitors for the firms’ main product	BEEPS
indirect ex	The percentage of sales from indirect exports of the firms	BEEPS
direct ex	The percentage of sales from direct exports of the firms	BEEPS
foreign own	The percentage of foreign ownership	BEEPS
family own	The percentage of the firm is owned by the same family	BEEPS
female own	A dummy variable that equals one if amongst the owners of the firm, there are females, and zero otherwise	BEEPS
suff capital	A dummy variable that equals one if the answer is “No need for a loan - establishment had sufficient capital”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
complexity	A dummy variable that equals one if the answer is “Application procedures were complex”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
unfav interest	A dummy variable that equals one if the answer is “Interest rates were not favorable”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
high collateral	A dummy variable that equals one if the answer is “Collateral requirements were too high”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
insuff loans	A dummy variable that equals one if the answer is “Size of loan and maturity were insufficient”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
unapproved	A dummy variable that equals one if the answer is “Did not think it would be approved”, and zero otherwise. This is based on the BEEPS question: “What was the main reason why this establishment did not apply for any line of credit or loan?”	BEEPS
rejected	A dummy variable that equals one if the answer is “Application was rejected” or “Application was withdrawn”, and zero otherwise. This is based on the BEEPS question: “Referring only to this most recent application for a line of credit or loan, what was the outcome of that application?”	BEEPS
fin obstacles	Based on the BEEPS question as follows: “To what degree is Access to Finance an obstacle to the current operations of this establishment?”. No obstacle=0, Minor obstacle=1, Moderate obstacle=2, Major obstacle=3, and very severe obstacle=4 This variable is a dummy variable that equals one if the answers to this question equal or above 2, and zero otherwise.	BEEPS
forest cover	The natural logarithm of one plus the country-level forest area (in kilometers) divided by country population density (population per square kilometers)	World Bank Development Indicators
GDP per capita	GDP (Gross Domestic Product) per capita	World Bank Development Indicators

Table 1. Sample distribution and the mean of losses due to extreme weather (loss weather variable) by country

	N	%	Mean of *loss weather*
Albania	374	1.390	0.155
Armenia	541	2.011	0.096
Azerbaijan	208	0.773	0.077
Belarus	599	2.227	0.100
Bosnia and Herz.	343	1.275	0.146
Bulgaria	766	2.848	0.112
Croatia	336	1.249	0.101
Cyprus	360	1.338	0.133
Czech Rep.	487	1.811	0.119
Egypt	3,066	11.399	0.023
Estonia	359	1.335	0.128
Georgia	574	2.134	0.099
Greece	572	2.127	0.187
Hungary	804	2.989	0.103
Italy	758	2.818	0.044
Jordan	590	2.193	0.058
Kazakhstan	1,406	5.227	0.065
Kosovo	268	0.996	0.093
Kyrgyz Rep.	360	1.338	0.117
Latvia	358	1.331	0.128
Lebanon	511	1.900	0.115
Lithuania	357	1.327	0.087
Malta	242	0.900	0.182
Moldova	359	1.335	0.162
Mongolia	359	1.335	0.117
Montenegro	149	0.554	0.121
Morocco	641	2.383	0.133
North Macedonia	360	1.338	0.097
Poland	1,299	4.829	0.052
Portugal	1061	3.945	0.093
Romania	798	2.967	0.078
Russia	1,315	4.889	0.032
Serbia	361	1.342	0.133
Slovak Rep.	426	1.584	0.070
Slovenia	401	1.491	0.130
Tajikistan	341	1.268	0.044
Tunisia	615	2.286	0.072
Turkey	1,626	6.045	0.022
Ukraine	1,326	4.930	0.103
Uzbekistan	1,222	4.543	0.043
Total	26,898	100	0.080

The table illustrates how firms are spread out across various countries in the BEEPS survey, highlighting the percentage each country contributes to the total number of firms, and providing a clear picture of the average financial losses these firms face due to extreme weather conditions, which is captured by the *loss weather* variable.

Table 2. Sample distribution and the mean of losses due to extreme weather (loss weather variable) by industry

	N	%	Mean of *loss weather*
Manufacturing	2,354	8.752	0.114
Retail	4,524	16.819	0.082
Services	5,381	20.005	0.115
Food & Beverages	3,195	11.878	0.094
Textiles	437	1.625	0.046
Garments	1,236	4.595	0.031
Non-Metallic Mineral Products	934	3.472	0.080
Fabricated Metal Products	1,490	5.539	0.056
Machinery & Equipment	1,410	5.242	0.054
Rubber & Plastics Products	124	0.461	0.032
Other Manufacturing	3,032	11.272	0.069
Construction	347	1.290	0.029
Hotels	98	0.364	0.122
Wholesale	187	0.695	0.128
Textiles & Garments	308	1.145	0.042
Wholesale & Retail	126	0.468	0.056
Leather Products	131	0.487	0.015
Chemicals	161	0.599	0.006
Petroleum products, Plastics & Rubber	180	0.669	0.006
Basic Metals & Metal Products	186	0.692	0.016
Machinery & Equipment, Electronics & Vehicles	177	0.658	0.006
Wood Products, Furniture, Paper & Publishing	184	0.684	0.049
Services of Motor Vehicles/Wholesale/Retail	438	1.628	0.005
Hospitality & Tourism	258	0.959	0.012
Total	26,898	100	0.080

The table provides a comprehensive breakdown of the distribution of firms across various industries, detailing their respective contributions to the total firm count, as well as the average losses they incur due to extreme weather events (denoted as the *loss weather* variable).

Table 3. Summary statistics

Variables	Obs.	Mean	Std.	Q1	Median	Q3	Min	Max
loss weather	26,898	0.080	0.271	0.000	0.000	0.000	0.000	1.000
tangible assets	26,638	0.367	0.482	0.000	0.000	1.000	0.000	1.000
machine/equip ($m)	8,879	2.276	88.613	0.010	0.035	0.138	0.000	5551.000
land buildings ($m)	9,775	0.539	35.078	0.000	0.000	0.000	0.000	3440.000
internal funds (%)	7,679	73.443	35.073	50.000	100.000	100.000	0.000	100.000
owners/equity (%)	7,684	3.959	15.063	0.000	0.000	0.000	0.000	100.000
banks (%)	7,685	15.410	28.580	0.000	0.000	20.000	0.000	100.000
non-bank fin (%)	7,696	1.069	7.049	0.000	0.000	0.000	0.000	60.000
suppliers/customers (%)	7,684	3.767	14.037	0.000	0.000	0.000	0.000	95.000
gov grant (%)	7,703	0.747	4.902	0.000	0.000	0.000	0.000	40.000
friends/others (%)	7,701	0.608	4.081	0.000	0.000	0.000	0.000	35.000
leasing	26,656	0.184	0.387	0.000	0.000	0.000	0.000	1.000
firm size (thousands)	26,689	0.150	10.252	0.009	0.020	0.067	0.001	1,673.000
firm age	26,416	20.377	13.400	11.000	18.000	26.000	3.000	75.000
competitor (thousands)	24,401	0.110	0.138	0.005	0.200	0.200	0.000	10.000
indirect ex ((%)	26,506	3.722	13.663	0.000	0.000	0.000	0.000	90.000
direct ex (%)	26,507	10.332	24.863	0.000	0.000	0.000	0.000	100.000
foreign own (%)	26,563	6.215	22.502	0.000	0.000	0.000	0.000	100.000
family own (%)	26,384	44.535	47.296	0.000	0.000	100.000	0.000	100.000
female own	26,651	0.296	0.457	0.000	0.000	1.000	0.000	1.000

This table presents a detailed summary of the descriptive statistics for all variables. Each variable is characterized by its *number of observations* (*Obs.*), which provides insight into the dataset's size for that variable. The mean offers an average value, highlighting the central point of the data's distribution, while the *standard deviation* (*Std.*) shows the extent of data dispersion around this average. The *first quartile* (*Q1*) marks the 25th percentile, indicating that 25% of the data points fall below this value, and it serves as a measure of the data's lower spread. The median (*Median*) represents the dataset's middle value, ensuring that half of the data points lie below this level. The *third quartile* (*Q3*) represents the 75th percentile, illustrating the upper spread of the data with 75% of the values falling below this point. The *minimum* (*Min*) and *maximum* (*Max*) values define the dataset's range, highlighting the extreme values in the variable's distribution.

Table 4. Correlations.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 loss weather	1																			
2 tangible assets	0.13*	1																		
3 machine/equip	-0.01	.	1																	
4 land buildings	0.00	.	0.00	1																
5 internal funds	-0.06*	.	0.01	0.01	1															
6 owners/equity	0.03*	.	0.00	0.00	-0.33*	1														
7 banks	0.03*	.	0.00	-0.01	-0.73*	-0.10*	1													
8 non-bank fin	0.00	.	0.00	0.00	-0.20*	-0.02*	-0.04*	1												
9 suppliers/customers	0.04*	.	-0.01	0.00	-0.34*	-0.03*	-0.06*	-0.01	1											
10 gov grant	0.02	.	0.00	0.00	-0.17*	-0.02*	-0.01	-0.01	-0.02	1										
11 friends/others	-0.02	.	0.00	0.00	-0.18*	0.01	-0.03*	-0.02	0.02*	0.01	1									
12 leasing	0.09*	0.27*	0.01	-0.01	-0.14*	0.00	0.13*	0.07*	0.06*	0.01	-0.01	1								
13 firm size	0.06*	0.21*	0.04*	0.02*	-0.03*	-0.04*	0.05*	0.02	0.00	0.04*	-0.03*	0.12*	1							
14 firm age	0.03*	0.04*	-0.02	0.01	0.00	-0.04*	0.01	0.01	0.02	0.04*	-0.03*	0.02*	0.23*	1						
15 competitor	-0.04*	-0.16*	-0.02	-0.02	0.02	0.00	0.00	-0.01	0.00	-0.03*	-0.01	-0.09*	-0.10*	-0.06*	1					
16 indirect ex	0.03*	0.04*	-0.01	0.00	-0.02	-0.01	0.01	0.03*	0.01	0.02	0.00	0.04*	0.12*	0.02*	0.02*	1				
17 direct ex	0.03*	0.16*	0.03*	0.03*	-0.03*	-0.03*	0.04*	0.03*	0.00	0.02	-0.01	0.09*	0.30*	0.10*	-0.07*	-0.02*	1			
18 foreign own	0.02*	0.10*	0.04*	0.03*	0.05*	-0.02	-0.06*	0.02	-0.02	-0.02	0.02	0.09*	0.23*	-0.01*	-0.08*	0.06*	0.29*	1		
19 family own	0.05*	0.10*	-0.01	0.00	-0.07*	0.02	0.06*	0.03*	0.01	0.00	0.00	0.08*	-0.12*	0.09*	-0.08*	0.03*	0.04*	-0.07*	1	
20 female own	0.03*	0.09*	-0.01	-0.01	0.00	0.00	-0.01	0.01	0.00	0.01	-0.02*	0.05*	0.01	0.07*	-0.06*	0.01*	0.02*	-0.04*	0.17*	1

This table reports the Pearson correlations between each pair of variables of interest. p-values are reported in parentheses. The missing correlation coefficients are the ones between *tangible assets* (i.e., a dummy variable that equals one if firms purchase any new or used fixed assets, such as machinery, vehicles, equipment, land or buildings, including expansion and renovations of existing structures in the fiscal year, and zero otherwise) and types of fixed assets (*machine/equip* and *land buildings*) and financial sources that firms use to fund their fixed assets purchases (including *internal funds*, *owners/equity*, *banks*, *non-bank fin*, *suppliers/customers*, *gov grant* and *friends/others*). These missing correlations are because the values of *tangible assets* all equal one (i.e., no variation in *tangible assets*, in case firms do purchase fixed assets and use funds specifically for fixed asset purchases). * denotes the significance level at 5%.

Table 5. Weather-related losses and firm fixed asset purchases.

	(1)	(2)	(3)
	tangible assets	*machine/equip*	*land buildings*
Panel A: Logit (column 1) and OLS estimates			
loss weather	0.5639***	0.2313***	0.6479***
	(0.056)	(0.082)	(0.169)
firm size	0.3846***	0.7845***	0.6799***
	(0.013)	(0.024)	(0.046)
firm age	-0.0052***	0.0005	0.0056
	(0.001)	(0.002)	(0.004)
competitor	-0.0581***	-0.0169	0.0400
	(0.009)	(0.016)	(0.029)
indirect ex	0.0006	0.0030*	0.0005
	(0.001)	(0.002)	(0.004)
direct ex	0.0037***	0.0048***	0.0024
	(0.001)	(0.001)	(0.002)
foreign own	0.0004	0.0020*	-0.0020
	(0.001)	(0.001)	(0.002)
family own	0.0027***	0.0009	0.0033***
	(0.000)	(0.001)	(0.001)
female own	0.0826**	-0.1139**	-0.0043
	(0.035)	(0.057)	(0.114)
constant	-1.4404***	7.4217***	-0.2230
	(0.157)	(0.110)	(0.206)
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	23,090	7,969	7,978
Adj-R2		0.2449	0.1105
Pseudo-R2	0.1700		
Panel B: Coefficient stability and selection bias from unobservable in OLS estimations			
Oster's (2019) bound (β^{*}, β)		[0.2312, 0.4796]	[0.6479, 1.0131]
Oster's (2019) absolute δ for $\beta = 0$		3.2509	5.0578

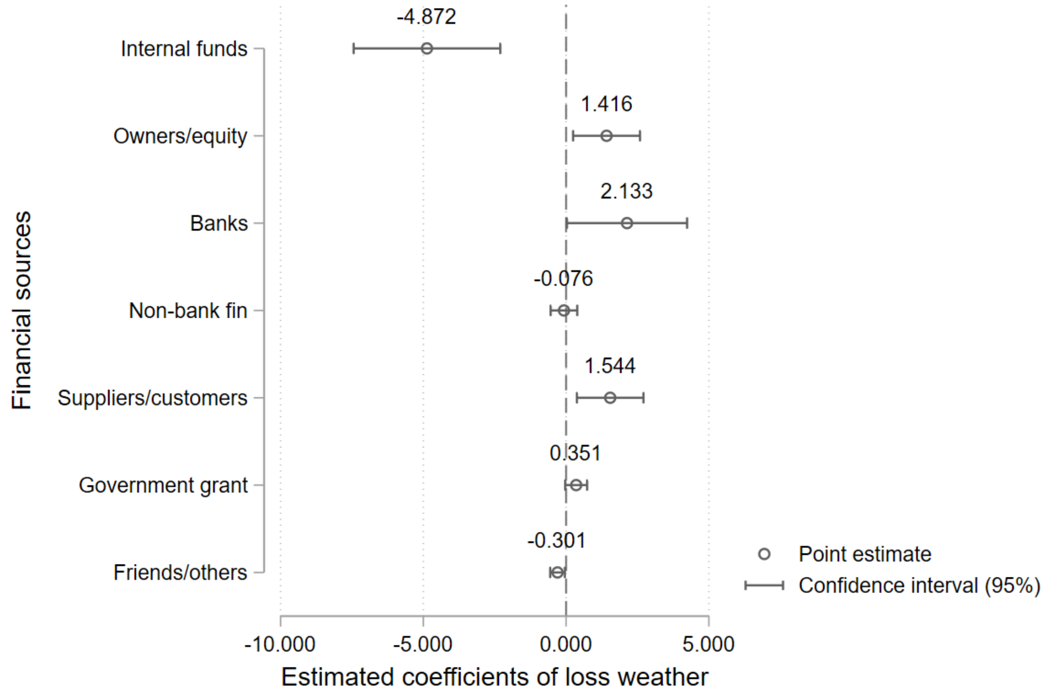
This table examines the impact of *loss weather* on firm fixed asset purchases. The dependent variables are *tangible assets* (i.e., a dummy variable that equals one if firms purchase any new or used fixed assets, such as machinery, vehicles, equipment, land or buildings, including expansion and renovations of existing structures in the fiscal year, and zero otherwise) in Column 1; *machine/equip* (i.e., the natural logarithm of one plus the amount of purchases of new or used machinery, vehicles, and equipment) in Column 2; and *land buildings* (i.e., the natural logarithm of one plus the amount of purchases of land and buildings, including expansion and renovations of existing structures) in Column 3. A logistic regression is used in Column 1, while Columns 2-3 employ OLS regressions. The independent variable of interest is *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%. This table additionally showcases the outcomes of the coefficient stability test, which was formulated by Oster in 2019 (see Panel B). The δ statistic serves as a measure of the significance of unobserved confounders when compared to observed control variables, particularly in terms of their capacity to nullify the main findings. β^{*} represents the adjusted coefficient under the assumption that δ equals 1 and R_{max} is 1.3 times R (where R denotes the R-squared value of the model that only includes observed controls, and R_{max} represents the R-squared value of a hypothetical model that incorporates both observed and unobserved control variables, being 30% higher than R). In the event that all unobserved confounders were taken into consideration, β^{*} would effectively capture the impact of adverse weather conditions on actions related to fixed asset management in the OLS estimations. An intercept, omitted for brevity, is included in all the regressions.

Table 6. Weather-related losses and financial sources used to fund firm fixed asset purchases.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	internal funds	*owners/equity*	*banks*	*non-bank fin*	*suppliers/customers*	*gov grant*	*friends/others*
loss weather	-4.8722***	1.4163**	2.1325**	-0.0756	1.5436***	0.3515*	-0.3011**
	(1.310)	(0.597)	(1.074)	(0.238)	(0.595)	(0.196)	(0.130)
firm size	-1.6739***	-0.2340	1.8628***	0.0735	-0.0494	0.1425***	-0.1117**
	(0.361)	(0.158)	(0.299)	(0.069)	(0.137)	(0.049)	(0.044)
firm age	0.1246***	-0.0246*	-0.0887***	-0.0070	-0.0074	0.0109*	-0.0030
	(0.034)	(0.013)	(0.027)	(0.007)	(0.014)	(0.006)	(0.004)
competitor	0.4737*	-0.2428**	0.0212	-0.0710	-0.0367	-0.0202	-0.0494
	(0.242)	(0.102)	(0.197)	(0.048)	(0.101)	(0.033)	(0.031)
indirect ex	-0.0341	-0.0014	0.0033	0.0089	0.0151	0.0039	0.0024
	(0.030)	(0.011)	(0.025)	(0.008)	(0.012)	(0.005)	(0.004)
direct ex	-0.0327*	-0.0037	0.0343**	0.0019	0.0029	-0.0002	0.0012
	(0.018)	(0.007)	(0.015)	(0.004)	(0.007)	(0.003)	(0.002)
foreign own	0.0997***	0.0004	-0.0943***	0.0015	-0.0153**	-0.0070***	0.0050*
	(0.017)	(0.007)	(0.013)	(0.004)	(0.006)	(0.002)	(0.003)
family own	-0.0309***	0.0030	0.0230***	0.0005	0.0065	-0.0006	0.0014
	(0.010)	(0.005)	(0.008)	(0.002)	(0.004)	(0.001)	(0.001)
female own	0.6449	0.4384	-0.9650	0.0500	-0.1952	-0.0287	-0.1116
	(0.921)	(0.391)	(0.756)	(0.184)	(0.374)	(0.123)	(0.106)
constant	77.2078***	5.5099***	9.6992***	1.0592***	3.8205***	0.0821	1.1893***
	(1.742)	(0.801)	(1.413)	(0.326)	(0.704)	(0.227)	(0.227)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,880	6,885	6,882	6,890	6,881	6,897	6,894
Adj-R2	0.0540	0.0441	0.0447	0.0811	0.0445	0.0465	0.0348
Oster's (2019) bound ($\beta*$, β)	[-5.801, -4.8721]	[1.4163, 1.553]	[2.1325, 2.7390]	[-0.1318, -0.0756]	[1.5436, 1.6959]	[0.3515, 0.3587]	[-0.3011, -0.2365]
Oster's (2019) absolute δ for β = 0	12.2069	21.7896	9.4705	4.1027	21.1037	51.8170	-17.2433

This table examines the impact of *loss weather* on the choices of financial sources used to fund firm fixed asset purchases. We construct the dependent variables from the BEEPS question: "*Over fiscal year, please estimate the proportion of this establishment's total purchases of fixed assets that were financed from the following sources:*" *internal funds* (Internal funds or retained earnings), *owners/equity* (Owners' contribution or issued new equity shares), *banks* (Borrowed from banks: private and state-owned), *non-banks fin* (Borrowed from non-bank financial institutions, which include microfinance institutions, credit cooperatives, credit unions, or finance companies), *suppliers/customers* (Purchases on credit from suppliers and advances from customers), *gov grant* (Government grants), and *friends/others* (other, moneylenders, friends, relatives, etc.). Therefore, these financial sources are exactly raised for fixed asset purchases. All columns employ OLS regressions. The independent variable of interest is *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%. The δ statistic serves as a measure of the significance of unobserved confounders when compared to observed control variables, particularly in terms of their capacity to nullify the main findings. $\beta*$ represents the adjusted coefficient under the assumption that δ equals 1 and R_{max} is 1.3 times R (where R denotes the R-squared value of the model that only includes observed controls, and R_{max} represents the R-squared value of a hypothetical model that incorporates both observed and unobserved control variables, being 30% higher than R). In the event that all unobserved confounders were taken into consideration, $\beta*$ would effectively capture the impact of adverse weather conditions on financial resources related to fixed asset management in the OLS estimations.

Figure 1. Financial sources for firm fixed asset purchases.



This figure shows the coefficient of variable *loss weather* in each regression in Table 6. The error bar represents the 95% confidence interval.

Table 7. Weather-related losses and leasing.

	(1)	(2)	(3)
	leasing	*leasing*	*leasing*
loss weather	0.5086***	0.4466***	0.4791***
	(0.061)	(0.086)	(0.113)
firm size	0.2663***	0.2704***	0.1105***
	(0.016)	(0.026)	(0.026)
firm age	-0.0111***	-0.0107***	-0.0094***
	(0.002)	(0.003)	(0.003)
competitor	-0.0180*	-0.0014	0.0005
	(0.011)	(0.017)	(0.017)
indirect ex	0.0020	0.0013	0.0046**
	(0.001)	(0.002)	(0.002)
direct ex	0.0004	-0.0001	-0.0003
	(0.001)	(0.001)	(0.001)
foreign own	0.0015*	0.0004	0.0004
	(0.001)	(0.001)	(0.002)
family own	0.0014***	-0.0000	0.0011
	(0.000)	(0.001)	(0.001)
female own	0.0455	0.0698	-0.0008
	(0.042)	(0.065)	(0.068)
constant	-3.3263***	-1.7608***	-4.0215***
	(0.226)	(0.322)	(0.397)
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	23,116	6,165	14,523
Pseudo-R2	0.1499	0.1304	0.1175

This table examines the impact of *loss weather* on firm leasing financing decisions. The dependent variable (*leasing*) in all columns is a dummy variable that equals one if in the fiscal year the firms use any assets, such as machinery, vehicles, equipment, land, or buildings, under leasing, and zero otherwise. All columns employ logistic regressions. The independent variable of interest is *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%. The first column presents results from the full sample, the second from a subsample of disaster-affected firms that raised financial funds (excluding leasing) and purchased fixed assets, while the last column shows results from a subsample of disaster-affected firms that neither raised any non-leasing finance nor purchased any fixed assets.

Table 8. Propensity scores matching method (PSM).

This table examines the impact of *loss weather* on firm fixed asset purchases, financial sources for fixed asset purchases and leasing. Based on *loss weather* (i.e., a dummy if over the last three years the firms experience monetary losses due to extreme weather events (such as storms, floods, droughts, or landslides), and zero otherwise), we conduct the PSM for the treatment group (firms suffer from weather-related losses) and control group (firms do not suffer from weather-related losses).

Panel A: Propensity score regressions (Pre-Match) and Diagnostic regressions (Post-Match) (Dependent variables: loss weather)

	Outcome=tangible assets		Outcomes=machine/equip or land buildings		Outcomes=financial sources		Outcome=leasing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-Match	*Post-Match*	*Pre-Match*	*Post-Match*	*Pre-Match*	*Post-Match*	*Pre-Match*	*Post-Match*
	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather
firm size	0.1665***	-0.0180	0.1433***	-0.0406	0.1283***	0.0020	0.1677***	0.0003
	(0.021)	(0.028)	(0.030)	(0.041)	(0.032)	(0.042)	(0.021)	(0.027)
firm age	0.0024	0.0010	0.0040	0.0007	0.0041	-0.0001	0.0023	-0.0005
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)
competitor	-0.0017	0.0029	0.0316	0.0360	0.0358*	-0.0239	-0.0020	0.0019
	(0.014)	(0.019)	(0.020)	(0.028)	(0.021)	(0.030)	(0.014)	(0.019)
indirect ex	0.0061***	-0.0018	0.0051**	0.0023	0.0038	-0.0028	0.0062***	-0.0012
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
direct ex	0.0012	-0.0001	0.0007	-0.0007	-0.0003	0.0006	0.0011	-0.0003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
foreign own	-0.0025**	0.0008	-0.0034**	0.0009	-0.0030**	0.0011	-0.0024**	0.0016
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
family own	0.0014**	-0.0001	0.0004	0.0008	-0.0003	0.0010	0.0015**	0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
female own	0.0041	-0.0183	-0.0395	0.0347	-0.0377	-0.0128	0.0082	-0.0413
	(0.055)	(0.073)	(0.074)	(0.104)	(0.080)	(0.107)	(0.055)	(0.074)
constant	-3.3283***	0.0800	-2.1624***	-0.2181	-1.6719***	-0.1314	-3.3406***	-0.1147
	(0.271)	(0.361)	(0.346)	(0.457)	(0.364)	(0.467)	(0.271)	(0.359)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,937	3,666	8,092	1,846	6,868	1,710	22,963	3,668,
Pseudo-R2	0.0719	0.0029	0.0444	0.0088	0.0516	0.0071	0.0720	0.0042

In Panel A, due to different outcomes (i.e., fixed asset purchases, financial sources for fixed asset purchases and leasing), we conduct logistic regressions (*Pre-Match* Columns 1, 3, 5 and 7), where the dependent variable is *loss weather*, to estimate propensity scores. Next, based on the estimated propensity scores, we match firms in the treatment group and control group, using nearest-neighbor and exact matching (in the same industry, year, and country). After matching, we conduct diagnostic regressions (*Post-Match* Columns 2, 4, 6 and 8) to check the success in our matching. All *Post-Match* are based on matched samples, showing that all firm-specific characteristics do not significantly impact on *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%.

Table 8. Propensity scores matching method (PSM). (continued)
Panel B: Re-estimations based on matched samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	tangible assets	machine/equip	land buildings	internal funds	owners/equity	banks	non-bank fin	suppliers/customers	gov grant	friends/others	leasing	leasing	leasing
loss weather	0.5696***	0.1969*	0.5051**	-4.4512**	0.0732	2.0027	0.0194	1.8113**	0.7898***	-0.2785	0.4411***	0.4525***	0.3490**
	(0.074)	(0.111)	(0.226)	(1.730)	(0.809)	(1.416)	(0.318)	(0.750)	(0.225)	(0.188)	(0.083)	(0.126)	(0.149)
firm size	0.4598***	0.8786***	0.8622***	-1.6897**	-0.4220	2.6148***	0.1455	-0.2424	0.0321	-0.2219**	0.3315***	0.2684***	0.2630***
	(0.033)	(0.049)	(0.099)	(0.752)	(0.357)	(0.621)	(0.123)	(0.287)	(0.095)	(0.102)	(0.034)	(0.053)	(0.063)
firm age	-0.0060**	-0.0011	-0.0100	0.0752	-0.0017	-0.0415	-0.0093	-0.0229	0.0101	-0.0040	-0.0092***	-0.0086*	-0.0108*
	(0.003)	(0.004)	(0.009)	(0.064)	(0.030)	(0.054)	(0.014)	(0.027)	(0.011)	(0.006)	(0.003)	(0.005)	(0.007)
competitor	-0.0591***	0.0215	-0.0500	-0.1431	-0.0449	0.2750	0.0009	-0.0460	0.0201	-0.0400	-0.0395	-0.0341	-0.0144
	(0.022)	(0.034)	(0.066)	(0.527)	(0.237)	(0.428)	(0.101)	(0.233)	(0.067)	(0.065)	(0.024)	(0.037)	(0.043)
indirect ex	0.0010	0.0097***	0.0146	-0.0530	-0.0232	0.0737	-0.0091	0.0043	0.0094	0.0021	-0.0005	0.0021	-0.0013
	(0.003)	(0.003)	(0.009)	(0.058)	(0.021)	(0.049)	(0.006)	(0.025)	(0.009)	(0.008)	(0.003)	(0.004)	(0.006)
direct ex	0.0048***	0.0070***	-0.0019	-0.0241	-0.0081	0.0530*	0.0022	-0.0194	-0.0035	0.0033	0.0012	0.0006	0.0000
	(0.002)	(0.002)	(0.005)	(0.037)	(0.014)	(0.031)	(0.007)	(0.015)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
foreign own	-0.0035*	0.0031	-0.0026	0.0760*	0.0211	-0.1018***	0.0062	-0.0267*	-0.0032	0.0075	0.0011	-0.0006	-0.0018
	(0.002)	(0.002)	(0.006)	(0.041)	(0.020)	(0.029)	(0.008)	(0.015)	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)
family own	0.0027***	-0.0004	0.0034	-0.0299	0.0057	0.0167	0.0022	0.0053	0.0001	0.0018	0.0015	-0.0016	0.0017
	(0.001)	(0.001)	(0.003)	(0.021)	(0.011)	(0.017)	(0.003)	(0.010)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
female own	-0.0499	-0.0093	-0.2257	0.0242	1.0443	-0.9087	0.2088	-0.2642	0.0893	-0.1669	0.0246	0.1145	0.0863
	(0.082)	(0.121)	(0.253)	(1.905)	(0.897)	(1.556)	(0.333)	(0.848)	(0.241)	(0.204)	(0.091)	(0.134)	(0.163)
constant	-0.2869	7.0250***	0.1256	79.6673***	6.3789***	4.8570	0.3612	5.5012***	-0.1237	1.6124***	-1.8620***	-0.6492	-3.5066***
	(0.381)	(0.248)	(0.472)	(3.871)	(1.889)	(3.169)	(0.670)	(1.691)	(0.343)	(0.532)	(0.414)	(0.554)	(0.982)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	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	Yes
Obs.	3,654	1,846	1,846	1,710	1,710	1,710	1,710	1,710	1,710	1,710	3,595	1,362	1,609
Adj-R2		0.2607	0.1290	0.0357	0.0822	0.0373	0.0200	0.0513	0.0453	0.0191			
Pseudo-R2	0.1413										0.1405	0.1318	0.1114

Panel B re-examines the impact of weather-related losses (loss weather) on all the outcomes (firm fixed asset purchases, financial sources for fixed asset purchases and leasing) based on matched samples. The dependent variables are firm fixed asset purchases (*tangible assets*, *machine/equip* and *land buildings*), financial sources for fixed asset purchases (*internal funds*, *owners/equity*, *banks*, *non-bank fin*, *suppliers/customers*, *gov grant* and *friends/others*), and *leasing*. The independent variable of interest is *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%.

Table 9. Two-stage least square estimation (2SLS).

This table re-examines the impact of *loss weather* on firm fixed asset purchases, financial sources for fixed asset purchases and leasing, using a 2SLS with an instrument variable.

Panel A: First-stage regression analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	1st stage for tangible assets	1st stage for machine/equip	1st stage for land buildings	1st stage for internal funds	1st stage for owners/equity	1st stage for banks	1st stage for non-bank fin	1st stage for suppliers/customers	1st stage for gov grant	1st stage for friends/others	1st stage for leasing	1st stage for leasing (subsample)	1st stage for leasing (subsample)
	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather	loss weather
forest cover	-0.0051***	-0.0062***	-0.0061***	-0.0071***	-0.0072***	-0.0073***	-0.0074***	-0.0072***	-0.0073***	-0.0073***	-0.0050***	-0.0068***	-0.0039***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
firm size	0.0124***	0.0145***	0.0139***	0.0122***	0.0125***	0.0125***	0.0128***	0.0128***	0.0128***	0.0128***	0.0124***	0.0126***	0.0050***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.002)
firm age	0.0002	0.0005	0.0005	0.0006	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0002	0.0005	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
competitor	-0.0020**	0.0033	0.0038*	0.0032	0.0031	0.0035	0.0033	0.0034	0.0033	0.0033	-0.0020**	0.0030	-0.0026**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
indirect ex	0.0005***	0.0005*	0.0006**	0.0003	0.0003	0.0004	0.0003	0.0003	0.0003	0.0003	0.0005***	0.0004	0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
direct ex	0.0002**	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002*	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
foreign own	-0.0001	-0.0003**	-0.0003**	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001	-0.0003*	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
family own	0.0001***	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0001***	0.0000	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female own	0.0103**	0.0011	0.0018	0.0037	0.0043	0.0043	0.0041	0.0042	0.0040	0.0042	0.0106**	0.0022	0.0118**
	(0.004)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.004)	(0.009)	(0.005)
GDP per capita	0.0089**	0.0053	0.0020	0.0021	0.0026	0.0024	0.0031	0.0031	0.0033	0.0031	0.0089**	0.0045	0.0069
	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)	(0.008)	(0.004)
constant	0.0165	0.0996	0.1267*	0.1595**	0.1563**	0.1584**	0.1506*	0.1502*	0.1497*	0.1504*	0.0145	0.1447*	-0.0009
	(0.038)	(0.074)	(0.074)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.038)	(0.083)	(0.042)
Industry FE	Yes	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	Yes
Obs.	22,909	7,878	7,893	6,808	6,813	6,810	6,818	6,809	6,825	6,822	22,935	6,180	14,442
Kleibergen-Paap F-stat	40.9564	12.0967	11.8778	14.0743	14.5693	14.8116	15.3328	14.7707	15.0988	15.1602	39.1893	11.9804	22.3503
Kleibergen-Paap F-stat p-value	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000

This Panel A shows the results of the first-stage estimations of the 2SLS method, where the dependent variable in all columns is *loss weather*, and the instrument variable is *forest cover* (the natural logarithm of one plus the country-level forest area (in kilometers) divided by country population density (population per square kilometers)). All the control variables are the same as the baseline, but we also include country-level GDP (Gross Domestic Product) per capita. As forest cover is at country level, we only include industry and year fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%.

Table 9. Two-stage least square estimation (2SLS). (continued)
Panel B: Second-stage regression analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	tangible assets	machine/equip	land buildings	internal funds	owners/equity	banks	non-bank fin	suppliers/customers	gov grant	friends/others	leasing	leasing	leasing
fitted loss weather	2.0088***	13.8555***	20.8569***	-91.2172***	44.2038***	70.1502**	-0.3972	-33.7186**	4.8652	-4.0254	1.8031***	1.7552***	1.0961***
	(0.392)	(4.433)	(7.080)	(34.986)	(14.835)	(28.670)	(4.265)	(14.295)	(3.120)	(2.864)	(0.356)	(0.621)	(0.379)
firm size	0.0469***	0.5687***	0.3415***	-0.4553	-0.7727***	0.9202*	0.0928	0.3375	0.0862	-0.0834	0.0109**	0.0247**	0.0017
	(0.006)	(0.077)	(0.120)	(0.598)	(0.267)	(0.483)	(0.086)	(0.247)	(0.061)	(0.055)	(0.005)	(0.010)	(0.003)
firm age	-0.0020***	-0.0058	-0.0032	0.1495***	-0.0512**	-0.1151***	-0.0009	0.0268	0.0055	-0.0010	-0.0017***	-0.0026***	-0.0008***
	(0.000)	(0.006)	(0.009)	(0.052)	(0.022)	(0.040)	(0.008)	(0.020)	(0.007)	(0.005)	(0.000)	(0.001)	(0.000)
competitor	-0.0196***	-0.0611*	-0.0294	0.5941*	-0.2487*	-0.1527	-0.0673	0.0515	-0.0532	-0.0264	-0.0033	-0.0083	0.0003
	(0.003)	(0.034)	(0.055)	(0.315)	(0.144)	(0.257)	(0.047)	(0.132)	(0.035)	(0.032)	(0.002)	(0.005)	(0.002)
indirect ex	-0.0007*	-0.0045	-0.0116	-0.0131	-0.0165	-0.0172	0.0139*	0.0236	0.0027	0.0046	-0.0003	-0.0001	0.0000
	(0.000)	(0.005)	(0.008)	(0.042)	(0.018)	(0.033)	(0.008)	(0.016)	(0.005)	(0.004)	(0.000)	(0.001)	(0.000)
direct ex	0.0010***	0.0036	0.0010	-0.0314	-0.0123	0.0405**	0.0051	0.0024	-0.0006	0.0007	0.0001	0.0004	-0.0001
	(0.000)	(0.002)	(0.004)	(0.023)	(0.010)	(0.019)	(0.004)	(0.009)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)
foreign own	0.0007***	0.0073***	0.0057	0.0740***	0.0101	-0.0773***	0.0018	-0.0226***	-0.0052**	0.0055**	0.0008***	0.0007*	0.0001
	(0.000)	(0.003)	(0.004)	(0.023)	(0.010)	(0.018)	(0.004)	(0.009)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)
family own	0.0004***	0.0015	0.0047**	-0.0411***	0.0031	0.0333***	0.0030*	0.0032	-0.0008	0.0018	0.0001	0.0002	0.0001
	(0.000)	(0.001)	(0.002)	(0.013)	(0.006)	(0.010)	(0.002)	(0.005)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
female own	0.0276**	-0.1343	-0.1033	1.4397	0.1452	-1.7394*	0.0850	-0.1218	0.0826	-0.1095	-0.0118	0.0024	-0.0161*
	(0.011)	(0.123)	(0.198)	(1.183)	(0.533)	(0.963)	(0.180)	(0.483)	(0.131)	(0.112)	(0.010)	(0.020)	(0.009)
GDP per capita	0.0471***	0.8022***	0.0063	-2.2503**	-2.4397***	1.8244**	0.3833***	2.0987***	0.5420***	-0.3092***	0.1161***	0.1637***	0.0674***
	(0.009)	(0.109)	(0.171)	(1.038)	(0.483)	(0.831)	(0.144)	(0.393)	(0.090)	(0.111)	(0.008)	(0.016)	(0.007)
constant	-0.2292**	-2.1902*	-1.7666	109.3108***	23.0687***	-15.5012	-3.8598**	-10.5722**	-6.2875***	4.8134***	-1.1189***	-1.6292***	-0.5788***
	(0.096)	(1.260)	(2.050)	(12.426)	(5.549)	(10.116)	(1.580)	(4.731)	(1.128)	(1.172)	(0.083)	(0.195)	(0.072)
Industry FE	Yes	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	Yes
Obs.	22,909	7,878	7,893	6,808	6,813	6,810	6,818	6,809	6,825	6,822	22,935	6,180	14,442

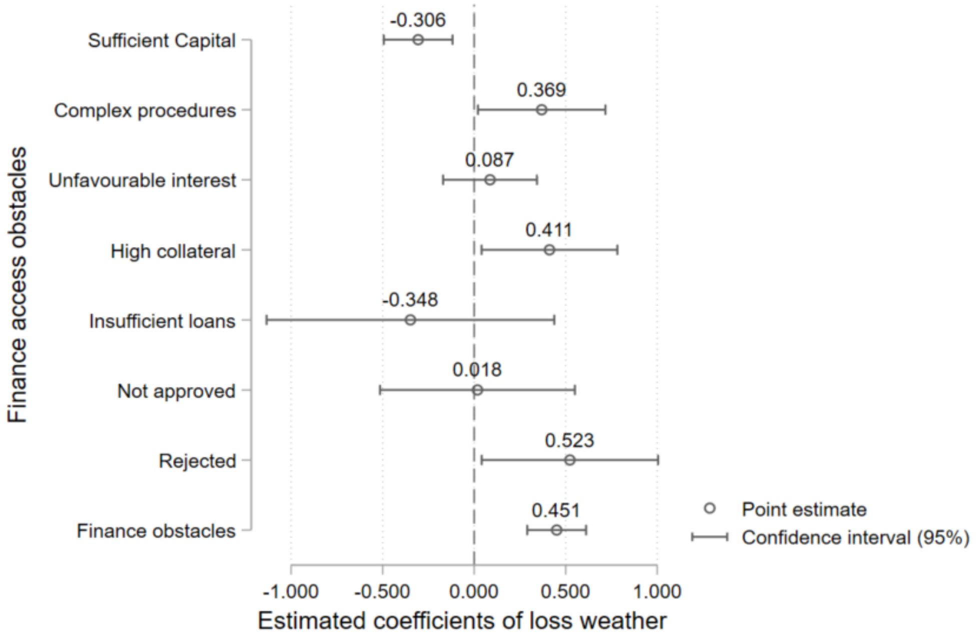
This Panel B presents the results of the second-stage regressions of the 2SLS method. The dependent variables are firm fixed asset purchases (*tangible assets*, *machine/equip* and *land buildings*), financial sources for fixed asset purchases (*internal funds*, *owners/equity*, *banks*, *non-bank fin*, *suppliers/customers*, *gov grant* and *friends/others*), and *leasing*. The independent variable of interest is fitted *loss weather*. All columns include industry, year, and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%.

Table 10. Why do weather-affected firms choose leasing, instead of raising other financial sources for fixed asset purchases?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	suff capital	*complexity*	*unfav interest*	*high collateral*	*insuff loans*	*unapproved*	*rejected*	*fin obstacles*
loss weather	-0.3058***	0.3690**	0.0868	0.4115**	-0.3479	0.0181	0.5232**	0.4508***
	(0.096)	(0.178)	(0.131)	(0.189)	(0.401)	(0.272)	(0.246)	(0.082)
firm size	0.1137***	-0.0782**	-0.1116***	-0.1045**	0.1815***	-0.0938	-0.3132***	-0.0290*
	(0.019)	(0.036)	(0.026)	(0.043)	(0.057)	(0.067)	(0.069)	(0.016)
firm age	0.0044**	-0.0117***	-0.0008	-0.0122***	-0.0012	0.0033	-0.0016	-0.0021
	(0.002)	(0.004)	(0.002)	(0.004)	(0.007)	(0.006)	(0.006)	(0.002)
competitor	-0.0020	0.0468*	-0.0097	-0.0458*	-0.1005**	0.0467	0.0724	0.0089
	(0.012)	(0.025)	(0.016)	(0.027)	(0.042)	(0.038)	(0.045)	(0.011)
indirect ex	-0.0022	-0.0008	-0.0019	0.0046	0.0047	0.0023	0.0049	-0.0010
	(0.002)	(0.003)	(0.002)	(0.004)	(0.006)	(0.005)	(0.005)	(0.002)
direct ex	0.0014	-0.0076**	0.0032**	-0.0075**	0.0003	-0.0035	-0.0030	-0.0014
	(0.001)	(0.003)	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.001)
foreign own	0.0052***	-0.0014	-0.0062***	-0.0056	-0.0037	-0.0029	0.0042	-0.0041***
	(0.001)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
family own	0.0007	-0.0021**	-0.0011*	0.0023**	-0.0018	-0.0012	-0.0037*	-0.0014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)
female own	0.0203	-0.2272**	0.0469	0.0777	-0.1941	-0.1089	-0.0995	-0.0577
	(0.052)	(0.105)	(0.068)	(0.116)	(0.193)	(0.157)	(0.175)	(0.045)
constant	0.4368*	-2.5762***	-2.0423***	-2.2883***	-5.3637***	-2.9098***	2.6318***	0.2828
	(0.238)	(0.522)	(0.320)	(0.587)	(1.103)	(0.661)	(0.957)	(0.195)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,385	11,889	12,215	12,030	10,430	11,832	1,603	14,525
Pseudo-R2	0.0789	0.0650	0.1150	0.0581	0.1119	0.0620	0.1358	0.1039

This table examines the reasons for why weather-affected firms do not raise other financial assets for fixed asset purchases, rather than leasing. We restrict our sample to a subsample where firms have not raised non-leasing financial funds to purchase fixed assets, but choose leasing, and investigate what problems that weather-affected firms face. The dependent variables are *suff capital* (No need for a loan - establishment had sufficient capital), *complexity* (Application procedures were complex), *unfav interest* (Interest rates were not favorable), *high collateral* (Collateral requirements were too high), *insuff loans* (Size of loan and maturity were insufficient), *unapproved* (Did not think it would be approved), *rejected* (Application was rejected/withdrawn) and *fin obstacles* (a dummy variable that equals one if firms rank the finance access obstacle equivalent or above two out of four scales). The independent variable of interest is *loss weather*. All columns include industry, year and country fixed effects. Robust standard errors (in parentheses) are clustered at firm-industry-country level to adjust for heteroskedasticity. *, **, and *** denote the significance levels at 10%, 5% and 1%.

Figure 2. Finance obstacles that weather-affected firms face.



This figure shows the coefficient of variable *loss weather* in each regression in Table 10. The error bar represents the 95% confidence interval.