Adapting to climate risks through cross-border investments: industrial vulnerability and smart city resilience

Yao An¹,² · Ning Liu³ · Lin Zhang¹,³,⁵ · Huanhuan Zheng⁴

Received: 2 March 2022 / Accepted: 26 August 2022 / Published online: 14 September 2022
© The Author(s), under exclusive licence to Springer Nature B.V. 2022

Abstract
Climate change entails potential risks for investors, and its effects on investment has spread beyond physical borders. This study investigates how multinational corporations (MNCs) incorporate climate risks into their decisions regarding foreign direct investments (FDIs). We find that large differences in the climate risks of home and host cities discourages FDI by increasing cross-border adaptation costs. Such impacts are particularly pronounced among environmentally sensitive industries that are more exposed to climate risks. Further analysis reveals that city-based smartness factors mitigate the negative impacts of climate risk differences on FDI by reducing adaptation costs and engendering new business opportunities. This study provides new evidence on the profound effects of climate risks on FDI and how smart cities can increase their resilience to climate risks in the context of international business.

Keywords Climate risk · Cross-border investments · Business and the environment · Smart city · Resilient effect

1 Introduction

Studies have shown that global warming triggers labor migration, undermines human productivity, and disrupts global supply chains.¹ Multinational corporations (MNCs) that mobilize global resources to optimize their production networks are exposed to

¹ Supplementary material. Dell et al. (2012) estimate the interaction between climate change and economic growth. Dell et al. (2014) also assess the potential economic effects of future climate change on the particular channels of labor productivity, political stability, energy use, health, and migration. Burke et al. (2016) and van Vuuren et al. (2020) find that refining a climate policy can delay and mitigate impact of uncertainties and damages on economic development.

* Lin Zhang
l.zhang@cityu.edu.hk

¹ School of Energy and Environment, City University of Hong Kong, Kowloon, Hong Kong
² Institute of Energy, Environment, and Economy, Tsinghua University, Beijing, China
³ Department of Public and International Affairs, City University of Hong Kong, Kowloon, Hong Kong
⁴ Lee Kuan Yew School of Public Policy, National University of Singapore, Singapore, Singapore
⁵ Center for Ocean Research in Hong Kong and Macau (CORE), Hong Kong, Hong Kong
significant economic and social burdens as global warming accelerates. It has become increasingly important for MNCs to incorporate climate change risk into their decision-making processes, especially in the location choices of foreign direct investments (FDI) (Andersson et al. 2016; Bender et al. 2019; Li and Gallagher 2022). Foreign direct investment is a business decision for the multinational corporations from home city to acquire a substantial stake in a foreign business or to purchase physical assets, such as plant and equipment, with operational control ultimately residing with the parent company. And the firms in host city receive investment to carry out a set of economic activities embracing production, employment, sales, purchase and use of intermediate goods and fixed capital. The cities of potential FDI destinations contain important information of climate change risk for several reasons. First, cities are major players in the governance of climate change (Bulkeley 2010; Bulkeley et al. 2014). Second, cities produce most of the global emissions of greenhouse gases (Dhakal 2010). Third, urban vulnerabilities to climate change are closely related to the natural and geographic environment as well as technology advancement of cities (Seto et al. 2010; Fernández and Peek 2020). We are interested in whether and how MNCs extrapolate information from city-level climate change risk to inform their investment decisions.

To achieve the goals of the Paris Agreement, many countries have pledged for net zero carbon emissions by 2050. How various urban climate policies are designed to meet national carbon targets depends on policy makers’ perceptions of climate change risk. Policy makers have to implement more stringent climate policies if they perceive a larger gap between current and target emissions. Different pursues of climate policies across major world cities create both risks and opportunities for international businesses. A climate policy that regulates greenhouse gas emissions imposes additional administrative costs on firms that must disclose information and comply with regulations. It also increases firms’ production costs by compelling firms to internalize their social cost of emissions. A number of MNCs, carbon-intensive ones in particular, have reallocated their production facilities across borders in response to climate policies and extreme events (Babiker 2005; Linnenluecke et al. 2011). MNCs that have developed strategies to comply with location-specific regulatory rules in their home cities face significant challenges in host cities with different environmental and regulatory practices. Thus, MNCs need to consider the adaptation costs, driven by the heterogeneous climate risks that inform different policies and regulations when investing abroad.

MNCs are also exposed to new business opportunities that arise from global climate actions. Policies dedicated to mitigating climate change stimulate technological innovation, from which firms usually earn a monopolistic markup (Nesta et al. 2014). As long as climate risks are priced according to the policy instruments in a market, developing firm-specific green advantages form the primary sources of firms’ profitability, growth, and business sustainability (Kolk and Pinkse 2008). Private sectors also join the campaign to save the planet through sustainable, responsible, and impact (SRI) investing in climate responsible firms that enable them to improve the access capital at a lower cost (Chava 2014; Pástor et al. 2021). Heterogeneous climate practices and preferences, which depend fundamentally on climate risk, increase the difficulty for MNCs to identify climate-related opportunities abroad.

How do MNCs incorporate city-level climate change risks into their FDI decisions to manage risks and exploit opportunities? To answer this question, we follow Buggle
and Durante (2021) to measure climate risk in a city by the standard deviation of its monthly temperature over the past ten years. Such a measure captures the aggregate impact of interwind factors, such as public and private climate actions, urban development, technology advance, and nature environment, on global warming. It saves us from addressing the omitted variable concerns and confounding factors when measuring climate risk indirectly with potential determinants of global warming. Moreover, as policy makers extrapolate policy effectiveness from observed temperature variations, adjust their perceptions of climate risk, and revise their actions accordingly, such a measure of climate risk inform MNCs of future regulatory changes. Interested in how MNCs respond to climate risk from the adaptation cost perspective, we focus on the difference between the climate risk in home and host cities. Given the slow-moving nature of temperature, such a measure of climate risk that is based on historical temperature variations is relatively exogenous. It is unlikely to be affected by MNCs’ business activities, facilitating the identification of its impact on MNCs’ cross-border direct investments.

Brownfield investments refer to transnational mergers and acquisitions (M&A), embracing merging with or buying an existing facility. Greenfield investments consist of constructing a new non-existent facility from the ground in host country. There are two major reasons why we use greenfield FDI rather than brownfield FDI. First, comparing with brownfield FDI, greenfield FDI are more sensitive to physical climate risk. For instance, increased flooding and rainfall shut down the business at Toyota’s manufacturing facilities in Southeast Asia and rising sea levels hits the Chinese infrastructure investments in Pakistan. Second, our dataset covers greenfield FDI only. The cross-border M&A data from separate data sources such SDC have too many missing observations on M&A value. Besides, it is difficult to map the target of acquisitions into city-level climate risk because the target could spread over multiple cities. Our investigation concentrates on how do MNCs incorporate city-level climate change risks into FDI decisions to manage risks and exploit opportunities. The data availability for greenfield FDI in city level fits well with our focus. Using the greenfield cross-border direct investments from 6713 home cities of MNCs and 12,284 of the host cities for their investment destinations over the sample period 2003–2017 (Fig. 4 in the Appendix), we document robust evidence that greenfield foreign direct investments (FDIs) fall as the climate risk difference between home and host cities increases. That is, MNCs invest more (million USD) in host cities that are more similar to their home cities. Prior research has emphasized the importance of industrial differences in MNCs’ exposure to the risks and opportunities arising from climate change (Fleming et al. 2006; Kolk & Pinkse 2008). In line with the literature, we argue that FDIs in environmentally sensitive industries are more responsive to city-level climate risk differences because they heavily rely on the natural environment and resources (Fleming et al. 2006; Huang et al. 2018; Rao et al. 2021). We find evidence that supports this prediction, provided that the climate risk in a home city is lower than that in a host city.

After documenting the negative impact of intercity climate risk differences on cross-border direct investments and industrial vulnerability, we explore possible channels through which a city mitigate such a negative impact. FDIs transfer technology and knowledge, attract capital, and create job opportunities, which are found to benefit overall urban productivity and economic growth (Helpman 2006). Many cities rely on FDIs for their economic growth; how can they overcome climate risk, especially if
a risk difference between home and host cities deters FDI? We explore whether host cities reshape MNCs’ investment responses to climate risk differences by promoting smart city initiatives.

The literature on urban resilience has shown how cities respond to and bounce back from pandemics and natural disasters (Liu et al. 2021). Research of urban resilience to large global challenges, such as climate change, mainly focuses on vulnerable coastal cities (Balica et al. 2012). In this study, we focus on the role of smart cities on MNCs’ investment decisions by mitigating the adaptation costs due to climate risk differences. IBM has defined a smart city as “one that makes optimal use of all the interconnected information available today to better understand and control its operations and optimize the use of limited resources”. The essential goal of a smart city is to achieve sustainability by embracing scaled services, reducing costs and seeking efficiencies (Bibri & Krogstie 2017). Smart city planning and development enhances a city’s resilience and sustainability (Baron 2012). The relative smartness of a host city that is empowered by new technologies enables it to promote sustainable development and to be more resilient and better prepared for future shocks of climate change (e.g., extreme weather, flood risks, or heatwaves), thereby lessening investors’ burden of adapting to climate risk differences between home and host cities. Consistent with this, we find that the impact of climate risk differences on cross-border direct investments is attenuated when host cities are “smarter” than home cities.

This study contributes to the literature on international business and sustainable development to tackle climate risks in two ways, both of which have important policy implications. First, it bridges the gap between climate risk and FDI through documenting new evidence that a city-level climate risk difference discourages cross-border direct investments. MNCs’ FDIs are long-term, bearing the brunt of climate risks and any related policies. While some MNCs shift their production facilities to less regulated markets to bypass domestic climate policies (Aragón-Correa et al. 2016; Berry et al. 2021), others improve green and sustainable development in both their home and host countries (Brucal et al. 2019; Nippa et al. 2021). For instance, MNCs have actively innovated green technologies (Kim et al. 2021), engaged in ESG activities (Zhou and Wang 2020), and reduced their carbon emissions (Nippa et al. 2021). Some studies have highlighted how MNCs engage in activities that could potentially influence or prevent future climate risks. We complement this strand of literature by showing how MNCs incorporate climate risks into their long-term investment decisions by selecting investment destinations that imply lower adaptation costs to manage climate risks and to capture related opportunities.

Second, this study highlights the substantive role host cities’ resilience to climate risks, especially their “smartness,” plays in shaping MNCs’ FDI decisions. In his seminal work, Stern (2008) systematically analyzed the underlying economics of climate change and how climate change should be incorporated into policy-making decisions at the macro level. Since then, climate change policies have been a core concern for governments of various levels, which have driven changes in production techniques through

---

2 Initially, smart cities were prompted in the developed countries where Japan and EU are the two most representative projects. In Japan, it seeks to make its city more environmental soundly and resilient especially after the Great East Japan Earthquake (Yamagata & Seya 2013). In EU, the primary target was to reduce greenhouse gas emissions. The initiatives centers on smart economy, smart mobility, smart environment, smart people, smart living, and smart governance (EU 2014).
stringent regulations (Shapiro and Walker 2018), increased productivity through Porter-type induced innovations (Berman and Bui 2001; Alpay et al. 2002), and contributed to firms’ long-term value creation through market-based instruments, such as green taxes or green bonds (Karydas and Zhang 2019; Flammer 2021). Among these initiatives, smart city development is of a relatively recent vintage. Amid increasing concerns about global climate change, a city needs to endure risks and survive crises by means of the pressing issues confronted by policy-makers and stakeholders. However, little is known about how effective smart city development is for resolving climate change concerns (Neirotti et al. 2014). There are two major reasons why we choose smart city as the urban decision-making factor. First, the data to measure smartness of a city is available. Additionally, one of our main research questions is to explore how the urban development can resolve climate change concerns and attract cross-border direct investments in a growing climate uncertainty. The essential goal of a smart city is to achieve sustainability by embracing scaled services, reducing costs and seeking efficiencies (Bibri & Krogstie 2017). Smart city planning and development enhances a city’s resilience and sustainability (Baron 2012). Compared with other factors of urban such as eco-city and livable city, the features of smart city fit our research question well. By integrating the key features of smart cities into an empirical model, our study indicates a direction that allows governments to increase their cities’ resilience to climate risks through proactive policy-making and smart city building. Our results identify four key facets of smart city development that can improve urban resilience to climate change: smart parking, blockchain ecosystems, environmental performance and smart buildings. These findings add to the international business literature by shedding light on how the superior competitiveness of smart cities attract cross-border direct investments in a growing climate uncertainty.

2 Hypothesis development

There has been increasing literature on how uncertainties regarding nature and, more specifically, climate risks, have reshaped modern business decision making. The emerging body of literature has provided insights into how market strategies and nonmarket strategies have been adopted by businesses to confront the challenges of climate change (Huang et al. 2018; Tashman and Rivera 2016). Investors consider investment in areas with more volatile temperature changes to be riskier, as scientific evidence has revealed some negative impacts of climate risks on business performance and local economic growth (Allman 2021; Kotz et al. 2021; Lupton et al. 2021). Besides physical risk, climate risks that a MNC has to confront is transitional risk like regulatory, legal, or reputational risks. A climate policy that mitigates or adapts to climate change imposes additional administrative costs on firms that must disclose information and comply with regulations. MNCs that have developed strategies to comply with location-specific regulatory rules in their home cities face significant challenges in host cities with different environmental and regulatory practices. In such case, MNCs will take the adaptation costs due to the climate risk volatility differences between home and host cities that inform different policies and regulations when investing abroad. In international business activities, whether and how businesses address intercity climate risk gaps is a
salient issue in investment decision making that needs further analysis. In international business activities, whether and how businesses address intercity climate risk gaps is a salient issue in investment decision making that needs further analysis.

We propose that intercity climate risk differences reduce FDI investment chiefly due to adaptation costs. Climate risk differences between home and host cities lead to two types of adaptation costs: ecological adaptation costs to manage potential environmental risks and possible consequences and institutional adaptation costs to adhere to local climate change regulations, which differ from those in home cities. The more similar the two cities are in terms of their climate risk conditions, the lower the costs for MNCs to invest in new business practices and climate risk mitigations, or to apply their existing ones, in the host city. For example, companies’ investment strategies and measures to cope with historic, abnormal weather or with long-term forecasts of climate risks in their home country could be easily adapted to FDI host cities that share similar regional climate risk profiles (Casson and Silva 2013). Meanwhile, the smaller the gap of temperature volatility is between the home and host cities, the lower the cost for multinational managers to conform to current and future environmental regulatory pressures in the destination city, which may share similar regulatory measures or restrictions via regarding climate change. In contrast, international businesses put investment decisions on hold if they anticipate heightened regulatory and policy uncertainties in the host city due to climate change threats.

Therefore, we hypothesize a negative linkage between intercity differences in climate risk and FDI volume between city pairs.

Hypothesis 1: Increases in the climate risk difference between home and host cities reduces FDI

Increased climate risks challenge international businesses. Nevertheless, specific industries might suffer more than others that can potentially benefit from climate change due to new opportunities (Fleming et al. 2006; Kolk & Pinkse 2008). The vulnerability of certain industries could stem from their heavy dependency on moderate weather (Fleming et al. 2006) or rainfall conditions (Rao et al. 2021) or (access to) natural resources (Huang et al. 2018), all of which are particularly vulnerable to ecological changes. For example, the landscape of agriculture and its trade activities could change dramatically due to rising global temperatures and risks of flooding, desertification, and rising sea levels. The larger the gap between the home and host city’s climate risk is, the greater the costs and uncertainties for MNCs in natural resource-intensive sectors to either secure reliable access to critical resources or mitigate the underlying causes of ecological uncertainties. Therefore, investment in such industries is highly vulnerable to relative climate risks, which are associated with higher adaptation costs for foreign investment, as we argue in Hypothesis 1. Similarly, industries with significant environmental impacts (e.g., chemical, paper manufacturing, or textile) are also receptive to rising adaptation costs via home-host city differences in ecological and regulatory uncertainties. In contrast, when MNCs invest in less ecologically sensitive industries (e.g., business services, real estate, or those that use climate-friendly technologies), they are less susceptible to the adaptation costs arising from the temperature volatility gap between home and host cities.

Therefore, we propose:

Hypothesis 2: The negative influence of climate risk difference on FDI is stronger on investments in environmentally sensitive industries
The heterogeneous influences of climate risk differences also result from a host city’s resilience, especially its infrastructure- and policy-based solutions, to overcome future challenges from climate change. In assessing the gap between their home and host cities, MNCs could identify the strengths and weaknesses of the host city in adapting to and mitigating the surging potential risks related to climate change. While some cities are already vulnerable or are likely to be heavily affected, more cities are taking measures to assist them in becoming climate-resilient. Among various city-level pledges and initiatives, those related to smart city planning and development are pertinent to countering adaptation costs and are particularly salient for foreign investors. A smart city uses information and communication technologies (ICTs) to increase its operational efficiency, share information with residents and improve government services and citizen welfare. Therefore, technology and people are two of the main concerns of the holistic concept of a smart city (Neirotti et al. 2014).

Various dimensions of city smartness have been discussed that embrace innovative solutions to promote intelligent infrastructures, smart governance, and the development of low-carbon industries to foster climate-smart urban development. For example, smart city programs with technical and nontechnical enablers significantly enhance a city’s performance in environmental sustainability and its economic competitiveness (Nicolas et al. 2020). Thus, with a mix of resilience-building actions, smart cities are attractive locations for international businesses to strengthen the resilience of their dispersed operations. Rather than a buzzword, smartness therefore indicates not only lower costs to address the adverse effects of climate shocks but also opportunities and alternatives that international businesses can exploit in their host cities via new business models and firm-government coevolutions (Kolk & Pinkse 2008; Lundan & Cantwell 2020). Accordingly, we hypothesize that host city smartness will lessen the influence of intercity climate risk differences on FDI volume.

Hypothesis 3: The negative influence of climate risk differences on FDI is weaker if the host city is smarter than the home city

3 Data

To test the hypotheses discussed above, we construct unique, annual global city pair-level panel data that contain bilateral FDI and meteorological proxies, a series of smart city indicators, and financial, economic and geographic information from 2003 to 2017. In the following sections, we describe the data sources and the construction of the variables used in our empirical analysis. The Appendix Table 4 provides the summary statistics for the main variables.

3.1 Greenfield FDIs

We obtain the monthly greenfield FDIs from Financial Times Ltd.’s fDi Markets. It reports the dollar amounts, number of created jobs, transaction dates, industry and destination cities of each FDI project, and the names and home cities of the multinational firms responsible for each FDI project. The bilateral FDI data are only available from 2003 forward. We focus on the sample from January 2003 to December 2017, which are the latest high-quality gridded temperature data available. Our sample covers 221,742 FDI projects, which
originate from 6713 cities in 165 distinct markets. The cross-border investments during the research period flow into 12,284 cities in 198 distinct markets. We find that the USA has the highest number of home (1636) and host (2333) cities. The bilateral FDI projects are then aggregated into 80,577 city pairs. Among all city pairs, there are 415 FDI projects from New York to London, which are the most intensive bilateral investment city linkages in our sample. Each FDI refers to a greenfield FDI unless otherwise specified.

3.2 Climate risk differences

We rely on climatic data from 2003 through 2017 to measure climate risk. Specifically, we focus on the climate variability in temperature to measure climate risk. Monthly temperature information is taken from the Terrestrial Air Temperature and Precipitation data of the National Oceanic and Atmospheric Administration (NOAA). The high-quality gridded dataset, both in terms of its spatial resolution and temporal frequency, consists of monthly global observations from stations in NOAA, measured in 0.5° × 0.5°, from January 1900 to December 2017. We construct measures of annual variability from the raw monthly temperature data, which are initially extracted at the cell level. We obtain the longitude and latitude of cities from OpenCagedata.com. The locations of source and destination cities are matched to the four surrounding grid cells, and we assign each city an average of the nonmissing temperature values from the five associated grid points. With the monthly average temperature data, we compute the standard deviation of each observed climate at the city level for each month over the past ten years prior to the year in question, which quantifies the monthly variability of temperature in city $i$. We then sum the monthly standard deviation for the year of interest as the proxy for climate risk (denoted as $\text{risk}_i$), as suggested by Buggle and Durante (2021).

The climate risk difference of a city pair ($\text{difference}_{sd}$) is defined as the absolute difference between home or source city ($s$) and host or destination ($d$) city: $|\text{risk}_s - \text{risk}_d|$. Figure 2 demonstrates the percentile distribution of climate risk differences between city pairs. Overall, it shows that investments into 58.9% of FDI projects were made by MNCs from home cities with relatively high climate risks to host cities with relatively low climate risks, while 41.2% of FDI projects are from home cities with relatively low climate risk to host cities with relatively high climate risk.

3.3 Smart cities index

We collect a set of proxies for smart cities from EasyPark, which covers 24 factors relating to smart cities globally. The proxies cover a comprehensive smart city index with subdimensions composed of transport and mobility, innovation economy, and sustainability. The subdimensions are specifically measured through the indicators of smart parking, blockchain ecosystems, environmental performance and smart buildings. The EasyPark index lists the top 100 smart cities worldwide. As the smartness score is only available for the top 100 cities, we conduct a series of robustness checks to integrate cities with no scores.

---

3. There are 62,981 (78%) city pairs that have only one FDI project record during our sample period and 78 city pairs with zero investment value for their corresponding project.

4. Source: https://psl.noaa.gov/data/gridded/data.UDel_AirT_Precip.html.

5. Source: https://easyparkgroup.com/
3.4 Control variables

We control for the yearly average temperature and precipitation for both the home and host cities, as in Buggle and Durante (2021). The information on climatic variables is obtained from NOAA. Following Erel et al. (2012), we calculate the great-circle distance between each city pair based on their locations, which measures the shortest distance between two points on the surface of a sphere.

We construct a dummy variable that equals one if the source and destination cities share a common language (English, Chinese, German or others). We further control for whether the cities in a pair are located on the same continent (i.e., South Asia, East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, North America, Sub-Saharan Africa and the Middle East and North Africa) (Erel et al. 2012). The information on the two dummy variables are obtained from the Center for Prospective Studies and International Information (CEPII).

4 Empirical analysis

4.1 Estimation strategy

Our primary interest is to study the impact of climate risk differences on bilateral FDI from one city to another. Using data at the city-pair level allows us to control for all city-specific factors that may potentially affect our outcomes of interest and for the common background shared by city pairs. Our econometric strategy is summarized by the following equation:

$$\text{log}(\text{FDI} + 1)_{sdt} = \beta_0 + \beta \cdot \text{difference}_{sdt} + X_{sdt}'\Theta + \delta_t + \gamma_{sd} + \Phi_{st} + \Phi_{dt} + \epsilon_{sdt}$$

where source (s) and destination (d) city pairs are indexed by sd, and t refers to year. The natural logarithm of FDI plus one for city pair sd in year t is denoted by $\text{log}(\text{FDI}_{sdt} + 1)$. difference_{sdt} denotes the climate risk difference in city pair sd at time t. $X_{sdt}'$ is a set of control variables related to the source–destination city pair, including the average annual temperature and precipitation for both source and destination cities, the natural logarithm of geographic distance between the city pair ($\ln \text{Geo}_{sd}$) and two dummy variables for source and destination cities that share a common language ($\text{lang}_{sd}$) and are located on the same broadly defined continent ($\text{Cont}_{sd}$).

In addition, we control for a variety of fixed effects to capture unobserved heterogeneity. City pair and year-of-sample fixed effects are denoted by $\gamma_{sd}$ and $\delta_t$. $\gamma_{sd}$ controls for time-invariant city pair characteristics, such as the composition of sources and destinations. $\delta_t$ flexibly absorbs unobserved common factors that vary over time, such as globalization. Following Bai (2009), we incorporate two additional interactive fixed effects: interaction between year and source city as well as between year and destination city, which are indexed by $\Phi_{st}$ and $\Phi_{dt}$. The interactive fixed effects absorb unobserved time-varying characteristics that are common to a certain city in a given year but differ across source or destination cities, such as changes in climate regulations or trade policies. $\epsilon_{sdt}$ is the residual error term, adjusted for autocorrelation at the city pair level. It captures the impacts on bilateral FDI flows of other factors that are excluded by Eq. (1). Standard errors are clustered at the city pair level in all equations. The parameter of interest $\beta$ captures the impact of climate risk differences on bilateral FDI.
4.2 Baseline results

For an overview of the broad relation between climate risk and FDI, we first compute the average climate risk (or variability) at the country level over the past ten years and plot the climate risk differences against the bilateral FDI for each country pair over the entire sample period. We obtain a total of 5,084 observations, with each observation indicating one “country pair” over the entire sample period. Figure 1 shows that FDI is concentrated in country pairs with relatively low climate risk differences, providing preliminary evidence that multinational firms direct their FDIs to countries with similar climate risks.

We further examine the extent to which the influence of climate risk differences on bilateral FDI varies across city pairs. To evaluate this pattern, we rely on a multivariate specification that controls for other potentially relevant variables. Table 1 presents the estimation results, using different empirical specifications. Columns 1 and 2 control for the average annual temperature and precipitation for source and destination cities. Columns 3 and 4 control for the time-invariant factors, including the natural log of geographic distance and two dummies regarding language and continent. Our result supports Hypothesis 1; the home-host city difference in climate risk reduces FDI. The coefficient of climate risk difference in column 1 is negative and statistically significant ($\beta = -0.013, p = 0.000$). On average, MNCs invest 49.336 million USD in host cities per year. Therefore, a one-standard-deviation decrease in the climate risk difference between two cities (4.270) increases city-pair FDI by 2.721 million USD yearly. The negative relation between climate risk difference and FDI remains significant in columns 2–4, although the magnitude declines.

\[ \text{The coefficient of climate risk difference on FDI between home and host city in column 1 is } -0.013. \]
\[ \text{Thus, the changes in investment for a one-standard-deviation (4.270) decrease in climate risk difference equals } 49.336 \times 4.270 \times (e^{-0.013} - 1) = -2.721. \]
We verify our results using alternative dependent variables, including the number of FDI projects and the number of jobs created. As in the previous analysis, we take the natural logarithmic transformation of one plus these variables. We also consider the alternative independent variables embracing climate risk differences that are measured by precipitation for each city pair, and the differences in PCA (temperature risk difference and precipitation risk difference) climate risk for each city pair. The results in Appendix Table 5 show similar evidence; multinational firms direct more numbers of FDI projects and create more numbers of jobs.

### Table 1: The impact of climate risk difference on FDI

The table presents the baseline estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at the city pair level. The dependent variable is the natural logarithm of FDI plus one for city pair sd in year t. The main explanatory variable is the climate risk difference, measured by the absolute difference of climate risk between source (s) and destination (d). Columns 1 and 2 control for the yearly average temperature and precipitation for source and destination cities. In addition, columns 3 and 4 control for the time-invariant factors including natural log of geographic distance, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city × year fixed effects, and destination city × year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable: log (1 + FDI) | (1)  | (2)  | (3)  | (4)  |
|-----------------------------------|------|------|------|------|
| Climate risk difference          | −0.013*** | −0.003 | −0.006*** | −0.005 |
|                                  | (0.002)  | (0.010) | (0.002)  | (0.010) |
| Source city temperature          | 0.008   | −0.133 | 0.012   | −0.159*** |
|                                  | (0.029)  | (0.090) | (0.029)  | (0.072) |
| Source city precipitation        | 0.002   | 0.107   | −0.001  | 0.148   |
|                                  | (0.035)  | (0.159) | (0.035)  | (0.142) |
| Destination city temperature     | 0.036*  | 0.104   | 0.040*  | 0.065   |
|                                  | (0.021)  | (0.076) | (0.022)  | (0.085) |
| Destination city precipitation   | 0.016   | 0.038   | 0.014   | 0.051   |
|                                  | (0.022)  | (0.073) | (0.023)  | (0.075) |
| Same continent                   | 0.211*** | −0.688  |         |         |
|                                  | (0.024)  | (0.512) |         |         |
| Log (geography proximity)        | −0.007  | 0.253   |         |         |
|                                  | (0.011)  | (0.415) |         |         |
| Same language                    | 0.066*** | 1.231   |         |         |
|                                  | (0.026)  | (0.788) |         |         |
| Constant                         | 2.057*** | 1.842   | 1.920*** | 0.121   |
|                                  | (0.593)  | (1.507) | (0.596)  | (3.840) |
| Adj-R²                           | 0.251   | 0.299   | 0.256   | 0.301   |
| Observations                     | 77,861  | 35,255  | 76,091  | 34,616  |
| Time FE                          | Yes     | Yes     | Yes     | Yes     |
| City pair FE                     | No      | Yes     | No      | Yes     |
| Source City × Year, Destination  | Yes     | Yes     | Yes     | Yes     |
| City × Year FE                   |         |         |         |         |

*p < 0.10, **p < 0.05, ***p < 0.01
job opportunities in destination cities that are more similar to their home city. Therefore, the negative association between climate risk difference and FDI in Table 1 is robust to alternative measures of FDI and climate risk difference.

### 4.3 Environmentally sensitive industries

As Hypothesis 2 suggests, some industries are more exposed to climate risks than others. Copeland and Taylor (1999) proposed a stock term of “environmental capital,” which is meant to capture the productivity-relevant aspects of environmental quality. They defined an environmentally sensitive industry for which the productivity is related to the stock of environmental capital. In addition, resource-intensive industry is also regarded as environmentally sensitive sector since its productivity is associated with the stock of resources in (Brander and Taylor 1997). To examine whether the relation between FDI and climate risk differences is more pronounced in environmentally sensitive industries, we classify FDI projects based on their North American Industry Classification System (NAICS) code and follow Copeland and Taylor (1999) and (Brander and Taylor 1997) to identify environmentally sensitive industries. As these classifications do not include power generation industries, we add fossil fuel power generation to our environmentally sensitive industries for a robustness check.

We expand the baseline specification to include the interaction between climate risk difference and an industry dummy, which equals 1 for environmentally sensitive industries and 0 otherwise. Column 1 of Table 2 reports a positive coefficient of the interaction term ($\beta = 0.001, p = 0.607$), suggesting a nonsignificant moderating effect when the full sample is applied. One possible reason is that the directional flow of FDIs matters. As shown in Fig. 2, 41% of total FDI flows from cities with low climate risks to cities with high climate risks, and the remaining 59% of FDI flows from cities with high climate risks to cities with low risks.

We therefore split our sample into two parts: one is for FDI projects where climate risk in the home city is lower than that of the host city (column 2), and the other where the situation is the opposite (column 3). In column 2 of Table 2, the coefficient of the interaction term is negative and statistically significant ($\beta = -0.019, p = 0.000$). This implies that the negative effect of climate risk differences on FDI is stronger in environmentally sensitive industries when the climate risk of the home city is lower than that of the host city. In column 3 of Table 2, the coefficient of the interaction term becomes nonsignificant ($\beta = -0.003, p = 0.380$), suggesting that the negative relation between climate risk differences and FDI is consistent between environmentally sensitive and less sensitive industries if the climate risk in the home city is higher than that of the host city. Columns 4–6 of Table 2 show similar results, where the definition of environmentally sensitive industries includes the fossil fuel power generation sector.

Overall, the estimated coefficients in columns 2 and 5 of Table 2 indicate that a one-standard-deviation increase in the climate risk gap (4.270) decreases FDI flows from a relatively low climate risk city to a host city’s environmentally sensitive industries by 3.96–4.38 million USD yearly. In other words, for FDI projects from cities with lower climate risks, the larger the climate risk differences between the home and host cities,

---

7 Full details of environmentally sensitive industry are not included in this article in order to optimize space. The specific environmentally sensitive sector can be retrieved from: [OSF | Supplementary Material for the List of Environmentally Sensitive Industry](https://osf.io/).

---

 Springer
the greater the costs and uncertainties for MNCs in environmentally sensitive sectors to secure resources and manage investment activities. Investments in such industries are highly vulnerable to relative climate risks.

4.4 The smart city

4.4.1 The resilient effects of a smart city

To understand how smart cities affect the relation between climate risk differences and FDI, we expand the baseline model to include the interaction between climate risk differences and a smart city dummy (smart), which equals one if the host city ranks higher than the home city. In our sample, the smartness scores are only available for the top 100 cities. We exclude city pairs lacking scores for both home and host cities, as we cannot compare the relative smartness of the two cities.

Table 6 in the appendix reports the estimation results, using various measures of city smartness. Column 1 reports a positive and statistically significant coefficient of the interaction term ($\beta = 0.045, p = 0.028$). This means that FDIs are less responsive to climate risk differences when the host city is smarter than the home city, supporting Hypothesis 3. Calculating the sum of the coefficients of climate risk difference and the interaction term yields 0.016, which is positive and marginally significant ($F = 2.57, p = 0.077$). This implies that a one-standard-deviation increase in climate risk difference reduces FDI by 6.053 million USD yearly when the host city is not as smart as the home city. However, when the host city is smarter than the home city, city smartness helps alleviate the negative effects of climate risk, increasing FDI by 3.563 million USD yearly. We label this as the resilient effect of smart cities in the presence of climate risks.

Employing various subdimensions of city smartness, we repeat the analysis and report the estimation results in Table 6 in the Appendix. Figure 3 illustrates the findings. The horizontal axis denotes four subdimensions of smartness. The vertical axis represents the estimated effects of relative city smartness on the climate-FDI relation. The green and gray bars display the estimated interaction coefficients and climate-FDI relation coefficients, respectively. The spikes in each bar denote the 95% confidence intervals. Thus, the estimated coefficients of the interaction terms are positive and statistically significant for all smart city indicators. This provides evidence that smart cities strengthen the resilience of FDIs to climate risk differences.

4.4.2 Dealing with selection bias

Our estimated results may suffer from sample selection bias when defining the dummy indicator of relative smartness in city pairs. To draw a robust conclusion, we re-estimated our model with alternative sample choices. We provide the additional analyses in Appendix Table 7 (a)–(c). All specifications include time fixed effects, city pair fixed effects, source city by year fixed effects, and destination city by year fixed effects.

First, the main analysis uses a dummy indicator to compare the relative smartness between source and destination cities. Notably, any two cities can have little difference in terms of smartness, which biases our estimation. To address this concern, we compute the absolute difference in smartness scores of all city pairs and then winsorize at the left 10th percentile. As shown in Appendix Table 7 (a), the estimated coefficient of the interaction term is positive and statistically significant ($\beta = 0.034, p = 0.064$) in column 1. The
The impact of smartness gaps on home and host cities

In this section, we further explore how a smart city’s resilience effect on the climate-FDI relation is affected by the smartness gap between home and host cities, using a full sample. If the level of the smartness gap increases investments, we will observe that FDI volume significantly differs for city pairs with substantial smartness gaps. We first construct a new proxy for smartness by applying principal component analysis (PCA), based on the aforementioned four subdimensions of scores. We test the assumption by constructing the dummy indicator to measure the closeness of the smartness difference. This equals one if the absolute differences of PCA, whether the total or subdimensional smartness indices, are in the top 50th percentile (closeness). We then interact the dummy with difference × smart.

Table 3 presents the results. Most of the coefficients for the triple interaction terms (difference × smart × closeness) exhibit the expected negative sign for the top 50th percentile. In particular, the effect of the PCA smartness index is negative and statistically significant (β = 0.049, p = 0.058), as shown in column 2. This implies that for a city pair in which the host city is more resilient than the home city and the smartness scores are close, the resilient effect of smart cities on the climate-FDI relation is weakened. In other words, the negative effect of climate risk differences on FDI is stronger if the two cities in a pair have a relatively narrower smartness gap. Quantitatively, a one-standard-deviation increase in climate risk difference is associated with a 10.074 million USD decrease in FDI when the destination cities are more resilient and when the relative smartness is close (in the top 50th percentile).

Overall, the results strongly demonstrate that the magnitude of the resilience effect varies widely among city pairs with different degrees of relative smartness. FDI tends to increase when the host cities are smarter and when the smartness gaps between source and destination cities are substantial.

The robustness check

We further investigate whether effect of climate-FDI relation matters for the city size. In addition, we conduct sets of robustness checks to explore the alternative smart city...
measurements as well as the heterogenous effect of resilient effect among industrial sectors. The empirical details are demonstrated in Supplementary Material.8

5 Discussion and conclusion

Despite the increasing research with respect to the impacts of climate risks on MNCs’ cross-border investments, little is known about how the city-level climate risk difference affect FDI as well as how the MNCs’ incorporate climate risk into their long-term investment decisions. Previous literature related to cross-border concentrated more on the theory of externalities, such as the extent to which some MNCs shift their production facilities to less regulated markets to bypass domestic climate policies (Aragón-Correa et al. 2016; Berry et al. 2021), others improve green and sustainable development in both their home and host countries (Brucal et al. 2019; Nippa et al. 2021). Another strand of literature related to climate change focuses more on the financial impact of climate risk on firm performance, asset value and cost of capital (Huang et al. 2018; Bernstein et al. 2019; Kling et al. 2021). In our study, we complement the literature by highlighting how MNCs engage in activities that could potentially prevent or influence the climate risks. Specifically, our research documents new evidence that a city-level climate risk difference discourages outward foreign investment. Although in Li and Gallagher’s (2022) work, they have precisely examined the exposure of MNCs’ overseas investments to physical climate risks, we bridge the gap between climate risk and FDI through highlighting the substantive role of host cities’ resilience to climate risks, especially their “smartness,” plays in shaping MNCs’ FDI decisions. By integrating the key features of smart cities into an empirical model, our study indicates a direction that allows governments to increase their cities’ resilience to climate risks through proactive policy making and smart city building.

Although abundant evidence on how climate change affects real economic activities, it is still unclear if and how international businesses anticipate and adapt to these challenges by incorporating relative climate risks and urban resilience into their investment decisions. The first contribution is that the paper investigates how the climate risk differences between

---

8 We construct a dummy proxy to identify the primary city if home or host city is a prominent one (We define the type of city following the website: https://simplemaps.com/data/world-cities). We further expand the baseline model to include the interaction between climate risk differences and primary city dummy (difference primary city). The results are exhibited in Appendix Table 8. The results imply that the effect of climate risk on FDI decisions matters for the size of home or host city to some extent. In column 1, the coefficient of the interaction term is positive and significant which indicates the negative effect of climate risk differences on FDI is weaker when outward direct investments flow to primary host city. To address the heterogenous resilience effect, we interact the dummy for environmentally sensitive industry with difference smart. The results are demonstrated from column 1 to 5 in Appendix Table 9 and generally indicate that the resilient effect of smart cities on the climate-FDI is stronger in environmentally sensitive industry. Additionally, we construct a dummy variable equal to one if a city pair where the host city is listed within top 100. We expand the resilient effects model to include a triple interaction between climate risk difference, environmentally sensitive industry dummy and smartness city dummy within top-100 list (difference smart within top 100 industry). The robustness result is shown in column 6 of Appendix Table 9. The triple interaction term implies that a city pair in which the host city is within top-100 smartness list while home city is not, the resilient effect of smart cities on climate-FDI relation is stronger in environmentally sensitive industry. The interaction term for Difference Smart shows that the magnitude of resilient effect for smartness within top-100 cities is larger and significant than that of between top 100 and non-top-100.
Table 2  Stronger impacts in environmentally sensitive industries. The table presents the industrial estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variable is the natural logarithm of FDI plus one for city pair \( sd \) in year \( t \). All columns present the interaction of climate risk difference with the industry classification for each city pairs. Based on the North American Industry Classification System (NAICS) code of environmentally sensitive industries (American Enterprise Institution 2018), the dummy variables equal to one if the investing firm belongs to environmentally sensitive industries (Columns 1–3). In addition, in columns 4–6, we add fossil fuel power generation into environmentally sensitive industries for robustness check. Based on the relative climate risk between city pairs, we separate the full sample into two group in columns 2–3 and 5–6. All regressions control for the yearly average temperature and precipitation for source and destination cities as well as the time-invariant factors including natural log of geographic distance, and two dummies on the language and continent. All specifications include time fixed effects, industry fixed effects, source city × year fixed effects, and destination city × year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1 + FDI) | | | | | | |
|---|---|---|---|---|---|---|
| Environmentally sensitive industry | Environmentally sensitive & fossil fuel power generation industry | | | | | |
| All | Relative climate risk (source < destination) | Relative climate risk (source > destination) | All | Relative climate risk (source < destination) | Relative climate risk (source > destination) |
| Difference | \(-0.008^{***}\) | 0.018 | \(-0.071^{**}\) | \(-0.008^{***}\) | 0.018 | \(-0.072^{**}\) |
| | (0.002) | (0.044) | (0.035) | (0.002) | (0.044) | (0.036) |
| Difference × Industry Indicator | 0.001 | \(-0.019^{***}\) | \(-0.003\) | 0.003 | \(-0.021^{***}\) | \(-0.002\) |
| | (0.002) | (0.005) | (0.003) | (0.002) | (0.005) | (0.003) |
| Meteorological variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Other control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj-\(R^2\) | 0.347 | 0.390 | 0.319 | 0.347 | 0.390 | 0.319 |
| Observations | 76,091 | 23,881 | 42,740 | 76,091 | 23,881 | 42,740 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Source City × Year, Destination City × Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

\(*p<0.10, \**p<0.05, \***p<0.01\)
cities affect MNCs’ cross-border direct investments. We pair cities according to bilateral FDIs and construct their climate risk differences based on grid level meteorological information from 2003 to 2017. This allows us to capture both the spatial resolution and temporal frequency of climate risks among any two cities. The results show that wider climate risk differences between home and host cities discourages FDI, through increasing MNCs’ adaptation costs to manage climate risks and identify related opportunities. At the sectoral level, the effects of climate risk differences on FDI are stronger for environmentally sensitive industries, especially on FDIs that flow from relatively low climate risk home cities to high climate risk host cities.

Second, we contribute to the literature by further revealing how city-level heterogeneity can attract FDI by exploring urban resilience to climate risks through various smart city initiatives. We find that the negative impact of climate risk differences on FDI is weakened if a host city is smarter than a home city. The relative smartness of a host city that is empowered by new technologies makes it capable of promoting sustainable development, enhancing its resilience to climate risks. Our result regarding the role of smart cities reflects the opportunities and alternatives that MNCs can exploit in their host cities, via new business models and firm-government to cope with climate risk. It also suggests that city governments that seek to boost urban economic growth by attracting investments could enhance a city’s environmental sustainability and economic competitiveness through smart city planning and development.

In addition, our empirical analysis is subject to several limitations due to data availability from city level, although we have implemented a series of robustness tests to reduce the bias. First, our sample encompasses thousands of home cities or host cities involving greenfield cross-border direct investment projects. However, we can only identify their smartness ranked within top 100 but fail to precisely capture extent of other cities’ smartness. Second, we measure climate

![Histogram of climate risk difference between city pairs](image)
risk in a city by the standard deviation of its monthly temperature over the past 10 years, while hardly investigate how MNCs decide their overseas investments exposing to extreme weather conditions such as heat waves, floods, hurricanes, and typhoon. These limitations prevent us from estimating the climate-FDI relation in a more elaborate manner. These limitations would be interesting for future research to address.
Table 3 The role of smart cities. The table presents the estimation results of how resilience effects of smartness on climate-FDI relation is affected by the smartness gap between home and host city using full sample. The regressions involve unbalanced panel of bilateral FDI between 2003 and 2017 at city pair level. The dependent variable is the natural logarithm of FDI plus one for city pair $sd$ in year $t$. We first construct a new proxy for smartness by applying principal component analysis (PCA) based on four subdimensions of scores. We construct a variable closeness of the smartness difference, which equals to one if the absolute differences of PCA, total, or subdimensional smartness indices are in the top 50th percentile (closeness). We then interact the dummy with the previous interaction term (difference $\times$ smart), including natural log of geographic distance, and two dummies on the language and continent. All specifications include time fixed effects, industry fixed effects, source city $\times$ year fixed effects, and destination city $\times$ year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1 + FDI) | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------------------|-----|-----|-----|-----|-----|-----|-----|
|                                | Total smart | PCA | Total smart | Environmental performance | Blockchain ecosystems | Smart parking | Smart building |
| Difference                      | $-0.019$ | $-0.020$ | $-0.019$ | $-0.017$ | $-0.018$ | $-0.017$ | $-0.018$ |
|                                | (0.013) | (0.014) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| Difference $\times$ Smart       | $0.036**$ | $0.044**$ | $0.032*$ | $0.032*$ | $0.030$ | $0.031*$ | $0.038**$ |
|                                | (0.018) | (0.021) | (0.019) | (0.019) | (0.018) | (0.018) | (0.019) |
| Difference $\times$ Smart $\times$ Closeness | $-0.049*$ | $0.021$ | $-0.011$ | $0.004$ | $-0.008$ | $-0.022$ |
|                                | (0.026) | (0.036) | (0.037) | (0.039) | (0.040) | (0.035) |
| Meteorological variables       | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other control variables        | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj-$R^2$                      | 0.301 | 0.301 | 0.301 | 0.301 | 0.301 | 0.301 | 0.301 |
| Observations                   | 34,616 | 34,616 | 34,616 | 34,616 | 34,616 | 34,616 | 34,616 |
| Time FE                        | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City pair FE                   | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Source City $\times$ Year, Destination City $\times$ Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

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

Table 4 Summary statistics

| Variable                                           | Obs  | Mean   | Std. dev | Min   | Max    |
|----------------------------------------------------|------|--------|----------|-------|--------|
| FDI (million USD)                                  | 117,183 | 49.336 | 263.687  | 0.000 | 34,000.000 |
| Climate risk difference for city pairs             | 117,133 | 5.627  | 4.270    | 0     | 31.799 |
| Average temperature in source city                 | 117,174 | 12.670 | 5.441    | −6.820| 30.035 |
| Average precipitation in source city               | 117,174 | 8.184  | 4.375    | 0.000 | 36.818 |
| Average temperature in destination city            | 117,142 | 15.423 | 7.039    | −16.013| 31.038 |
| Average precipitation in destination city          | 117,142 | 8.460  | 5.458    | 0.000 | 51.369 |
| Geographic proximity                                | 117,183 | 6224.576 | 2909.070 | 0.000 | 12,432.140 |
| Same Continent                                     | 117,175 | 0.343  | 0.475    | 0     | 1      |
| Same Language                                      | 114,485 | 0.227  | 0.419    | 0     | 1      |
| Absolute differences of smart cities scores for city pairs | 8432 | 1.085  | 0.766    | 0     | 3.430  |
| Environmental performance                          | 8432 | 3.319  | 2.260    | 0     | 8.690  |
| Blockchain ecosystem                               | 8432 | 3.039  | 2.419    | 0     | 8.770  |
| Smart parking                                      | 8432 | 3.016  | 2.284    | 0     | 9.000  |
| Smart building                                     | 8432 | 3.019  | 2.017    | 0     | 8.920  |
Table 5 Baseline results for alternative dependent and independent variables. The table presents the estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variables are the natural logarithm of number of FDI projects plus one in columns 1 and 2 and the natural logarithm of number of jobs created plus one in columns 3 and 4 for city pair sd in year t. The main explanatory variable in columns 1–4 is temperature-measured climate risk difference for each city pair. From columns 5–8, the dependent variables are the natural logarithm of FDI volume plus one for city pair sd in year t. The main explanatory variable in columns 5 and 6 is climate risk difference measured by precipitation for each city pairs and in columns 7 and 8, the main explanatory variable is the differences in PCA (temperature risk difference and precipitation risk difference) climate risk for each city pairs. Regressions also control for the yearly average temperature and precipitation for source and destination cities, the time-invariant factors including the natural log of geographic distance, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city × year fixed effects, and destination city × year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

|                | (1)           | (2)           | (3)           | (4)           | (5)           | (6)           | (7)           | (8)           |
|----------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| **Alternative dependent variable** | Log (1 + Number of FDI) | Log (1 + Jobs Created) | Precipitation | PCA           |               |               |               |               |
| **Difference** | −0.003***     | −0.001        | −0.003        | 0.005         | −0.002***     | −0.006**      | −0.003***     | −0.008**      |
| **Meteorological variables** | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           |
| **Other control variables** | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           |
| **Adj-R²**     | 0.084         | 0.432         | 0.301         | 0.351         | 0.256         | 0.301         | 0.256         | 0.301         |
| **Observations** | 76,091        | 34,616        | 76,091        | 34,616        | 76,091        | 34,616        | 76,091        | 34,616        |
| **Time FE**    | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           |
| **City pair FE** | No            | Yes           | No            | Yes           | No            | Yes           | No            | Yes           |
| **Source City × Year, Destination City × Year FE** | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           | Yes           |

*p < 0.10, **p < 0.05, ***p < 0.01
Table 6  The effects of relative smartness on climate-FDI relation. The table presents the estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variables are the natural logarithm of FDI volume plus one for city pair \( sd \) in year \( t \). The main explanatory variable is the climate risk difference and its interaction with the dummy for relative smart of destination versus source city for each city pairs. The dummy equals one if the smart cities indices of the destination cities are higher than the indices of the source cities or only the city pairs where source city has no smartness scores. Sample excludes the city pairs for which both source and destination cities have no scores. All regressions control for the yearly average temperature and precipitation for source and destination cities as well as the time-invariant factors including the natural log of geographic distance between the city pair, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city \( \times \) year fixed effects, and destination city \( \times \) year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1+FDI) | Total smart city | Environmental performance | Blockchain ecosystems | Smart parking | Smart building |
|-------------------------------|------------------|---------------------------|-----------------------|--------------|---------------|
| Difference                    | −0.029*          | −0.025*                   | −0.028*               | −0.026*      | −0.028*       |
| (0.015)                       | (0.014)          | (0.014)                   | (0.014)               | (0.014)      | (0.014)       |
| Difference \( \times \) Smart | 0.045**          | 0.036*                    | 0.040**               | 0.038**      | 0.043**       |
| (0.020)                       | (0.020)          | (0.019)                   | (0.019)               | (0.020)      |
| Meteorological variables      | Yes              | Yes                       | Yes                   | Yes          | Yes           |
| Other control variable        | Yes              | Yes                       | Yes                   | Yes          | Yes           |
| Adj-\( R^2 \)                  | 0.307            | 0.307                     | 0.307                 | 0.307        | 0.307         |
| Observations                  | 25,124           | 25,124                    | 25,124                | 25,124       | 25,124        |
| Time FE                       | Yes              | Yes                       | Yes                   | Yes          | Yes           |
| City pair FE                  | Yes              | Yes                       | Yes                   | Yes          | Yes           |
| Source City \( \times \) Year Destination \( \times \) Year FE | Yes | Yes | Yes | Yes | Yes |

\*\( p < 0.10 \), \**\( p < 0.05 \), \***\( p < 0.01 \)
Table 7 Robustness checks. The table presents the estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variables are the natural logarithm of FDI volume plus one for city pair $sd$ in year $t$. The main explanatory variable is the climate risk difference and its interaction with the dummy for relative smart of destination versus source city for each city pairs. The dummy equals one if the smart cities indices of the destination cities are higher than the indices of the source cities or only the city pairs where source city has no smartness scores. Regressions also control for the yearly average temperature and precipitation for source and destination cities as well as the time-invariant factors including the natural log of geographic distance between the city pair, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city $\times$year fixed effects, and destination city $\times$year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1 + FDI) | (1) | (2) | (3) | (4) | (5) |
|----------------------------------|-----|-----|-----|-----|-----|
| Total smart city                 |     |     |     |     |     |
| Environmental performance        |     |     |     |     |     |
| Blockchain ecosystems            |     |     |     |     |     |
| Smart parking                    |     |     |     |     |     |
| Smart building                   |     |     |     |     |     |
| Difference                       | $-0.019$ | $-0.017$ | $-0.018$ | $-0.017$ | $-0.017$ |
|                                 | $(0.013)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ | $(0.012)$ |
| Difference $\times$ Smart        | $0.034^*$ | $0.029$ | $0.033^*$ | $0.030^*$ | $0.032^*$ |
|                                 | $(0.018)$ | $(0.018)$ | $(0.018)$ | $(0.018)$ | $(0.018)$ |
| Meteorological variables         | Yes | Yes | Yes | Yes | Yes |
| Other control variable           | Yes | Yes | Yes | Yes | Yes |
| Adj-$R^2$                        | 0.301 | 0.303 | 0.300 | 0.301 | 0.300 |
| Observations                     | 34,270 | 34,263 | 34,329 | 34,616 | 34,246 |
| Time FE                          | Yes | Yes | Yes | Yes | Yes |
| City pair FE                     | Yes | Yes | Yes | Yes | Yes |
| Source City $\times$ Year FE     | Yes | Yes | Yes | Yes | Yes |
| (b) Sample excludes the city pairs where source city has no smartness scores while destination city has |
| Difference                       | $-0.025^*$ | $-0.022^*$ | $-0.023^*$ | $-0.022^*$ | $-0.023^*$ |
|                                 | $(0.014)$ | $(0.013)$ | $(0.013)$ | $(0.013)$ | $(0.013)$ |
| Difference $\times$ Smart        | $0.069^{**}$ | $0.056^*$ | $0.055^*$ | $0.055^*$ | $0.060^{**}$ |
|                                 | $(0.031)$ | $(0.032)$ | $(0.029)$ | $(0.030)$ | $(0.030)$ |
| Meteorological variables         | Yes | Yes | Yes | Yes | Yes |
Table 7 (continued)

| Dependent variable log (1 + FDI) | (1) Total smart city | (2) Environmental performance | (3) Blockchain ecosystems | (4) Smart parking | (5) Smart building |
|----------------------------------|----------------------|-------------------------------|---------------------------|------------------|-------------------|
| Other control variable          | Yes                  | Yes                           | Yes                       | Yes              | Yes               |
| Adj-$R^2$                        | 0.283                | 0.283                         | 0.283                     | 0.283            | 0.283             |
| Observations                     | 23,896               | 23,896                        | 23,896                    | 23,896           | 23,896            |
| Time FE                          | Yes                  | Yes                           | Yes                       | Yes              | Yes               |
| City pair FE                     | Yes                  | Yes                           | Yes                       | Yes              | Yes               |
| Source City × Year, Destination City × Year FE | Yes | Yes                           | Yes                       | Yes              | Yes               |

(c) Full sample analysis where the dummy of smart is defined to be zero if home city has relative higher smartness scores, host city has no smartness scores while home city has as well as both home and host city have no score for a city pair

| Difference | −0.019 | −0.017 | −0.018 | −0.017 | −0.018 |
|           | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| Difference × Smart | 0.036** | 0.030* | 0.031* | 0.030* | 0.034* |
|           | (0.018) | (0.018) | (0.018) | (0.017) | (0.018) |
| Meteorological variables | Yes | Yes | Yes | Yes | Yes |
| Other control variable | Yes | Yes | Yes | Yes | Yes |
| Adj-$R^2$ | 0.301 | 0.301 | 0.301 | 0.301 | 0.301 |
| Observations | 34,616 | 34,616 | 34,616 | 34,616 | 34,616 |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| City Pair FE | Yes | Yes | Yes | Yes | Yes |
| Source City × Year, Destination City × Year FE | Yes | Yes | Yes | Yes | Yes |

*p < 0.10, **p < 0.05, ***p < 0.01
Table 8 Heterogenous effects of climate-FDI relation among city size. The table presents the estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variables are the natural logarithm of FDI volume plus one for city pair $sd$ in year $t$. The main explanatory variable is the climate risk difference and its interaction with the dummy for relative smart of destination versus source city for each city pairs. We first construct a dummy proxy to identify the primary city if home or host city is a prominent one. We then interact the dummy with climate risk difference. All regressions control for the yearly average temperature and precipitation for source and destination cities as well as the time-invariant factors including the natural log of geographic distance between the city pair, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city $\times$ year fixed effects, and destination city $\times$ year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1 + FDI) | (1) Primary host city | (2) Primary home city |
|----------------------------------|-----------------------|-----------------------|
| Difference                       | $-0.029^*$            | $-0.002$              |
|                                  | (0.016)               | (0.012)               |
| Difference $\times$ primary city | $0.035^*$             | $-0.006$              |
|                                  | (0.019)               | (0.016)               |
| Meteorological variables         | Yes                   | Yes                   |
| Other control variable           | Yes                   | Yes                   |
| Adj-$R^2$                        | 0.301                 | 0.301                 |
| Observations                     | 34,616                | 34,616                |
| Time FE                          | Yes                   | Yes                   |
| City pair FE                     | Yes                   | Yes                   |
| Source City $\times$ Year, Destination City $\times$ Year FE | Yes | Yes |

*p < 0.10, **p < 0.05, ***p < 0.01
Table 9  Heterogenous resilience effect among industrial sectors. The table presents the estimation results of unbalanced panel regressions of bilateral FDI between 2003 and 2017 at city pair level. The dependent variables are the natural logarithm of FDI volume plus one for city pair $d$ in year $t$. The main explanatory variable is the climate risk difference and its interaction with the dummy for relative smart of destination versus source city for each city pairs. We interact the dummy for environmentally sensitive industry with previous interaction term (difference $\times$ smart) from column 1 to 5. In column 6, we construct a new proxy for smartness equal to one if a city pair where the host city is listed within top 100. We expand the resilient effects model to include a triple interaction between climate risk difference, environmentally sensitive industry dummy and smartness city dummy within top-100 list (difference $\times$ smart within top 100 $\times$ industry). Regressions also control for the yearly average temperature and precipitation for source and destination cities as well as the time-invariant factors including the natural log of geographic distance between the city pair, and two dummies on the language and continent. All specifications include time fixed effects, city pair fixed effects, source city $\times$ year fixed effects, and destination city $\times$ year fixed effects. Clustered (city pair) standard errors are shown in the parenthesis.

| Dependent variable log (1+FDI) | (1) Total Smart City | (2) Blockchain Ecosystems | (3) Environmental Performance | (4) Smart Parking | (5) Smart Building | (6) Top 100 |
|-------------------------------|----------------------|---------------------------|-------------------------------|-------------------|-------------------|-----------|
| Difference                    | −0.029*              | −0.028**                  | −0.025*                       | −0.026*           | −0.028*           | −0.010    |
|                               | (0.015)              | (0.014)                   | (0.014)                       | (0.014)           | (0.014)           | (0.0111)  |
| Difference $\times$ Smart     | 0.043**              | 0.038**                   | 0.035*                        | 0.036*            | 0.042**           | 0.015     |
|                               | (0.020)              | (0.019)                   | (0.020)                       | (0.019)           | (0.020)           | (0.018)   |
| Difference $\times$ Smart $\times$ Industry | 0.009 | 0.011* | 0.012 | 0.013** | 0.004 | 0.017* ** |
|                               | (0.006)              | (0.006)                   | (0.007)                       | (0.007)           | (0.007)           | (0.007)   |
| Meteorological variables      | Yes                  | Yes                       | Yes                           | Yes               | Yes               | Yes       |
| Other control variable        | Yes                  | Yes                       | Yes                           | Yes               | Yes               | Yes       |
| Adj.-$R^2$                    | 0.307                | 0.307                     | 0.307                         | 0.307             | 0.307             | 0.631     |
| Observations                  | 25,124               | 25,124                    | 25,124                        | 25,124            | 25,124            | 34,616    |
| Time FE                       | Yes                  | Yes                       | Yes                           | Yes               | Yes               | Yes       |
| City pair FE                  | Yes                  | Yes                       | Yes                           | Yes               | Yes               | Yes       |
| Source City $\times$ Year,    | Yes                  | Yes                       | Yes                           | Yes               | Yes               | Yes       |
| Destination City $\times$ Year FE | Yes     | Yes                       | Yes                           | Yes               | Yes               | Yes       |

*p < 0.10, **p < 0.05, ***p < 0.01
Acknowledgements We are grateful for the insightful comments from the editor and three reviewers.

Author contribution All authors contributed to the study conception and design. Data collection and analysis were performed by Y.A. and L.Z. The first draft of the manuscript was jointly written by all authors. All authors read and approved the final manuscript.

Funding This work was supported by National Natural Science Foundation of China (Project No. 72140005), Research Grants Council of the Hong Kong Special Administrative Region (Project No. CityU 21610019), Singapore MOE grant, and CORE project grant. CORE is a joint research centre for ocean research between QNLM and HKUST.

Data availability Greenfield FDI s data are from Financial Times Ltd.’s fDi Markets, which is a commercial data source and is not publicly available. Climate-related information is taken from the Terrestrial Air Temperature and Precipitation data of the National Oceanic and Atmospheric Administration.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Conflict of interests The authors have no relevant financial or non-financial interests to disclose.

References

Allman E (2021) Pricing climate change risk in corporate bonds. SSRN Electron J. https://doi.org/10.2139/ssrn.3821018

Alpay E, Buccola S, Kerkvliet J (2002) Productivity growth and environmental regulation in Mexican and U.S. food manufacturing. Am J Agric Econ 84:887–901. https://doi.org/10.1111/1467-8276.00041

Andersson M, Bolton P, Samama F (2016) Hedging climate risk. Financ Anal J 72:13–32. https://doi.org/10.2469/faj.v72.n3.4

Aragón-Correa JA, Marcus A, Hurtado-Torres N (2016) The natural environmental strategies of international firms: old controversies and new evidence on performance and disclosure. Acad Manag Perspect 30:24–39. https://doi.org/10.5465/AMP.2014.0043

Babiker MH (2005) Climate change policy, market structure, and carbon leakage. J Int Econ 65:421–445. https://doi.org/10.1016/j.jinteco.2004.01.003
Bai J (2009) Panel data models with interactive fixed effects. Econometrica 77:1229–1279. https://doi.org/10.3982/ecta6135

Balica SF, Wright NG, van der Meulen F (2012) A flood vulnerability index for coastal cities and its use in assessing climate change impacts. Nat Hazards 64:73–105. https://doi.org/10.1007/s11069-012-0234-1

Baron M (2012) Do we need smart cities for resilience. J Econ Manag 10:32–46

Bender J, Bridges TA, Shah K (2019) Reinventing climate investing: building equity portfolios for climate risk mitigation and adaptation. J Sustain Financ Invest 9:191–213. https://doi.org/10.1080/20430795.2019.1579512

Berman E, Bui LTM (2001) Environmental regulation and productivity: evidence from oil refineries. Rev Econ Stat 83:498–510. https://doi.org/10.1162/00346550152480144

Bernstein A, Gustafson MT, Lewis R (2019) Disaster on the horizon: the price effect of sea level rise. J Financ Econ 134:253–272. https://doi.org/10.1016/j.jfineco.2019.03.013

Berry H, Kaul A, Lee N (2021) Follow the smoke: the pollution haven effect on global sourcing. Strateg Manag J. https://doi.org/10.1002/smj.3288

Bibri SE, Krogstie J (2017) Smart sustainable cities of the future: an extensive interdisciplinary literature review. Sustain Cities Soc 31:183–212. https://doi.org/10.1016/j.scs.2017.02.016

Brander JA, Taylor MS (1997) International trade and open-access renewable resources: the small open economy case. Can J Econ 30:526–552

Brucal A, Javorcik B, Love I (2019) Good for the environment, good for business: foreign acquisitions and energy intensity. J Int Econ 121:103247. https://doi.org/10.1016/j.jinteco.2019.07.002

Buggle JC, Durante R (2021) Climate risk, cooperation and the co-evolution of culture and institutions. Econ J 131:1947–1987

Bulkeley H (2010) Cities and the governing of climate change. 101146/annurev-environ-072809-101747

Bulkeley H, Edwards GAS, Fuller S (2014) Contesting climate justice in the city: examining politics and practice in urban climate change experiments. Glob Environ Chang 25:31–40. https://doi.org/10.1016/j.gloenvcha.2014.01.009

Burke M, Craxton M, Kolstad CD et al (2016) Opportunities for advances in climate change economics. Science (80) 352:292–293. https://doi.org/10.1126/science.aad9634

Casson M, da Silva LT (2013) Foreign direct investment in high-risk environments: an historical perspective. Bus Hist 55:375–404. https://doi.org/10.1080/00076791.2013.771343

Chava S (2014) Environmental externalities and cost of capital. Manage Sci 60:2223–2247. https://doi.org/10.1287/mnsc.2013.1863

Copoland BR, Taylor MS (1999) Trade, spatial separation, and the environment. J Int Econ 47:137–168. https://doi.org/10.1016/S0022-1996(98)00020-8

Dell M, Jones BF, Olken BA (2012) Temperature shocks and economic growth: evidence from the last half century. Am Econ J Macroecon 4:66–95. https://doi.org/10.1142/ANNREV-ENVIRON-072809-101747

Dell M, Jones BF, Olken BA (2014) What do we learn from the weather? The new climate-economy literature. J Econ Lit 52:740–798

Dhakal S (2010) GHG emissions from urbanization and opportunities for urban carbon mitigation. Curr Opin Environ Sustain 4:277–283. https://doi.org/10.1016/j.cosust.2010.05.007

Erel I, Liao RC, Weisbach MS (2012) Determinants of cross-border mergers and acquisitions. J Finance 67:1045–1082. https://doi.org/10.1111/j.1540-6261.2012.01741.x

EU (2014) In: Union, E (Ed.), Directorate general for internal policies. Policy Department A: economic and scientific policy. Mapp. smart cities EU. http://www.europarl.europa.eu/studies

Fernández CG, Peek D (2020) Smart and sustainable? Positioning Adaptation to Climate Change in the European Smart City. Smart Cities 2020 3:511–526. https://doi.org/10.3390/SMARTCITIE20200027

Flammer C (2021) Corporate green bonds. J Financ Econ. https://doi.org/10.1016/j.jfineco.2021.01.010

Fleming J, Kirby C, Ostliek B (2006) Information, trading, and volatility: evidence from weather-sensitive markets. J Finance 61:2899–2930

Helpman E (2006) Trade, FDI, and the organization of firms. J Econ Lit XLIV:589–630

Huang HH, Kerstein J, Wang C (2018) The impact of climate risk on firm performance and financing choices: an international comparison. J Int Bus Stud 49:633–656. https://doi.org/10.1057/s41267-017-0125-5

Karydas C, Zhang L (2019) Green tax reform, endogenous innovation and the growth dividend. J Environ Econ Manage 97:158–181. https://doi.org/10.1016/j.jeem.2017.09.005

Kim I, Pantzalis C, Zhang Z (2021) Multinationality and the value of green innovation. J Corp Financ 69:101996. https://doi.org/10.1016/J.JCORPFIN.2021.101996
