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Does Climate Affect Investments: Evidence from Firms in the United States

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Abstract

This study updates the existing literature on the adverse effects of climate change on firms' performance by providing an alternative perspective that climate change can have potential growth benefits. We examine the effects of climate shocks on firms' investments. Using a spatial autoregressive model with United States (U.S.) firm-level data from 1985 to 2019, we find that increased frequency of climate shocks is positively associated with investments for firms, with larger spillover effects on neighbouring firms. These findings remain consistent for various robustness checks which include sub-sample analysis, different outcome variables and controlling for financial characteristics of the firms. The results highlight that contrary to current evidence, climate change can create incentives for firms to increase investments in adjusting their production processes to cleaner technologies.

Keywords: Climate shocks, Corporate investments, Spatial econometrics,

Production network structure

JEL Classification: C31, D24, D92, Q54

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1. Introduction

Climate change continues to be an ongoing global challenge, with its impacts threatening the economies of rich and poor countries alike. For example, the hurricanes in Florida and across Latin America and the Carribbeans, the floods across several countries in South Asia and the droughts being experienced in Africa have affected livelihoods through destruction of homes, loss of crops, and loss of lives (Steiner et al., 2017). In addition, the impact of climate change for least developed countries has contributed to delayed progress on development outcomes, such as access to health and education, while for middle-income and developed countries, impacts have included increased wealth and income inequalities (Chisadza et al., 2023; Sheng et al., 2023). According to the World Health Organization, an estimated 250,000 additional deaths per year are expected between 2030 and 2050 due to climate change impacts, such as food insecurity, diseases and poor access to health infrastructure (WHO, 2023). As such, mitigating climate change risks has become a central issue for policymakers and researchers.

Firms are also changing how their businesses operate amidst the climate change as they face different impacts. For example, evidence shows that climate change increases costs of financincing, influences stock market behaviour and investment decisions, increases uncertainty about new business opportunities and negatively affects firm's value (Cepni et al., 2024; Ahmed et al., 2024; Agoraki et al., 2024). However, while much of the existing literature focusses on adverse impacts of climate change on firm's performance, new evidence is emerging that recognises investment opportunities for firms that are able to adapt and innovate in response to the climate change (Ma et al., 2023; Bagh et al., 2024; Srivastava et al., 2024). Investments contribute to economic growth through infrastructure development and human capital accumulation. Therefore, understanding the growth-promoting potential of climate change as a driver of investments can open up alternative or complementing measures for countering the adverse impacts of climate risk.

We contribute to this relatively underexplored theme by advancing evidence on how climate shocks can affect investment levels in the United States (U.S.). We enrich the literature in three ways. First, we shift the narrative focussing on the negative impact of climate change by arguing that climate shocks can act as incentives that stimulate investment demand by encouraging firms to transition to low carbon emissions or renewable energy technologies. Second, our sample comprises of all the listed companies on the United States' stock market including large global financial firms whose investment decisions pertaining to climate change can have spillover effects on the rest of the world, thus making our findings relevant for policy reform. In addition, our analysis extends over a long period of time from 1985Q1 to 2019Q4 which takes into account several extreme weather and financial shocks that have occured in the United States, thus allowing us to infer relatively accurate climate shock effects on investments. Our analysis also uses the spatial autoregressive model (SAR) that addresses spatial autocorrelation within the data and allows us to observe, not only the direct effects of climate shocks on each firm, but also the indirect effects on neighbouring firms. Neighbouring firms may have more influence on each other than firms that are far apart.

Lastly, we focus on the United States as our country of interest because it has a diverse climate with different regions experiencing extreme cold and heat episodes, hurricanes and tornadoes. Climate change is having far-reaching effects on the population with some regions experiencing increased precipitation and flooding, while others suffer from drought (NOAA, 2023). Key findings from the Jay et al. (2023) show that climate change in the United States is exacerbating existing social inequalities in low income regions and communities of colour, while at the same time harming the psychological well-being of the population. Moreover, the impacts of extreme climate events are costing the country an estimated US$150 billion each year with expenses expected to increase with rising global warming. According to the Environmental Protection Agency report, a total of more than 19,000 Americans have succumbed to cold-related causes (EPA, 2024a), and 14,000 have perished from heat-related causes between 1979 and 2022 (EPA, 2024b). Extreme floods, hurricanes and wildfires also kill many more people each year (EPA, 2024b). The diverse climate profile coupled with developed financial markets and yet simultaneously experiencing severe impacts from climate change makes this country an interesting testing ground for our hypothesis on climate shocks and investment levels.

Our results indicate that increased frequency of climate shocks increases investment rates and capital expenditures for firms. These results remain consistent under various robustness checks, such as controlling for financial characteristics of firms, as well as restricting the sample to key periods that may have affected firms' performances, i.e. the Great Moderation and the Great Recession. The findings imply that policymakers should be cognisant of the potential welfare benefits from climate change and try create incentives for firms that encourage them to invest in climate risk mitigation strategies.

2. Literature Review

Ample evidence exists in the literature on the association between climate change and various development outcomes. For example, several studies indicate that climate change has affected agricultural income due to loss of crops and livestocks (Hallegatte and Rozenberg, 2017; Hsiang et al., 2017; Agovino et al., 2019), has resulted in job losses (Ahmad et al., 2022), and has increased poverty and income inequality (Taconet et al., 2020; Chisadza et al., 2023; Sheng et al., 2023). Moreover, climate change is attributed to increased conflicts and psychological trauma due to displacement and disrupted social capital (WHO, 2023; Castells-Quintana et al., 2022).

Extreme weather changes have not only resulted in environmental consequences but are also starting to be experienced in the business world, yielding severe physical and financial consequences for firms and their operations. Firms from various industries globally face direct and indirect effects of climate change, including operational disruptions, market volatility and regulatory constraints (Heo, 2021; Bolton and Kacperczyk, 2023). For example, continuous cloudy weather can decrease energy output from solar farms resulting in low crop yields and increased food prices (Ahmed et al., 2024), or real estate firms' revenues can be negatively affected if the houses are located in coastal areas (Murfin and Spiegel, 2020). Furthermore, climate change-related regulations may pose a threat to well-established firms' operations, such as those in the fossil fuel industry (Ridley, 2023). Moreover, evidence suggests that political instability as a result of climate change can affect firms' strategic decisions and operations (Jia and Li, 2020).

From a theoretical perspective, the real-options theory suggests that firms particularly prone to climate change may decrease capital expenditures due to disruptions to production processes as a way to maintain flexibility (Busch and Hoffmann, 2009; Tyler and Chivaka, 2011). According to Abhijeet Ghadge and Seuring (2020) extreme weather events, such as floods, can disrupt supply chains by damaging tranportation networks and infrastructure which delays deliveries of goods and services. These disruptions contribute to increased operating costs for firms through increased insurance premiums (Frame et al., 2020; Huynh et al., 2020). Several studies show that increased exposure to extreme weather negatively affects firms' revenues and operating income (Huang et al., 2022), firms' valuation (Bagh et al., 2024), corporate governance and market reaction (Bolton and Kacperczyk, 2023; Javadi and Masum, 2021; Venturini, 2022). Agoraki et al. (2024) find that across 67 countries, firms with high climate change exposure have reduced investment activity, while Ahmed et al. (2024) finds that in the United Kingdom (U.K.) high humidity can negativley influence stock index returns because high temperatures can increase the likelihood of floods or hurricanes which can disrupt firms' productive capacities and lower their stock prices. Firms also face challenges to finance their investments to adopt climate-friendly technologies as they face unfavourable financing terms, such as higher interest rates and more stringent collateral terms due to climate risk premiums required by banks (Nguyen et al., 2022; Pankratz et al., 2023). Cepni et al. (2024) find that higher exposure to climate risk is associated with higher cost of equity financing for U.S firms driven by uncertainty about new business opportunities. As a result, firms tend to adopt more conservative financing strategies but at the same time face increased climate risks by lowering leverage and increasing cash holdings (Ginglinger and Moreau, 2023; Li et al., 2022).

On the other hand, the saliency theory posits that managers may prioritise different corporate investment strategies depending on the firms' exposure to climate change (Ahmed et al., 2024). For example, firms operating in the outdoor recreation industry may experience lower revenues and stock prices during periods of extreme heat and poor air quality as consumers may be less willing to engage in outdoor activities, but firms in the airconditioning and purification sector may experience increased demand and higher stock prices during this same period (Tzouvanas et al., 2019). As such, investment managers may diversify their portfolios across different industries that are able to benefit from the climate change.

A third theoretical underpinning, referred to as risk-shifting, argues that firms may actually increase capital expenditures, preferring to shift their investments into more climate-friendly operations (Rao et al., 2022). According to Drempetic et al. (2020), climate risk exposure is expected to raise businesses' need for investment capital in order to improve their adaptability to climate change-related technologies. Firms particularly prone to climate change may be encouraged to shift to green technologies, thus stimulating investment demand (Nguyen and Phan, 2020). For example, Srivastava et al. (2024) find that over half of the U.K. firms expect climate change to have a positive impact on their investments in the medium term, with some of these investmets in addition to normal capital expenditures. Evidence also indicates that firms that shift investments towards addressing climate risk increase their financial performance and valuation (Giese et al., 2019; Fafaliou et al., 2022). Furthermore, Ma et al. (2023) show that across 34 countries, firms exposed to climate change opportunities have increased corporate investments, especially in countries with developed financial markets.

The studies discussed above highlight that the empirical literature to date is heavily weighted towards the adverse effects of climate change on firms' performances. However, there is growing awareness that climate change may create incentives for firms that are transitioning to climate change-orientated innovations. We position our study within the risk-shifting theory as this strand of literature is still sparse, thus providing us with scope to contribute further evidence on the discussion about climate change and growth opportunities.

3. Modelling Framework

3.1. Spatial Panel-Data Models

Along a baseline panel model, we focus for most of the part of this paper on a spatial version of the panel model. The spatial dimension is modeled through the production network dimension, see the data section.

We consider a the dependent variable y_t of dimension n and k regressors X_t of size $n \times k$. The spatial structure comes through the matrix W of size $n \times n$.

We start from a basic spatial model, the spatial autoregressive model, and then also consider alternative models like the Durbin model, as well the spatial autoregressive version characterized by autocorrelated errors.

$$y_t = \rho W y_t + X_t\beta + \mu + \epsilon_t \tag{1}$$

To characterize the spatial autoregressive specification[4] , we consider μ as indicating the parameters to be estimated. The coefficient ρ stands for the spatial autocorrelation. As assume we assume that $\epsilon_{i,t}N(0, \sigma_\epsilon^2)$ and $E(\epsilon_{it}\epsilon_{js}) = 0$ for $j \neq i$ or $t \neq s$.

Another approach can be based on the spatial Durbin model [5], which a

[4]denoted by SAR, from here on.
[5]denoted by SDM, from here on.

generalizes the SAR model.

$$y_t = \rho W y_t + X_t \beta + W X_t \theta + \mu + \epsilon_t \tag{2}$$

What is different is here is that there are also spatial effects for the independent variables. As an additional model, we use the SAR with characterized by autocorrelated errors, also known as the SAC model. We write the SAC model as follows:

$$y_t = \rho W y_t + X_t \beta + \mu_t + \nu_t \tag{3}$$

For the specific case of the SAC model, the errors are modeled through the following equation:

$$\nu_t = \lambda W \nu_t + \epsilon_t \tag{4}$$

Finally, we also take into account the a spatial errors model (SEM, hereafter). This is specified as:

$$y_t = X_t \beta + \mu_t + \nu_t \tag{5}$$

What is specific for this model is the modelling of the error term:

$$\nu_t = \lambda W \nu_t + \epsilon_t \tag{6}$$

As it becomes clear from last equation, the SEM model can be seen as a more specific model of the more general cases of the SAC or SDM versions.

4. Data

The dataset combines several types of data. The first type of data is related to climate shocks. This index, called the Actuaries Climate Index [6], ACI hereafter. This index measures the frequency of extreme weather and the changes in sea level. There are six components that ACI covers:

1. High temperatures;
2. Low temperatures;
3. Heavy rainfall;
4. Drought (consecutive dry days);
5. High wind; and
6. Sea level.

As for the two temperature components, they are defined as the change in the 90% percentile for high temperature, and in the 10% percentile for low temperature. The index is computed as:

$$ACI = mean(T90_{\text{std}} - T10_{\text{std}} + P_{\text{std}} + D_{\text{std}} + W_{\text{std}} + S_{\text{std}}) \tag{7}$$

Here T_90 is the 90% percentile for high temperature, $T10$ the 10% percentile for low temperature, P for heavy rainfall, D for drought, W for high wind and S for sea level.

We use a second dataset with data on US firms from Compustat database

[6]https://actuariesclimateindex.org/faqs/

which covers all listed companies on the stock market. The firm-level data is aggregated at sectoral level using sector classifications from the Bureau of Economic Analysis (BEA, hereafter). The data spans from 1985Q1 to 2019Q4, leaving us with 6,440 industry-time observations. The dependent variable is the firm-level investment rate. This is the dependent variable in our regressions. This is measured as the ratio between capital expenditures and property, plants and equipment, see (Cloyne et al., 2023).

We further use variables related to the balance sheets of the firms, namely liquidity and leverage. Liquidity is measured by summing up cash and short-term investments on one hand and computing the share with respect to total assets. We measure the leverage aby dividing total debt bytotal assets.

A third dataset is related to macroeconomic uncertainty at various forecast horizons as derived from Jurado et al. (2015), wherein the h-period-ahead uncertainty, is defined as the diffusion index involving conditional volatility of the purely unforecastable component of the future value of the large number of macroecomic and financial variables, based on the data set of Ludvigson and Ng (2009).

The final dataset we use is related to the network dimension. We follow closely the method described in Ozdagli and Weber (2017). Using the input-output tables [7], we compute a matrix of trade flows from industry to industry.

The IO Tables as constructed by BEA have two parts, the ”USE” and the

[7] the source is the Bureau of Economic Analysis

"MAKE" tables. For the case of "USE" tables, they comprise the utilization of commodities by users (which can be either intermediate or final). On the other hand, "MAKE" tables contain production data for the different industries, with rows describing industries and columns the commodity produced there.

To estimate the sector-by-sector matrix, we use the steps detailed by Ozdagli and Weber (2017). There are several steps which are described below. First, we determine market shares, denoted by SHARE, as:

$$\mathrm{SHARE} = \mathrm{MAKE} \circ (I \times \mathrm{MAKE}) \tag{8}$$

Here I stands for the matrix of ones having similar dimensions to "MAKE" and "USE" tables, and $\circ$ represents the so-called Hadamard operator.

Next, we evaluate REVSHARE which gives the value that a sector k' sells to a sector k:

$$\mathrm{REVSHARE} = \mathrm{SHARE} \times \mathrm{USE} \tag{9}$$

Finally, the REVSHARE matrix, i.e. known as revenue-share matrix, is further used to compute the percentage at which a sector k inputs get bought from a sector k'. The resulting matrix is called SUPSHARE and is obtained:

$$\mathrm{SUPPSHARE} = [\mathrm{REVSHARE} \circ (I \times \mathrm{USE})]' \tag{10}$$

The row-normalized version of this matrix is used as the spatial estimations as the matrix W where the main diagonal entries are also set to zero.

To combine the firm data with the production network data, we use concordances provided by the BEA between the BEA classification and the NAICS classification and combine the datasets by the NAICS classification.

5. Results

5.1. Model Selection

The presentation above on the spatial models highlighted the existence of alternative models that can be used in the modeling of the spatial effects. The macroeconomic literature lends towards the SAR model, see for example Ozdagli and Weber (2017) that use a SAR specification to model the spatial effects of monetary policy shocks on the stock market. A close approach is followed by Caraiani (2022) when evaluating the impact of oil policy shocks on investment rates at firm level.

We test here which of the specifications is justified. We focus on the baseline case, where we estimate the impact of daci and daci12 on the investment rate. We consider the SDM and test whether it can be simplified either to the SAR or to the SFM specifications.

We start by testing if the SDM can be simplified to the SAR specification and test: $\theta = 0$ and $\rho \neq 0$. The null hypothesis that $\theta = 0$ can be rejected as $\chi^2 = 6.9$ for daci and $\chi^2 = 6.6$ for daci12. Thus, SAR specification is to be preferred. Also, the estimated ρ is statistically different from zero.

Second, we test if the SDM can be rejected in the favor of the SEM version by considering the null hypothesis that $\theta = -\beta\rho$. But as this alternative is rejected, ($\chi^2 = 10.54$), the SDM model is prefered. In the second case, $\chi^2 = 9.12$ and again the null hypothesis is rejected.

We also test for fixed effects (FE) against random effects (RE) in the estimations of the model. To differentiate between the FE and the RE panel models, we use the Hausman test. For both cases (SDM or SAR), the Hausman test indicates FE model. The baseline model that we use is therefore the SAR model with FE.

5.2. Baseline Results

We look now at the estimations for the baseline regression model where there are no indirect effects, as well as the results for the spatial panel estimation where we can observe both the direct and indirect effects. Direct effects are the effects of the climate shocks on the firm, whereas indirect effects capture the spillover effects of climate shocks on neighbouring firms.

In Table 1, we can see the results for the baseline regressions. We look at both daci (first difference in ACI) and daci12 (12 lags difference for ACI). The results are robust across the different variables that are taken as endogenous: a shock in daci or daci12 has a statistical positive effect on rate of investments, capital expenditures (log_cap) or property, plants and equipment (log_ppe). We also observe that capital expenditures have larger coefficients than the other outcome variables suggesting that firms are increasing spend-

Table 1: Baseline Regression Results

	(1) (mean) rinvest	(2) (mean) rinvest	(3) log_cap	(4) log_cap	(5) log_ppe	(6) log_ppe
daci	0.0148^{***}		0.378^{***}		0.245^{***}	
	(0.00216)		(0.0381)		(0.0401)	
daci12		0.0326^{***}		1.340^{***}		1.094^{***}
		(0.00835)		(0.198)		(0.186)
Constant	0.123^{***}	0.123^{***}	5.067^{***}	5.028^{***}	7.517^{***}	7.479^{***}
	(0.000198)	(0.000460)	(0.00350)	(0.0109)	(0.00368)	(0.0102)
Observations	6440	6440	6440	6440	6440	6440
Adjusted R^2	0.007	0.004	0.017	0.026	0.009	0.021
F	46.75	15.22	98.45	45.89	37.38	34.75

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ing in new assets or improving existing fixed assets in an effort to mitigate climate risk. The results are in line with the risk-shifting theory that firms are shifting their investments into more eco-friendly production processes. These findings are also supported by Ma et al. (2023), Nguyen and Phan (2020) and Srivastava et al. (2024) who show that firms transitioning to cleaner technologies stimulate investment demand.

Table 2 below shows the estimates for the SAR specification using again daci and daci12 as explanatory variables. We observe statistically significant positive effects on the rate of investment, capital expenditures and property, plants, and equipment in line with our baseline results. For the direct effects, we find that an increase in the frequency of climate shocks for firms increases

Table 2: Baseline Spatial Regression Results

	(1) (mean) rinvest	(2) (mean) rinvest	(3) log_cap	(4) log_cap	(5) log_ppe	(6) log_ppe
Main						
daci	0.00380*		0.120***		0.0735*	
	(0.00196)		(0.0419)		(0.0396)	
daci12		0.00845		0.440**		0.350*
		(0.00823)		(0.212)		(0.189)
Spatial						
rho	0.741***	0.742***	0.691***	0.688***	0.690***	0.685***
	(0.0362)	(0.0362)	(0.0497)	(0.0503)	(0.0695)	(0.0704)
Variance						
sigma2_e	0.00202***	0.00202***	0.581***	0.580***	0.481***	0.480***
	(0.000377)	(0.000377)	(0.0753)	(0.0751)	(0.0681)	(0.0679)
LR_Direct						
daci	0.00421*		0.129***		0.0800*	
	(0.00220)		(0.0453)		(0.0433)	
daci12		0.00951		0.476**		0.380*
		(0.00918)		(0.230)		(0.206)
LR_Indirect						
daci	0.0102*		0.245***		0.156	
	(0.00587)		(0.0904)		(0.0994)	
daci12		0.0229		0.881**		0.712
		(0.0228)		(0.439)		(0.440)
LR_Total						
daci	0.0144*		0.374***		0.236*	
	(0.00799)		(0.130)		(0.138)	
daci12		0.0324		1.358**		1.092*
		(0.0318)		(0.653)		(0.623)
Observations	6440	6440	6440	6440	6440	6440
Adjusted R^2	0.0050	0.0030	0.0060	0.0093	0.0028	0.0068

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

investments for the same firms by 0.004 percentage points. These findings are robust for capital expenditures and property, plants and equipment with an increase of 0.1 percentage points recorded. For the indirect effects, except for property, plants and equipment, we also observe positive and statistically significant coefficients, with the indirect effects accounting for about two thirds of the total effects. The spill-over effects from climate shocks to neighbouring firms is larger for investments at 0.1 percentage points and for capital expenditures at 0.2 percentage points. These spill-over effects may suggest that as firms shift investments or capital expenditures to climate-friendly production processes, neighbouring firms may also be encouraged or forced to adapt accordingly so that they remain competitive in the same industry. We also observe that for investments in the long-run (12 lags), the positive effects become smaller and muted suggesting that firms may have transitioned by then and as such investments may be increasing at a slower rate as compared to initial period of changing business structures. On the other hand, the positive returns from climate shocks on capital expenditures and property, plants and equipmemt are persistent in the long-run.

5.3. Robustness

We extend the analysis by considering several additional estimations: sub-sample analysis, controlling for financial characteristics of firm as well as controlling for macroeconomic uncertainty.

5.3.1. Quantitative Easing period versus Great Moderation period

We look here at the effect of restricting the analysis to sub-samples. We look first at a sub-sample corresponding to the Great Moderation, from 1985 Q1 to 2007Q4. The Great Moderation was a period of decreased macroeconomic volatility experienced in the U.S. from the mid-1980s to the financial crisis in 2007. During this period, the country was characterised by low inflation, increased investments and positive economic growth (Hakkio, 2013). We also look at a second sub-sample corresponding to the unconventional monetary policy period (up to 2019Q4), containing basically the Great Recession and its aftermath. The Great Recession was a period of economic downturn from 2007 to 2009 after the bursting of the U.S housing bubble and the ensuing global financial crisis that spilled over to the rest of the world for several years afterwards. During this period several large financial firms in the U.S. experienced significant financial distress resulting in large disinvestments, high unemployment rates and decreased economic growth in the country (Weinberg, 2013). We choose these two sub-samples because the economic dynamics playing out in the U.S during the stable versus unstable periods may affect the association between climate shocks and investments differently. The estimates are presented in Appendix C.

While the results are generally robust for the two sub-samples in terms of positive coefficients across the specifications, we however observe more statistically significant coefficients in the Great Moderation sub-sample, especially for capital expenditures as well as property, plants and equipment, in comparison with the Great Recession sub-sample, were the effects on property, plants and equipment are relatively stronger. These findings highlight the weakening effects of the macroeconomic instability during the Great Recession on firms' ability to invest and spend on capital expenditures necessary for adapting to climate change. We can see again the spillover effects dominating the direct effects for all the cases.

5.3.2. Controlling for Firm-level Financial Variables

According to Srivastava et al. (2024), firms adopting green technologies are expected to finance these changes primarily with their internal cash reserves. Therefore, as a further robustness test, we look at the impact of liquidity, as well as leverage measured at firm-level. To better measure the impact, we interact the shocks with the two measures of financial characteristics. The estimates are shown in Appendix D.

Interacting with liquidity leads to similar results as for reference case, but with stronger coefficients. The indirect effects are also slightly more pronounced than for the baseline case. The results indicate that liquidity amplifies the positive effects of climate shocks on investments and other outcome variables. The availability of liquid assets, such as cash, can affect the realisation of potential investments for firms. These findings are in line with Ma et al. (2023) who find that the positive effect of climate change on corporate investments is larger for firms that are financially unconstrained.

The role of leverage, though retaining the positive effects of climate shocks on the outcome variables, appears to nullify the statistical significance, except for capital expenditures. According to Nguyen et al. (2022) and Javadi and Masum (2021), increased borrowing costs due to climate risks can leave firms vulnerable to increased spreads on bank loans and mortgages.

5.3.3. Controlling for Macroeconomic Uncertainty

As a third robustness estimation, we look at macroeconomic uncertainty as suggested in the study by Jurado et al. (2015). We consider uncertainty at various forecast horizons, at one month (mu_h1), three months (mu_h3) and at 12 months (mu_h12). However, we present the results only for forecast horizon at one month in Appendix E, since the estimates for the other cases are weaker.

The inclusion of macroeconomic uncertainty in the estimations does not attenuate the positive effects of climate shocks on the outcome variables, with the spillover effects larger than the direct effects on firms. These results remain consistent with our baseline spatial regression model findings. Macroeconomic uncertainty is positive and statistically significant mainly for property, plants and equipment.

6. Conclusion

According to the Intergovernmental Panel on Climate Change's (IPCC) Sixth Assessment Report, it is going to become harder to adapt as climate shocks are happening quicker and will become more severe sooner than previously anticipated (Adler et al. (2022)). Therefore, understanding the causes and consequences of climate change has become paramount for all, including individuals, stakeholders, governments and firms. The results from this study show that climate shocks have positive effects on investment rates for U.S. firms with larger spillover effects on neighbouring firms. These findings remain consistent across various robustness checks, such as using different outcome variables, using sub-samples, and including financial characteristics of firms.

This study offers insightful perspectives on climate change effects. First, climate shocks can have potential growth opportunities for firms, thus shifting the evidence-based focus from adverse impacts to exploring alternative avenues for leveraging the returns from climate change. Second, firms may opt to increase investments in production processes that are more climate friendly. This transition may be altruistic, to meet government climate change regulations or to avoid stiff carbon penalties, but either way it improves the profile of firms making them attractive to potential investors, which can in turn positively impact the firms' revenues and stock prices. Firms may also increase their investments in sectors that are likely to profit from climate shocks. Lastly, the financial characteristics of the firms can offset or reinforce the positive effects of climate change on firms. For example, firms with high liquidity and low leverage will be more capable to invest in and adopt stratgeies that address climate risk, compared to firms with low cash holdings and high borrowing costs. We believe the findings from this study can provide increased awareness and enrich knowledge on the nuanced dynamics involving climate change and firms' behaviour.

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Appendix A. Descriptive Statistics

	Mean	SD	Min	Max	N
(mean) rinvest	0.12	0.07	0.00	1.02	6,440.00
(mean) liquidity	0.09	0.06	0.01	0.75	6,440.00
(mean) lvrg	0.34	0.12	0.00	0.82	6,440.00
daci	0.09	0.33	-0.72	0.96	6,440.00
daci12	0.06	0.12	-0.15	0.35	6,440.00
(mean) mu_h1	0.63	0.08	0.53	1.08	6,440.00
(mean) fu_h1	0.89	0.18	0.64	1.50	6,440.00

Appendix B. Unit Root Tests

Table B.1.Unit Root Testsl

Variable	LLC	IPS	Breitung	Fisher-ADF	Fisher-PP
investment rate	-51.6263 (0.00)	-50.0783 (0.00)	-31.9626(0.00)	-49.4464(0.00)	-52.3745 (0.00)
liquidity	-6.0932 (0.00)	-13.4070(0.00)	-10.7618 (0.00)	-9.4508 (0.00)	-12.8833(0.00)
leverage	-0.1828 (0.42)	-8.4956(0.00)	-6.6589 (0.00)	-5.6848 (0.00)	-7.8763(0.00)
daci	-35.5547 (0.00)	-45.1675(0.00)	-27.3160(0.00)	-38.3587(0.00)	-50.6845(0.00)
daci12	-0.7442 (0.22)	0.3668(0.64)	-8.9464 (0.00)	-7.2434(0.00)	-2.1756(0.01)
mu_h1	-14.8894 (0.00)	-6.7963 (0.00)	-15.8933(0.00)	-20.1885(0.00)	-11.2643 (0.00)
fu_h1	-11.7795 (0.00)	-7.1943(0.00)	-14.1709(0.00)	-19.1704(0.00)	-11.1874(0.00)

Note: the corresponding p-values are in parentheses.

Appendix C. The Impact of Climate Shocks: Pre-QE Versus QE Samples

Table C.3: Spatial Regression Results: Pre-UMP

	(1) (mean) rinvest	(2) (mean) rinvest	(3) log_cap	(4) log_cap	(5) log_ppe	(6) log_ppe
daci	0.00422		0.0902**		0.0454	
	(0.00267)		(0.0392)		(0.0344)	
daci12		0.0102		0.525**		0.518***
		(0.0117)		(0.228)		(0.182)
Spatial						
rho	0.739***	0.740***	0.674***	0.662***	0.622***	0.602***
	(0.0368)	(0.0367)	(0.0485)	(0.0501)	(0.0772)	(0.0779)
Variance						
sigma2_e	0.00224***	0.00224***	0.536***	0.534***	0.406***	0.404***
	(0.000483)	(0.000483)	(0.0846)	(0.0839)	(0.0671)	(0.0664)
LR_Direct						
daci	0.00470		0.0971**		0.0490	
	(0.00299)		(0.0423)		(0.0372)	
daci12		0.0116		0.563**		0.548***
		(0.0130)		(0.246)		(0.196)
LR_Indirect						
daci	0.0114		0.170**		0.0762	
	(0.00798)		(0.0756)		(0.0670)	
daci12		0.0288		0.938**		0.765**
		(0.0330)		(0.421)		(0.389)
LR_Total						
daci	0.0161		0.267**		0.125	
	(0.0109)		(0.115)		(0.102)	
daci12		0.0404		1.501**		1.313**
		(0.0458)		(0.649)		(0.555)
Observations	4416	4416	4416	4416	4416	4416
Adjusted R^2	0.0351	0.0347	0.0028	0.0107	0.0007	0.0081

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Spatial Regression Results: UMP

	(1)	(2)	(3)	(4)	(5)	(6)
	(mean) rinvest	(mean) rinvest	log_cap	log_cap	log_ppe	log_ppe
daci	0.00250		0.104		0.164***	
	(0.00263)		(0.0732)		(0.0627)	
daci12		0.00123		0.359		0.929***
		(0.0112)		(0.332)		(0.301)
Spatial						
rho	0.770***	0.772***	0.674***	0.669***	0.213	0.0431
	(0.0515)	(0.0514)	(0.0616)	(0.0624)	(0.147)	(0.143)
Variance						
sigma2_e	0.00114***	0.00114***	0.271***	0.271***	0.165***	0.160***
	(0.000156)	(0.000156)	(0.0450)	(0.0449)	(0.0392)	(0.0397)
LR_Direct						
daci	0.00286		0.113		0.167**	
	(0.00298)		(0.0796)		(0.0651)	
daci12		0.00175		0.392		0.942***
		(0.0127)		(0.360)		(0.309)
LR_Indirect						
daci	0.00792		0.202		0.0543	
	(0.00889)		(0.155)		(0.0550)	
daci12		0.00323		0.669		0.0534
		(0.0378)		(0.659)		(0.151)
LR_Total						
daci	0.0108		0.315		0.221**	
	(0.0117)		(0.230)		(0.109)	
daci12		0.00497		1.061		0.995***
		(0.0501)		(1.004)		(0.357)
Observations	2208	2208	2208	2208	2208	2208
Adjusted R^2	0.0038	0.0002	0.0051	0.0072	0.0025	0.0058

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D. The Impact of Climate Shocks: Controlling for Financial Characteristics

Table D.5: Spatial Regression Results: The role of liquidity

	(1) (mean) rinvest	(2) (mean) rinvest	(3) log_cap	(4) log_cap	(5) log_ppe	(6) log_ppe
liq_daci	0.0496*		1.456***		1.206**	
	(0.0268)		(0.493)		(0.520)	
liq_daci12		0.164		6.876***		5.810**
		(0.128)		(2.537)		(2.470)
Spatial						
rho	0.741***	0.741***	0.691***	0.683***	0.688***	0.679***
	(0.0361)	(0.0362)	(0.0495)	(0.0503)	(0.0694)	(0.0704)
Variance						
sigma2_e	0.00202***	0.00202***	0.580***	0.578***	0.480***	0.478***
	(0.000378)	(0.000378)	(0.0750)	(0.0739)	(0.0678)	(0.0674)
LR_Direct						
liq_daci	0.0550*		1.570***		1.309**	
	(0.0301)		(0.536)		(0.573)	
liq_daci12		0.183		7.407***		6.277**
		(0.143)		(2.750)		(2.691)
LR_Indirect						
liq_daci	0.133*		2.981***		2.583*	
	(0.0800)		(1.130)		(1.483)	
liq_daci12		0.440		13.59**		11.71*
		(0.358)		(5.482)		(6.250)
LR_Total						
liq_daci	0.188*		4.551***		3.893**	
	(0.109)		(1.604)		(1.979)	
liq_daci12		0.622		21.00***		17.99**
		(0.497)		(7.952)		(8.545)
Observations	6440	6440	6440	6440	6440	6440
Adjusted R^2	0.0069	0.0059	0.0080	0.0144	0.0036	0.0092

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: Spatial Regression Results: The role of leverage

	(1)	(2)	(3)	(4)	(5)	(6)
	(mean) rinvest	(mean) rinvest	log_cap	log_cap	log_ppe	log_ppe
lvrg_daci	0.00506		0.278^{**}		0.165	
	(0.00542)		(0.113)		(0.116)	
lvrg_daci12		0.00468		0.906		0.790
		(0.0203)		(0.555)		(0.536)
Spatial						
rho	0.742^{***}	0.743^{***}	0.693^{***}	0.690^{***}	0.690^{***}	0.685^{***}
	(0.0361)	(0.0361)	(0.0495)	(0.0500)	(0.0695)	(0.0705)
Variance						
sigma2_e	0.00202^{***}	0.00202^{***}	0.581^{***}	0.581^{***}	0.481^{***}	0.481^{***}
	(0.000377)	(0.000377)	(0.0754)	(0.0753)	(0.0681)	(0.0680)
LR_Direct						
lvrg_daci	0.00573		0.301^{**}		0.180	
	(0.00606)		(0.123)		(0.127)	
lvrg_daci12		0.00593		0.986		0.862
		(0.0226)		(0.605)		(0.584)
LR_Indirect						
lvrg_daci	0.0142		0.576^{**}		0.351	
	(0.0154)		(0.256)		(0.279)	
lvrg_daci12		0.0152		1.846		1.613
		(0.0553)		(1.182)		(1.223)
LR_Total						
lvrg_daci	0.0200		0.877^{**}		0.531	
	(0.0214)		(0.369)		(0.396)	
lvrg_daci12		0.0211		2.832		2.475
		(0.0777)		(1.759)		(1.758)
Observations	6440	6440	6440	6440	6440	6440
Adjusted R^2	0.0034	0.0015	0.0049	0.0073	0.0025	0.0061

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix E. The Impact of Climate Shocks: Controlling for Uncertainty

Table E.7: Spatial Regression Results: The role of macroeconomic uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)
	(mean) rinvest	(mean) rinvest	log_cap	log_cap	log_ppe	log_ppe
daci	0.00353*		0.135***		0.0954***	
	(0.00195)		(0.0384)		(0.0361)	
daci12		0.00762		0.486**		0.419**
		(0.00825)		(0.204)		(0.184)
(mean) mu_h1	-0.00628	-0.00699	0.315	0.339	0.455*	0.497**
	(0.0107)	(0.0106)	(0.257)	(0.249)	(0.249)	(0.245)
Spatial						
rho	0.741***	0.741***	0.688***	0.684***	0.683***	0.676***
	(0.0362)	(0.0362)	(0.0492)	(0.0499)	(0.0691)	(0.0701)
Variance						
sigma2_e	0.00202***	0.00202***	0.581***	0.580***	0.480***	0.480***
	(0.000378)	(0.000378)	(0.0751)	(0.0749)	(0.0678)	(0.0676)
LR_Direct						
daci	0.00392*		0.146***		0.103***	
	(0.00219)		(0.0416)		(0.0397)	
daci12		0.00863		0.525**		0.454**
		(0.00922)		(0.222)		(0.200)
(mean) mu_h1	-0.00726	-0.00804	0.324	0.350	0.476*	0.520**
	(0.0112)	(0.0112)	(0.267)	(0.259)	(0.261)	(0.256)
LR_Indirect						
daci	0.00970		0.282***		0.207*	
	(0.00591)		(0.0935)		(0.110)	
daci12		0.0213		0.993**		0.867*
		(0.0232)		(0.445)		(0.468)
(mean) mu_h1	-0.0178	-0.0198	0.659	0.697	0.988	1.044
	(0.0276)	(0.0277)	(0.581)	(0.561)	(0.703)	(0.693)
LR_Total						
daci	0.0136*		0.428***		0.311**	
	(0.00802)		(0.128)		(0.143)	
daci12		0.0299		1.518**		1.321**
		(0.0322)		(0.647)		(0.637)
(mean) mu_h1	-0.0251	-0.0278	0.983	1.048	1.464	1.564*
	(0.0387)	(0.0388)	(0.839)	(0.810)	(0.937)	(0.919)
Observations	6440	6440	6440	6440	6440	6440
Adjusted R^2	0.0048	0.0029	0.0211	0.0243	0.0267	0.0304

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$