FINANCE IN THE FACE OF GLOBAL CHALLENGES

ESSAYS ON THE FINANCIAL ECONOMICS OF CLIMATE CHANGE AND THE AGENCY COST OF DEBT

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Finance in the Face of Global Challenges

Essays on
the Financial Economics of Climate Change
& the Agency Cost of Debt

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1 Introduction

Corporate finance theory narrowly defines the role of firms in society. The sole objective of firms is to maximize shareholder value, and thereby, firms contribute to economic growth and prosperity. The focus on shareholder value maximization is justified in the theory based on one important assumption: The assumption that public policy effectively manages societal challenges, and that it can ensure that corporate and societal interests remain aligned (Berk and DeMarzo, 2016). To safeguard this alignment, public policy faces two key tasks: as social welfare relies on the existence of a productive economy, policy makers and regulators have to provide the right framework for firms to operate as productively as possible. At the same time, they have to take measures against the production of externalities and intervene if firms' operations threaten societal well-being and the natural environment. If public policy can perform both tasks effectively, firms can focus on maximizing shareholder value. Firms generate economic growth, while policy makers establish the necessary conditions to achieve societal goals.

However, the severity and urgency of global challenges such as climate change and economic inequality raise doubts whether the roles of public policy and corporations can be neatly separated. Furthermore, these challenges pinpoint two issues of the separation of corporate and policy maker tasks in the pursuit of societal goals: By definition, global challenges require policy makers to coordinate and cooperate globally. Thereby, the establishment of more effective policies cannot be expected to happen overnight, and perhaps not in time to prevent climate change or to achieve ambitious development goals by 2030 as an interim report by the United Nations indicates (Leone, 2018). In addition, the funding that is needed to overcome global challenges is substantial. Both in the context of climate change and sustainable development goals, it is questionable whether the necessary financial resources could be provided by public means alone. According to the World Economic Forum (WEF), about $5.7 trillion in annual investments in green infrastructure will be needed by 2020 to make the economy resilient to climate change and to enable sustainable growth. Moreover, the WEF states that these investments would require a shift of $5 trillion U.S. dollars from business-as-usual investments into more sustainable investments in the private sector (World Economic Forum, 2013).

These issues are evident, and the demand for the corporate sector to take an active part in the face of global challenges is widespread. For instance, according to Dominic Waughray, Member of the Managing Board of the WEF, "business and government must forge new partnerships that are able to drive results much more quickly than our current international architecture allows" (United Nations, 2018), and the German government- and investor-backed Hub for Sustainable Finance voices that "[s]ustainable finance requires an entirely new relationship between the state and the financial sector – a relationship that serves societal goals and common integrity" (Hub for Sustainable Finance Germany, 2017). Without doubt, firms' voluntary reduction of negative externalities would help to accelerate the transition towards a more sustainable economy. Also, firms have access to capital markets, whereas institutions often objectively lack the funding that would be needed to finance sustainable change.

Implicitly, these demands require that firms redefine their objectives, and there is a strong divide between the traditional understanding of firm goals in corporate finance theory and the practical demand for the private sector to support public policy in addressing global challenges. In theory, this divide could be bridged by financial markets. In the simplest, ideal scenario, investors could establish a new definition of corporate goals. Such a redefinition would require that investors agree that firms should adopt objectives beyond shareholder value maximization, and that they could agree on which other societal objectives should then be pursued. Unfortunately, the opinions of different types of investors on how much profit should be given up to safeguard societal interests, and which measures firms should take to do so could probably not differ much more widely. Nevertheless, there are also more achievable scenarios how financial markets can help to bridge the divide between corporate and societal goals. If investors anticipate how global challenges will affect firms financially, market forces could incentivize firms to contribute to an economic transformation.

For instance, if global challenges affect firms in ways that are financially harmful, investors have incentives to motivate firms to adapt and to provide them with cheaper capital for adaptation projects. Moreover, capital markets can steer firms towards societal goals if investors value firms' commitment to societal and environmental goals, and reward them with a lowered cost of capital. However, financial markets cannot align societal and corporate objectives in these ways if investors do not anticipate both how firms are affected by global challenges and how firms can affect the severity of global issues. In practice, it is unclear if we can assume that investors understand these interrelationships. Do investors correctly assess how firms will be affected by societal challenges? And do we truly understand how firms will affect the progress towards more sustainable development?

This dissertation contributes to clarifying aspects related to these questions and studies finance and firm behavior in the face of global challenges. Taken together, the chapters address three different aspects. First, I investigate *how firms will be affected* by major societal challenges in the context of climate change. Second, I study how firms respond, and thereby also *how firms affect* the severity of global issues. And third, I test if *investors anticipate both how firms are affected and affect* the progress towards societal goals.

In Chapter 2, I investigate how *firms and investors are affected* by one of the most urgent challenges for present and future generations: climate change. Particularly, the assessment of the financial effects of physical climate hazards becomes more and more important, since it becomes less and less likely that substantial change can be prevented. In the chapter, I focus on the increase in the frequency of days with extremely high temperatures as the most prevalent projected trend and investigate the question of whether extreme temperature days have repercussions for firm performance. On the aggregate economic level, there is broad evidence that high temperatures decrease the supply and productivity of various economic inputs, and a variety of studies finds a negative relation between heat stress and productivity for unlisted firms, personal incomes, and aggregate economic losses. On the level of listed firms, however, the question of whether high temperatures decrease performance still remains the subject of heated debates.

To contribute to these debates, I use fine-grained global information on daily maximum temperatures and measure the past exposure of firms to temperature extremes at their primary locations over the past three decades. I then link the measure of temperature exposure with the financial performance records of a large, international sample of listed firms. Based on this dataset, I study if an increase in the number of days when temperatures are extreme at the firms' locations decreases their financial performance, or if listed firms are resilient to varying environmental conditions. In contrast to this resilience hypothesis, I find that both revenues and operating income decrease with the number of days when firms are exposed to adverse temperature conditions. Combined with extreme temperature projections of the Intergovernmental Panel on Climate Change (IPCC), the analyses in Chapter 2 indicate that firms will face substantial financial incentives to increase their investments in adaptation.

As it becomes less likely that climate change can be prevented, it also becomes more important to understand if investors accurately respond to the physical consequences of climate change. Particularly central banks have recently expressed the concern that investors might not fully anticipate the financial repercussions caused by climate change (Bank for International Settlements, 2018; Bank of England, 2019) and that this lack of anticipation could threaten financial stability. Therefore, Chapter 2 also investigates if analysts and investors anticipate the negative link between extreme temperatures and firm performance. The analyses in the chapter are based on a simple hypothesis: if extremely high temperatures adversely affect firms but if market participants underestimate their effect, financial performance expectations should be systematically too high in periods when firms are particularly exposed to adverse conditions. To test if this hypothesis holds, I calculate the deviation between analyst forecasts and actual earnings at announcement dates. Moreover, I estimate the abnormal returns around firms' earnings announcements, and link both proxies of investor surprises with the measures of the exposure of firms to extreme temperatures. In line with concerns regarding investor preparedness for climate change, I find that both analysts and investors do not anticipate the financial effects of heat, and that both earnings surprises and announcement returns become more negative with increases in extreme temperature days at the locations of the firms.

Until recently, firm-level research on the financial repercussions of physical climate hazards as well as on the awareness of investors of climate change has been scarce. Chapter 2 is most closely related to the concurrent study of Addoum, Ng, and Ortiz-Bobea (2019), who investigate extreme temperatures and firm performance in the United States, a study by Bernstein, Gustafson, and Lewis (2019), which documents that real estate exposed to sea level rise sells at a discount, as well as a study by Hong, Li, and Xu (2019), who find that investors do not fully take information on droughts into account.

The focus of CHAPTER 3 remains on climate change as a global challenge. However, in CHAPTER 3, I directly link the question of *how firms are affected* by climate change with the question of *how firms' adaptation to climate change could affect* sustainable economic development. While developed countries are responsible for a large share of past and future emissions, developing countries are over-proportionally exposed to the physical consequences of climate change. However, this exposure be costly both for directly affected firms and for firms located outside of developing, highly exposed countries. For instance, the costs of climate change could be shared through supply-chain networks. Further, the sharing of climate risks could become relevant for the projections of how climate change will reshape international economic dynamics: If the customers of firms that are highly exposed to intensifying climate hazards share the financial burden, they might choose to cooperate with alternative suppliers in safer locations instead. Therefore, climate change could shift economic activity from highly exposed, developing to less exposed, developed countries.

To empirically test these assumptions, I combine records of firms' supply-chain relationships and their financial performance with information on their exposure to floods and heatwaves in CHAPTER 3. I then study if climate shocks are shared through supply-chain links. Thereby, I find that firms are both directly and indirectly affected by climate shocks: Climate shocks to supplier firms have a direct negative effect on the revenue and operating income of the supplier itself. Also, such shocks indirectly decrease revenues and operating incomes of their remote customers, for instance due to production dependencies. In line with the fact that climate shocks to supply-chain partners are costly, I also find that trends in climate risk exposure influence the duration of supply-chain partner relationships. For instance, the results indicate that customers are more likely to terminate supply-chain relationships when suppliers prove to be more exposed to climate risk than customers expected. Further, I show that customers substitute such suppliers with competitors that operate in less climate-exposed areas.

To date, there are few studies on the firm-level operational adaptation to climate change-risk. Together with Lin, Schmid, and Weisbach (2018), Chapter 3 contributes to this new literature. Moreover, Chapter 3 is linked to the studies on the propagation of idiosyncratic shocks in supplier networks by Barrot and Sauvagnat (2016); Seetharam (2018); Boehm, Flaaen, and Pandalai-Nayar (2019).

Chapter 4 also relates to sustainable economic development as a global challenge, but stands in a very different context: corporate governance and its pricing implications for corporate debt securities. Compared to climate change, corporate governance might not be an obvious global issue. On the contrary, the name suggests that it might first and foremost represent a corporate matter. However, with internationally diverse investor bases, corporate governance has to be shaped and regulated across the borders of individual countries. At the same time, it is a serious challenge that concerns society at large: if companies are not governed as effectively as possible, *firms' compromised performance can negatively affect* the progress towards economic development goals. First, poor governance limits firm performance, and this sub-optimal performance can compound to sub-optimal national economic performance. Second, weak performance as a consequence of weak governance structures comes at the societal cost of reduced high quality employment. And third, firms with poor governance structures could have access to cheaper finance if these structures would be strengthened, and the access to finance at good conditions is an essential building block for economic growth. Hence, corporate governance also ranks high on policy makers agendas. For instance, the European Union (EU) has recently put a large initiative in practice with the Shareholder Rights Directive II. Through this initiative, the EU has made an effort to strengthen investor rights and prevent the economic harm that can be done through related-party transactions.

Chapter 4 relates to both of these aspects of corporate governance. In the chapter, I study corporate ownership, shareholder rights, and the risk of expropriation from a perspective that has received relatively little attention in corporate finance research: The perspective of bondholders. Based on corporate ownership data and corporate bond yield spreads, I find that greater insider ownership is associated with higher yield spreads. This positive relationship holds after the control for measures of risk-taking, and reveals that bondholders price-protect against greater insider ownership for reasons beyond insiders' heightened incentives to take risk. Beyond the focus of academic debates on the relation between insider ownership and risk-taking, I consider the consumption of private benefits as an economic channel through which insider ownership can hurt bondholders. Thereby, I find that bondholders anticipate that insider ownership can facilitate certain forms of expropriation.

Despite the rapid growth of the bond markets all around the world, the vast majority of studies on equity ownership, corporate governance, and bond valuation focuses on the United States. Chapter 4 adds to the international evidence (Ellul, Guntay, and Lel, 2009), and is closely related to the studies on bond valuation and managerial ownership (Anderson, Mansi, and Reeb, 2003), institutional ownership (Bhojraj and Sengupta, 2003; Huang and Petkevich, 2016), and government ownership (Borisova, Fotak, Holland, and Megginson, 2015).

2

Heat Exposure, Firm Performance, and Investor Surprises

2.1 Introduction

According to the Task Force on Climate Change-related Financial Disclosures (TCFD)[2.1], climate change is "one of the most significant, and perhaps most misunderstood, risks that organizations face today" (Task Force on Climate-related Financial Disclosures (TCFD), 2017, p.3). Central banks and financial regulators in particular have recently expressed the concern that investors might not anticipate the effects of climate change, that could endanger financial stability (Bank for International Settlements, 2018; Bank of England, 2019). With regard to corporate finance and investments, this concern is reflected in two fundamental but unanswered questions: First, do past records indicate whether physical climate risk affects the financial performance of listed firms? And second, if so, do investors anticipate that the physical risks of climate change affect firms' earnings? In this paper, we investigate both questions

This chapter is based on a working paper by Nora Pankratz (first author), co-authored with Rob Bauer and Jeroen Derwall (Maastricht University).

[2.1] The task force aims to help "companies disclose decision-useful information which will enable financial markets to better understand climate-related financial risks and opportunities" and was formed by the Financial Stability Board (FSB) in 2015 (Bloomberg, 2018).

in the context of extremely high temperatures for a sample of firms located in 57 countries. Understanding the financial effect of heat is particularly important as the IPCC projects high temperatures to become much more frequent (Intergovernmental Panel on Climate Change (IPCC), 2013). While major change has yet to occur, the new millennium has given a preview of what these projections entail as it has so far recorded 14 of the 15 hottest years since 1850 (World Meteorological Organization, 2017).

To address the question of whether temperatures directly affect the financial performance of listed firms, we estimate the past sensitivity of earnings to extremely high temperatures. We find that high temperatures negatively affect both revenues and operating income. Therefore, we subsequently test whether investors and analysts anticipate these effects on performance. We causally identify the net effect of extremely high temperatures on financial performance by using year-to-year variation in firms' exposure to days of extreme temperatures (*Extreme Temperature Days*). This variation is exogenous and randomly distributed, and therefore resembles an ongoing natural experiment[2.2]. In our empirical tests, we classify these days with two absolute and two place- and time-contingent temperature thresholds, that we derive by using spatially and temporally granular information on daily maximum temperatures from a global temperature reanalysis[2.3] data set. To link financials and temperature extremes, we determine the coordinates of firms' headquarters and spatially match them with the ERA-Interim grid. To ensure that our measure of heat exposure spans the majority of a firm's total operating activities, we use a sample of 4,400 firms with locally concentrated assets in Asia and Europe. Furthermore, we measure performance through quarterly and annual revenues and operating income, obtain analysts' ex-ante revenue and income estimates as a proxy for investor expectations of financial performance, and calculate daily abnormal returns around public earnings announcements.

The question of whether high temperatures affect the financial performance of listed firms remains a subject of heated debates. On the one hand, there is broad micro- and macroeconomic evidence that heat decreases the supply[2.4] of inputs; and various studies illustrate a negative relation between heat stress and the productivity

[2.2] See Auffhammer, Hsiang, Schlenker, and Sobel (2013) and Dell, Jones, and Olken (2014) for discussions of the econometric approach.

[2.3] Reanalyses combine past climate-related observations with scientific models to generate complete time series of climate outcomes such as temperatures, and are "among the most-used data sets in the geophysical sciences" (Copernicus Climate Change Service (C3S), 2019).

[2.4] Studies show that electricity prices increase with heat exposure (Pechan and Eisenack, 2014) while water supply decreases (Mishra and Singh, 2010).

of unlisted firms[2.5]; household incomes, and aggregate economic losses. Moreover, long-run temperature changes carry a positive equity risk premium (Bansal, Kiku, and Ochoa, 2016). Although the relative importance of all potential economic channels that drive these effects is difficult to identify, economic studies have stressed a persistent negative effect on the cognitive and physical performances of workers (see Pilcher, Nadler, and Busch (2002); Sepannen, Fisk, and Lei (2006) for reviews) and on the quantity of hours worked (Graff-Zivin and Neidell, 2014). In addition, some studies argue that the employee-related effects compound to economically relevant magnitudes that could explain the observed performance sensitivity at the firm level (e.g. Somanathan et al. (2015); Zhang et al. (2018)). In line with the high importance of labor as an input in many industries, some studies find that the negative economic relation between heat and output persists not only across but also within countries, with a documented decrease of 1.2 to 1.9% in municipal income per additional degree Celsius (Dell, Jones, and Olken, 2009). Countries in tropical and sub-tropical climates seem to be more severely affected by rising temperatures (Hsiang, 2010; Dell, Jones, and Olken, 2012). However, some studies document that this effect holds for both developed and developing countries and in- and outside of the agricultural sector (Burke, Hsiang, and Miguel, 2015b).

Based on these results, we adopt the alternative hypothesis that the aggregate negative economic effect of heat also manifests itself at the level of individual, listed firms. As air conditioning rates outside of the United States are low in most countries (International Energy Agency, 2018), we expect to find a sensitivity of firms to extreme temperatures in an international setting in the majority of industries – if labor productivity is indeed a strong driving channel for the observed aggregate economic effect. However, firms around the world could adjust to high temperatures in other ways, for instance by adapting the combination of inputs used or by rescheduling operations around temperature peaks. These efforts to adapt could be substantial, and the general economic logic indicates that firms adapt to the extent that the marginal benefits of additional measures equal the marginal costs. With our identification strategy, we capture firms' remaining sensitivity to heat net of all realized adaptation. Implicitly, we adopt the null hypothesis that if firms have already invested in adaptation to an extent that makes them resilient to fluctuations in their exposures to extreme temperatures, we should not observe a relation between exogenous variation in high temperature exposure and firm performance.

[2.5] E.g. Somanathan, Somanathan, Sudarshan, and Tewari (2015); Li, Cong, Gu, and Xiang (2016); Zhang, Deschenes, Meng, and Zhang (2018); Traore and Foltz (2017); Xie (2017).

We find that on average, an additional day of heat exposure significantly reduces both revenues and operating income: An additional day of heat decreases firms' quarterly sales turnover by 9% of the daily sales turnover, and the quarterly profitability by 14% of the average daily value. These estimates are economically significant and reject our null hypothesis. Relative to the average quarterly turnover, a quarter with a one standard deviation increase in the number of *Extreme Temperature Days* results in a decrease in quarterly revenues of 0.7%, compared to sales over assets under the average conditions which the firm experiences. Compared to the median total assets of the firms in our sample[2.6], this decrease corresponds to an absolute *quarterly* decrease of 9.9 million U.S. dollars. With regard to operating income over assets, a one standard deviation increase in the number of *Extreme Temperature Days* results in an absolute *quarterly* operating income reduction of 811.520 U.S. dollars given firms' median total assets.

To better understand the economic channels behind this effect, we conduct a series of cross-sectional tests. We find that the negative link between heat and performance is mainly driven by decreases in sales turnover and to a lesser extent by changes in the cost margin. Moreover, we exploit the international variation in our sample and find that the observed performance reduction is attenuated but generally remains observable when firms report that the locations of assets and sales are geographically separated. This finding indicates that the revenue decrease is not limited to temperature-related changes in demand-side dynamics, but is at least partially attributable to the physical impact of heat on firms' operations. Nevertheless, we also show that the effect increases in significance and magnitude if both the firms and their customers are affected by the same changes in heat exposure. In line with the physiologic evidence that heat exposure substantially reduces the performance of workers, we find that labor-intensive firms, which we classify both in absolute terms as well as relative to industry averages, experience the strongest negative reactions to extremely high temperature days. Given the low rates of cooling technology deployed in the studied countries (International Energy Agency, 2018), this labor-driven sensitivity of performance is plausible. In line with Addoum et al. (2019), we thereby find support both for the labor-performance and consumer-demand channels[2.7].

[2.6]Due to the skewed distribution of firms' total assets in our sample, we report the results in relation to the sample median instead of the mean.

[2.7]Our focus in this study is on understanding investor anticipation of the *net impact* of heat exposure on firm performance. A precise decomposition of the effect in terms of economic channels is important to better understand the cost of climate change and firms' potential to adapt to extreme temperatures, but goes beyond what we can accomplish in this paper.

Next, we investigate the question of whether financial markets anticipate the net physical effect of climate change on firms through all potential economic channels. Given that firms' revenues and income prove to be heat-sensitive, do investors and analysts anticipate the net performance repercussions of extreme temperatures at the firm level?

Whereas financial theory argues that asset prices quickly adjust to and reflect all publicly available information, recent debates by central banks, regulators, and the investment community raise doubts about the extent to which the market absorbs information on climate change. With regard to mitigating climate change and the transition to a low carbon economy, financial assessment is often complicated by policy and climate uncertainty. The case of extremely high temperatures as a physical risk, in contrast, provides a clean setting to test investors' anticipation for two reasons: First, information on heat exposure is widely and publicly available, particularly as analysts and investors can acquire information on a firm-by-firm basis[2.8]. Second, extreme temperatures cannot be influenced externally, and that enables an objective study of whether or not the performance repercussions are anticipated by participants in financial markets.

To find out whether investors have anticipated the effect of heat on financial performance to date, we conduct two tests. First, we use analysts' forecasts of revenue and operating income as a proxy for investors' expectations and test if performance surprises are negatively related to randomly distributed deviations in corporate exposure to heat above average conditions. If extremely high temperature days are financially material and analysts do not anticipate this effect, their forecasts of revenue and operating income should be systematically too high in periods when firms are affected by more extremely warm days than usual. Hence, deviations in the forecasts from the actual performance should become more negative with increasing heat exposure unless analysts correctly assess and incorporate information on high temperatures. To ensure that information on location-specific exposure is available, we use revenue and income forecasts that could have been updated after the heat exposure of the firm was realized, but before earnings were announced.

[2.8] Whereas reanalysis data on global temperatures may become public with a delay, market participants concerned with the performance of individual firms have timely access to extreme weather information from local forecasts and news reports.

Despite the fact that this test ensures that analysts have sufficient time to update their expectations, we find that surprises in revenue and operating income become more negative with increased corporate exposure to heat. The finding that the financial effect of heat is not fully anticipated is surprising in light of the efficient market hypothesis. Particularly, as the firms in our sample are local firms, the exposure to extreme weather conditions is more straightforward to assess than in the case of firms with global, complex production networks. Moreover, analysts are likely to be relatively more aware of local environmental events. At the same time, our sample largely consists of small firms, and analysts might not have the capacity to follow the firms closely enough to respond to local, environmental conditions; even if these conditions are performance relevant[2.9].

We conduct a second test to ensure that our findings are predictive of investors' capacity to assess the performance repercussions of heat in general that are not solely attributable to analysts' inertia in re-assessing small caps. In this second test, we study earnings announcement returns to investigate if investors are surprised by firms' financial sensitivity to heat. Again, we hypothesize that exogenous year-to-year changes in firms' heat exposure should not be systematically related to announcement returns if investors incorporate information on temperatures in their expectations on performance prior to the announcement. However, we find that announcement returns become more negative when firms are exposed to more days with extremely high temperatures. Hence, our results indicate that not only analysts but also investors do not fully anticipate the effect of heat on firm performance.

The first part of our study adds to the growing economic literature on heat exposure and firm productivity as well as the financial literature on the impact of climate hazards on firm performance and financing decisions. Most economic studies focus on unlisted firms in developing countries, and predominantly study economic measures of productivity: Somanathan et al. (2015) analyse the effect of extremely high temperatures on the productivity and attendance of workers in India and find a sizeable negative effect. Li et al. (2016) show that temperature shocks reduce Chinese firms' export quantities. Zhang et al. (2018) similarly find that heat reduces the productivity of a large sample of Chinese production facilities. Traore and Foltz (2017) study a detailed data set of firms in the Ivory Coast and find a negative link between temperatures and performance. Xie (2017) shows that thermal stress drives exit probabilities of Indonesian firms. Our results are in line with these findings; however, we show that the relation can be established in a wide range of relatively developed countries and

[2.9] On average, the number of estimates per revenue and income prediction is 2.7 in our sample in various industries, and persists in listed firms which have access to capital to invest in adaptive capacity. Moreover, our findings with regard to the consumer demand and employee performance channels are in line with the concurrent result of Addoum et al. (2019), who estimate firms' response functions to temperatures in general in the United States.

On the financial side, Barrot and Sauvagnat (2016) study the effect of natural disasters on sales growth and find that disasters negatively affect both the sales growth of directly exposed firms and their largest customers. Dessaint and Matray (2017) find that hurricane strikes reduce the market value of firms located in the United States. Brown, Gustafson, and Ivanov (2017) study cold spells and the use of credit and find that extreme cold represents a shock to firms cash holdings. In contrast to Addoum et al. (2019) and Brown et al. (2017), this study focuses on high temperature extremes. This choice is due to the projection that temperature distributions will shift to the right and that specifically high temperatures are expected to become more frequent in economically important areas. Moreover, we use measures for extremely high temperatures that can be consolidated with projections for increases of extreme temperature days of the IPCC, while we conduct robustness tests to ensure that our results are driven by heat and not by changes at the other extreme end of temperature distributions. Further, in line with Addoum et al. (2019), we find that while some firms are adversely affected, others benefit. For instance, our data shows that the financial performance of firms in the utility sector and in cold areas of the world, such as Scandinavia, increases when the exposure to high temperatures increases. However, an important insight that our consolidated view delivers is that the net effect over a large sample is negative, and substantial in economic terms.

Beyond the literature on the performance implications of environmental conditions, the second part of this study is linked to the literature on climate hazards and investor awareness. For instance, Jona, Lim, and Soderstrom (2016) find that corporate disclosures of adverse climate shocks reduce the market value of equity. Anttila-Hughes (2016) finds that NASA announcements of temperature records and ice shelve collapses affect the returns of energy companies. On the same note, Bernstein et al. (2019) find that real estate that is exposed to expected rises in the sea level sells at a discount. In contrast to these results, our findings show that heat exposure as another type of risk that is related to climate change has recently not been factored into investor expectations. Our findings are therefore in line with Hong et al. (2019), who study the food sector and find that information on droughts is predictive of the stock returns. Additionally, they find that trading on drought-related information is profitable, and that investors do not anticipate the link between drought conditions and firm performance. However, our results show that heat exposure matters beyond the food and agricultural sector and affect the economy at large, and that cross-sectional differences in the financial sensitivity to heat are more strongly determined by labor intensity than by industry classifications.

Moreover, our results connect to studies on the financial materiality of environmental information, which test how firms' impact on the environment is reflected in stock prices (e.g. Flammer (2013); Chava (2014); Krüger (2015)). In contrast to this perspective, we study the effect of the environment on the firms. Also, there is a large amount of literature on the direct effect of the weather on investors' sentiment and returns (Kamstra, Kramer, and Levi, 2003; Cao and Wei, 2005; Symeonidis, Daskalakis, and Markellos, 2010). Our study is different in that we focus on the link among the weather, real economic activity, and investor attention or the ability to assess this economic sensitivity to climate conditions within individual firms.

Further, our study closely connects to policy debates on climate change-related disclosure and global warming as a systemic financial risk. The Bank of England (Reuters, 2018) and the European Central Bank (Bank for International Settlements, 2018) have recently voiced growing concern with regard to the threat climate change poses to financial stability. Furthermore, legislators in France[2.10] and the European Union[2.11] have recently integrated climate risk into corporate and financial disclosure requirements - accompanied by the establishment of non-governmental and investor initiatives such as the Climate Disclosure Standards Board (CDSB) and the TCFD. To provide disclosure guidance, the European Bank of Development and Reconstruction (EBRD) released a report that proposes specific climate risk metrics, and suggests that firms should be required to assess the financial effect of their exposure to heat as one out of six first-order physical risks (European Bank for Reconstruction and and Development, 2018).

[2.10] "Article 173 of the French Law on Energy Transition and Green Growth passed August 2015 requires major institutional investors and asset management companies to [...] report on the impacts of both physical risks and transition risks caused by climate change [...]." (Four Twenty Seven, 2018a)
[2.11] "The EU laid out a clear plan to move towards mandatory climate risk disclosure as part of a new set of regulations to finance sustainable growth and support the transition to a low-carbon economy. The European Commission's Action Plan lays out a two year time line for implementation, with a goal to create a taxonomy for climate adaptation finance by the end of 2019." (Four Twenty Seven, 2018b)

The study proceeds as follows: After explaining how we measure extremely high temperatures in section 2, we show the effect of heat exposure on firm performance and cross-sectional tests in section 3. Section 4 shows the relation between heat exposure and analyst forecasts, and section 5 covers announcement returns. In section 6, we rule out alternative climate-related and economic explanations, and discuss the extrapolation of the results and implications for firm adaptation in section 7. Section 8 concludes.

2.2 Measuring Heat Exposure

2.2.1 Regional Concentration of Firm Operations

To measure firm-specific heat exposure, the firms' primary locations have to be identified. Moreover, different exposures to heat for subsidiaries, plants, and branches in different locations have to be consolidated at the corporate reporting level if firms operate globally. This consolidation requires weighting and adding location-specific exposures, based on the financial contribution of the various locations, their relative importance in production processes, and their sensitivity to temperature variability. Therefore, we address the research question in the context of local firms because the outlined weighting of different locations requires additional comprehensive assumptions.

To identify such firms with locally concentrated operations, we merge the financial data obtained from Compustat with Factset's international segment records. Publicly listed firms are obliged to disclose information on their activities by geographic segments in their interim financial reports by adding information on all segments representing more than 10% of total assets, sales, or income. The granularity of the reported segments differs across firms and ranges from state to continental levels. We limit the sample to firms that report segments on a country-by-country basis, and subsequently exclude firms that hold less than 80% of their total assets in their home country. If home countries are large and diverse in terms of climate zones, a headquarters-based measurement of extreme temperatures is likely to be imprecise - for instance, if a firm reports to hold all assets in the United States, these assets could still be spread out over a variety of different climate exposures at the same time. To ensure that operations are indeed exposed to similar weather, we restrict the sample to firms in countries with limited variation in climate zones. We base this restriction on a qualitative assessment that uses the Köppen Climate Classification

(Chen and Chen, 2017)[2.12]. The firms included in the final sample are mapped in Figure 2.1. In line with the expectation that local, listed firms are small firms, Table 2.1 shows that the total asset values in this sample lie between 19 and 196 million U.S. dollars thar are between the 25^{th} and the 75^{th} percentile, with a median of 61 million U.S. dollar in total assets. As we do not explicitly eliminate large firms from the sample, the mean firm size is much larger with 984 million U.S. dollars in assets. While this type of firms is not representative of the firms that make up most of the global stock market capitalization – the corresponding share of firms on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) in 2005 lies at less than 3% of the total capitalization – the firms in our sample are representative of a large number of firms. According to statistics by the U.S. Securities and Exchange Commission, firms with less than 303 million U.S. dollars in assets make up the lower 68.6% of firms listed on the NYSE and AMEX (SEC, 2005). In terms of other financial characteristics, the firms in this sample have a mean operating income before depreciation on assets of 8.1% per year and 2% per quarter.

2.2.2 Daily Temperatures

We obtain historical records of the daily maximum temperatures available on a global scale from the European Center for Medium-term Weather Forecasts to calculate a firm-specific measure of heat exposure. The ERA-Interim reanalysis data of the atmosphere provides continuous daily coverage of a $0.75 \times 0.75°$ grid dating back 1979 to today. Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, Bechtold, Beljaars, van de Berg, Bidlot, Bormann, Delsol, Dragani, Fuentes, Geer, Haimberger, Healy, Hersbach, Hlm, Isaksen, Kllberg, Koehler, Matricardi, McNally, Monge-Sanz, Morcrette, Park, Peubey, de Rosnay, Tavolato, Thpaut, and Vitart (2011) describe the data set in detail. The consistent coverage is a major advantage of the reanalysis data compared to station-based weather records. In contrast, the regional and spatial coverage of temperatures provided directly by weather stations varies substantially. Hence, using station-based data requires the interpolation of time periods of varying lengths. To match the firms in our sample with the

[2.12] Thereby, we include firms in Austria, Bahrain, Bangladesh, Belgium, Botswana, Bulgaria, Croatia, Denmark, Egypt, Estonia, Finland, France, Germany, Ghana, Great Britain, Greece, Hungary, Indonesia, Iceland, Ireland, Israel, Italy, Ivory Coast, Jordan, Korea, Kuwait, Latvia, Lebanon, Lithuania, Luxembourg, Malaysia, Malawi, Morocco, Netherlands, New Zealand, Nigeria, Norway, Oman, Palestine, Philippines, Poland, Portugal, Qatar, Roumania, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Tunisia, Turkey, Taiwan, Ukraine, and Vietnam in the analysis. Japanese firms drop out of our sample as we require firms to have quarterly financial performance records.

reanalysistemperature records, we obtain firm locations from Factset Fundamentals and cross-check whether the address countries match the Compustat Global records. Subsequently, we geocode street-level addresses using the Bing Maps API, and match firms and ERA-Interim grid nodes by minimizing the respective distance.

2.2.3 Classification Thresholds for Extreme Temperature Days

To test the effect of extreme temperature exposure on firm performance, we have to obtain a measure of the exposure to heat at the quarterly level, which is in line with the firms' financial reporting periods. We use the concept of extreme temperature days to classify whether temperatures at the locations of the firms are extremely high and whether the number of extreme temperature days per quarter align with the firms' performance, as quarterly firm performance could be viewed as the sum of daily financial output under a certain exposure to heat over the fiscal quarter. We use four different temperature thresholds for the classification: Two thresholds are absolute choices based on the physiological literature that argues that individual productivity begins to drop at 25° Celsius (Tanabe, Iwahashi, Tsushima, and Nishihara, 2013), and falls with an increasing rate beyond 30° Celsius (Seppanen, Fisk, and Faulkner, 2003). Further, we use two additional location-specific thresholds that are widely used to characterize heatwaves (Perkins and Alexander, 2013) and are very similar to the projections of future extreme temperature days made by the IPCC (IPCC, 2013a). These daily thresholds are determined endogenously and are based on past temperature distributions between 1980 and 1999 at the location. Days are classified as extremely warm, if their maximum temperature exceeds the 90^{th} or 95^{th} percentile of the historical distribution of temperatures on the same day as well as the previous and subsequent five days.

For all four measures, we count the number of days on which firms are exposed to extreme temperatures during a financial quarter. Then we construct an aggregate heat exposure measure on a monthly basis to accommodate different financial year ends and hence, variation across firms in terms of which months are associated with which fiscal quarters. To do so, we count the number of days per month a location was exposed to extreme heat. Subsequently, we sum the number of exposed monthly days and carefully match them with the fiscal reporting quarters.

There are both economic arguments for using universal, absolute thresholds to classify extreme temperature days as well as for place- and time-contingent thresholds. Physiologic studies show that there are absolute, general temperature thresholds below which variations are unrelated to physiological performance, but above which workers have to reallocate energy from task performance to physical cooling functions (e.g., Seppanen et al., 2003). At the same time, individuals and organizations are likely to adapt to typical weather conditions. Hence, the classification of temperatures as normal or extreme should depend on the average historical exposure to heat. To address both arguments regarding the general relation between economic performance and temperatures, we use both absolute and relative thresholds to classify extreme temperature days.

Table 2.1 shows the extreme temperature exposure of the firms in the sample from 1995 to 2017. Since we estimate all empirical tests based on within-firm variation, we show both the levels ($Days$) and the variation in the number of high temperature days ($Difference\ in\ Days > x$) during which firms are exposed to heat. All figures with regard to extreme temperature days in Panel A of Table 2.1 are at the quarterly level, and Panel D of Table 2.1 shows the annual figures. The variables labeled $Difference\ in\ Days > x$ refer to the deviation in the number of days of heat from the same quarter in previous and subsequent financial years. The average annual temperature per year and firm in this sample is 22° Celsius, with 14.6° Celsius at the 25^{th} percentile and 28.5° at the 75^{th} percentile. The wide range of average temperatures across the sample indicates that there are firms in various climate zones. This variation is also graphically illustrated by the map in Figure 2.1.

Due to this geographical dispersion, the distribution of the different numbers of extreme temperature days differs depending on the average conditions in different locations: The average number of days on which firms are exposed to temperatures above 25° Celsius is high with 51 out of a maximum of 91 days, but varies strongly between firms (25^{th} percentile: 0 days, 75^{th} percentile: 91 days). As these values indicate, the choice of absolute thresholds leads to a setting in which some firms in the sample are either "always treated" or "never treated". In other words, some firms are located in climate zones where the 25° and 30° temperature thresholds are always (never) exceeded. Thereby, the sample with within variation, which we rely on in all analyses, is somewhat restricted. When days are classified as exposed or not exposed to extreme temperatures based on percentile thresholds, most firms are "treated" in some years. In contrast to the strong regional differences in the cross-sectional variation in exposure to high temperatures, the within variation is internationally more consistent, and the standard deviation in the number of days exposed to heat deviating from the location-specific average is 6.9 days per quarter (6.5 days) and 18.1 days per year (16.5 days) under the 30° Celsius (95^{th} percentile) threshold.

2.3 Heat Exposure and Financial Performance

In our first analysis, we test whether firms are sensitive or resilient to short-term changes in exposure to extreme temperatures. To do so, we collect financial and accounting performance records from Compustat Global. To measure financial performance, we focus on quarterly revenues and operating income. Both revenues and operating income are narrowly defined metrics at the top of the income statement and therefore should be relatively less distorted by accounting choices as compared to metrics further down the income statement. In contrast to Somanathan et al. (2015) and Zhang et al. (2018), we focus on financial measures of performance instead of economic concepts that measure productivity. By doing so, we are able to align the tests for the sensitivity of performance to extreme temperatures with investor and analyst expectations. We scale both revenues and operating income by firms' total assets and convert all values from local currencies to U.S. dollars by using World Bank tables on exchange rates. Panel A of Table 2.1 shows the quarterly and Panel D the annual statistics. The firms have an average quarterly sales turnover of 23.229% and an average quarterly operating profit of 2.026%.

Our identification strategy accounts for long-term corporate decision-making that frequently involves the climate. For instance, production decisions might be based on the average climate exposure in a given location, or entrepreneurs might choose to establish businesses in places that provide optimal operational conditions. If firms with particular observable or unobservable characteristics choose to locate (produce) in a specific place (certain products or with particular technologies), these characteristics could be correlated both with the climate and the observed financial performance. In contrast, year-to-year differences in the realized weather cannot be influenced by the firms' decisions, and cannot be predicted with a high level of accuracy in the long run. Therefore, we can causally identify the impact of heat exposure on firm performance – net of all short-term adaptation potential that firms realize – based on the variation in the number of realized hot days over time. Compared to the location- and season-specific average temperature conditions, the exact realization in any given year is randomly distributed and exogenously determined (see Auffhammer et al. (2013) and

Dell et al. (2014) for a discussion of the approach). Figures 2.2 and 2.3 illustrate this variation and show that the number of days when firms are exposed to heat in a given year compared to the average number of days of exposure varies substantially by firm.

To isolate this variation, we use a pooled ordinary least squares (OLS) regression with firm × season fixed effects. We use firm × season (firm × financial quarter) instead of firm fixed effects to avoid comparing financial quarters in cold seasons with financial quarters in warm seasons for the same firm. Equations 2.1 and 2.2 outline the OLS specification,

$$\frac{revenues}{assets}_{ist} = \beta\ Extreme\ Temperature\ Days_{ist} + \mu_{is} + \gamma_{mt} + \epsilon_{ist} \tag{2.1}$$

$$\frac{operating\ income}{assets}_{ist} = \beta\ Extreme\ Temperature\ Days_{ist} + \mu_{is} + \gamma_{mt} + \epsilon_{ist} \tag{2.2}$$

where i stands for the firm, s stands for the quarter of the year ($s = 1, ..., 4$) by firm based on the financial reporting schedule of each firm. t stands for the observed year, μ_{is} represents the firm × financial quarter-fixed effect to absorb the firm-location and firm-season-specific levels of heat exposure, and γ_{mt} stands for an industry-quarter fixed effect to absorb the variation in financial performance due to technological change or industry-specific economic trends, with m as an index for $m = 1, ..., M$ industries determined by i. $Extreme\ Temperature\ Days$ stands for the number of days in a quarter that firm i experiences temperatures above one of the four thresholds. We cluster standard errors two-way at the firm and year level.

As location-specific variation in heat exposure over time cannot be actively influenced by the choices of the firm, there should be no firm-specific characteristics that can drive both the outcome and the measure of heat exposure. Hence, we do not include controls for time varying firm-level characteristics in the baseline analysis to avoid bad control problems[2.13] at the expense of the potentially unnecessarily high residual variance (Dell et al., 2014).

[2.13] For instance, firm characteristics could be "bad controls" (Angrist and Pischke, 2008) if heat exposure affects potential control variables through its impact on financial performance.

Table 2.2 shows our main result on the effect of extreme temperatures on financial performance. Panel A (B) shows that the number of days with temperatures exceeding 30° Celsius, the 90^{th} percentile, and the 95^{th} percentile temperatures are all negatively related to quarterly revenues. The effect of one additional day of heat exposure, on average, is associated with a 0.0182 (90^{th} percentile threshold, significant at the 1% level) to 0.0226 (30° Celsius threshold, significant at the 1% level) percentage point decrease in the quarterly revenues over assets. According to the results in Panel B of Table 2.2, firms' quarterly operating income similarly decreases by approximately 0.0031 percentage points (coefficients between -0.0027 and -0.0031, significant at the 5 and 10% level) for every additional day of exposure to heat (significant on the 10% level for the 30° Celsius and 95^{th} percentile thresholds, and on the 5% level for the 90^{th} percentile threshold). Only when days are classified as extreme temperature days based on the 25° Celsius threshold, do we not find a significant relation between heat and revenues or income. The threshold represents a lower boundary of temperatures that could be expected to be economically detrimental and lies close to the average annual temperature of 22° Celsius in the sample.

The estimated effect is both plausible and substantial in economic terms. First, with regard to the plausibility of the magnitude, we compare the estimates to the effects documented in the context of heat exposure and individual performance. Relative to the average revenue over assets in the sample divided by the days in the respective financial period (e.g., the quarterly ratio of 23.229% divided by 90 days), an additional *Extreme Temperature Day* of 30° Celsius reduces firms' financial performance by 8.8%. Related to the sample mean of operating income over assets per quarter of 2.026%, one additional *Extreme Temperature Day* of 30° Celsius corresponds to a reduction of 13.78% in the operating income share of an average day of a financial quarter (coefficient compared to 1.9% divided by 365). According to Seppanen et al. (2003), worker exposure to temperatures over 25° Celsius in the office environment leads to a performance loss of 2% per additional degree − a daily temperature of 30° Celsius would hence mean an expected performance loss of 10% of the performance. Naturally, our results could be driven by channels other than employee performance, but nevertheless, the results thereby fall into a similar range as the estimates from studies on heat and the employee performance channel.

Second, the estimates indicate that the effect is large in economic terms. A quarter with a one standard deviation increase in the number of *Extreme Temperature Days* compared to the average conditions results in a 0.15 to 0.16 percentage point reduction in revenues over assets (for the 30° Celsius threshold: standard deviation

= 6.9 days × the coefficient of -0.023, significant at the 1% level). Relative to the average quarterly turnover, these estimates show an average absolute reduction in revenues of 0.7% that is attributable to heat, and an absolute decrease of 9.9 million U.S. dollars given the mediantotal assets of the firms in our sample. With regard to operating income over assets, a one standard deviation increase in the number of *Extreme Temperature Days* results in a 0.027 percentage point reduction (for the 90^{th} threshold: standard deviation = 8.8 days × the coefficient of -0.0031, significant at the 5% level). Compared to the sample mean of 2.026%, the estimate shows a reduction of 1.3% that is attributable to heat, and an absolute *quarterly* operating income reduction of 811.520 U.S. dollars given firms' median total assets.

Our estimates indicate the effect of heat on performance net of all potential that firms have realized to adapt to extreme temperatures in the short run. For instance, firms may be able to adapt by rescheduling production throughout or across days, or substitute labor through other inputs. However, if firms reschedule production processes beyond financial quarters and can thereby neutralize the negative effect of heat on performance in parts or entirely, our estimates could overstate the actual effect. Hence, we estimate the effect of extreme temperature days on revenue and operating income by controlling for lagged heat exposure in Panel C and D of Table 2.2. Contrary to this concern, Panel C shows that the lagged effect of heat exposure on revenues is larger (e.g. coefficient for 90^{th} percentile threshold -0.0185, significant at the 1% level) than the immediate exposure (90^{th} percentile coefficient -0.0130, significant at the 5% level). Similarly, the lagged coefficients on the effect of extreme temperature days on operating income in Panel D are larger in magnitude than the immediate exposure coefficients except for the 25° Celsius threshold (30° Celsius, 90^{th} percentile significant at the 1% level, 95^{th} at the 5% level). Observing a delayed effect is plausible if extreme temperatures delay or distort operations to the extent that the financial repercussions only become visible when products are sold or services are billed in subsequent financial periods.

2.3.1 Economic Channels

Finding that firms are sensitive to high temperatures naturally raises the question of which economic channels drive this effect. Hence, we conduct a series of additional tests. First, we test if heat exposure also affects firms' cost margins, as some economic drivers should primarily manifest themselves in firms' variable costs. For instance, the increase in electricity consumption and prices caused by an increase in the use of cooling technology could negatively affect firms' operating profits in addition to changes in turnover. However, Panel A of Table 2.3 indicates that on average, the extent to which cost-related drivers contribute to explaining the results is limited. The cost of goods sold compared to revenues are hardly affected. Only when we use the 95^{th} percentile temperature thresholds to classify days as hot, do we find a statistically significant increase of 0.0159 percentage points (significant at the 5% level) in the cost of goods sold (COGS) per dollar of revenue. As Panel B shows, selling, general and administrative expenses (SGA) per dollar of revenue increase. However, this increase occurs by construction, as the negative effect of heat exposure on revenues estimated in Table 2.2 leads to a decrease in the denominator of the ratio. Furthermore, fixed costs cannot be adjusted in the short run, and hence, the expense ratio has to increase with the reductions in revenues. Thereby, the results do not show that firms' substantially change their spending behaviour as a response to high temperatures, and they do not show that changes in cooling cost or more generally the quantity and prices of other inputs are first-order drivers of the decrease in performance.

If the overall decrease mainly stems from changes in sales turnover and to a lesser extent from changes in the firms' cost efficiency, the general effect could still be driven by two different forces: On the one hand, heat exposure could indeed compromise firms' productivity as we hypothesize. On the other hand, the results could indicate that corporate and retail customers are on average also affected by heat, and subsequently reduce their consumption. To understand if either supply or demand effects (or both supply and demand effects) are at work, we exploit the geographic separation of assets and sales of a subset of the firms in our sample. In Table 2.4, we compare the effect on firms with geographically separated and non-separated sales and assets by interacting *Extreme Temperature Days* with *Revenues Abroad*. This variable is an indicator of whether firms' top revenue country is also their home country. The coefficient for this interaction is positive but only significant for the effect on revenues and the 30° Celsius and 90^{th} percentile thresholds in Panel A. Joint tests of the coefficients show that firms' are negatively affected in the estimates of the 30° Celsius and 90^{th} percentile thresholds (p-values are shown in the last line of Table 2.4). Hence, the results indicate that the negative relation between heat and performance is not limited to firms with exposed customers and that the results are not exclusively driven by demand effects. Nevertheless, the results simultaneously lend support to the idea that the effect is stronger when both customers and suppliers are affected by high temperatures. This finding is important from a managerial point of view: If firms are subject not only to production-related but also to demand shocks through heat exposure, more firm-level investment in adaptive capacity can only partially reduce the associated financial risk. Moreover, observing that the effect is stronger when customers are affected by heatwaves too is in line with the idea that heatwaves lead to a general economic slowdown that compounds in supply chain networks.

If the observed decrease in financial performance is indeed at least partially supply-related, the magnitude of the effect should vary with firms' operational sensitivity to heat. The literature argues that reduced labor supply (e.g. Graff-Zivin and Neidell (2014)) and productivity are major economic channels through which extreme temperatures reduce aggregate economic output. Hence, we test if labor-intensive firms are particularly affected by increases in *Extreme Temperature Days*. We obtain information on labor expenses from Factset and conduct two tests: We calculate the share of labor expenses to total expenses and assign firms into absolute and industry-benchmarked terciles based on their share of labor expenses. First, Panels A and B of Table 2.5 show the results for the assignment into terciles *regardless of their industry*. Compared to the lowest tercile, the effect is more pronounced in the second and most pronounced in the third and highest labor intensity tercile across all specifications. Second, we group firms into high, medium and low labor intensity terciles *relative to industry-specific averages* of labor expenses to total expenses in Panel C and D of Table 2.5. The results support the previous test, and the highest labor intensity terciles are most adversely affected by increases in exposure to extreme temperature days. This cross-sectional setting does not allow a causal interpretation, but altogether the results of both tests are in line with the micro-economic studies which show that labor productivity is an important channel through which heat exposure can harm the economy as a whole. Moreover, the evidence for a labor-related sensitivity of firm performance to temperatures is particularly plausible in an international setting, given that the rates for air conditioning deployed in the countries which we study are low (International Energy Agency, 2018).

2.3.2 Industry and Geographic Heterogeneity

With regard to the alternative economic channels, a common view is that extreme temperatures could be economically harmful *only* through sectors in which firm performance is a direct function of temperatures and that such sectors alone causes the aggregate economic losses. For instance, there is a direct relation between agricultural returns and extreme temperatures through the effect of weather and soil conditions on crop yields. Studies have illustrated this relation using financial returns in the food industry (Hong et al., 2019). To test if the agricultural industry is a major driver of the average decrease in performance, we repeat the baseline regressions but exclude agricultural industries (SIC code 0). In contrast to the common belief, the results in Panel A and B of Table 2.6 are similar in magnitude and significance. The fact that the negative relation between extreme temperatures and performance relation holds outside of the agricultural industry is in line with the studies showing that extreme temperatures negatively affect agricultural and non-agricultural economic activities (e.g., Burke et al. 2015b; Hsiang 2010). Moreover, the finding is consistent with the results of Addoum et al. (2019), and in line with the hypothesis that heat affects firm productivity at large, for instance through the employee performance channel.

In addition, we conduct two tests on the cross-sectional heterogeneity of the effect to ensure that the observed estimates indeed capture heat exposure, and not some other dynamic that is coincidentally correlated with extreme temperatures. First, if the observed effect comes from heat exposure, then it should be positive for those industries that directly benefit from extreme temperatures. For instance, firms in the utility sector could benefit from an increase in the number of high temperature days, as heat exposure increases the demand for cooling and therefore for electricity. Panels C and D of Table 2.6 show the effect of extreme temperatures on utility firms compared to all other firms (SIC digits starting with 49). The interaction terms are insignificant but positive, and joint tests of the coefficients show that the overall effect of high temperature days on firm performance in the utility sector is indistinguishable from zero (p-values between 0.71 and 0.98, shown in the last line of Panel C and D of Table 2.6). Second, if our measure of $Extreme\ Temperature\ Days$ does capture heat exposure, then the effect should turn from negative to neutral or positive in geographic areas where temperature increases are likely to represent an opportunity rather than a threat. In line with the idea that economies in countries with mild climates could on average benefit from shifts in temperature distributions, Panels E and F of Table 2.6 show that Scandinavian firms are to a lesser extent negatively - or even positively - effected by increases in the number of days that exceed the 90^{th} or 95^{th} percentile[2.14]. The joint tests of the coefficient for $Extreme\ Temperature\ Days$ and the interaction show that firms' operating income, on average, increases with increases in the number of days with temperatures over the 90^{th} or 95^{th} percentile threshold.

[2.14] We exclude the number of days above 30° Celsius in Panel E and F of Table 2.6 as the there were very few days above 30° Celsius in Scandinavia during the sample period.

2.4 Heat Exposure and the Accuracy of Analyst Forecasts

In sum, the results of the first part of the analysis indicate that heat exposure reduces revenue and operating income, and that this effect is related to productivity changes at the firm level. Hence, the findings show that information on extreme temperature days is relevant for financial projections of firm performance. However, policy-makers voice strong concerns that investors and financial analysts might not be prepared to take climate-related information into account when pricing securities. We empirically test if this policy assumption is justified. To do so, we investigate whether heat explains variation in analysts' forecast errors.

Analogous to the first analysis, we use the randomly distributed and exogenous variation in the number of extreme temperature days around the average number of days at the firm's location to identify the effect of shocks in heat exposure on the accuracy of analyst forecasts. If analysts do not incorporate information on the realized heat exposure in their predictions, then surprises in financial performance should become systematically more negative in periods when firms are exposed to more *Extreme Temperature Days* than on average. We calculate the $Performance\ Surprise$ as the deviation in the projected performance from the actual. To align both analyses, we focus on analysts' projections of revenues and income. We obtain these projections from IBES, and scale both forecast types by the firms' total assets. Due to few forecasts on operating income in IBES, we substitute them with forecasts of pre-tax income. Conceptually, this difference should not be problematic. The main difference between both values lies in the firms' interest expenses, which should be orthogonal to the firms' exposure to high temperatures, since this exposure is exogenous and varies from year to year. Panel B of Table 2.1 shows the descriptive statistics. The median suprise for both revenues and income over assets is negative but close to zero. The mean surprises in revenue and pre-tax income are negative with -0.081 and -0.104%.

We construct the test in a way that ensures that information on heat exposure is publicly available. This way, we can assume that analysts have sufficient time to incorporate this information in their projections. Figure 2.6 illustrates the timing of the test. Analysts project the performance of firms for any given financial quarter, and the quarter which the forecast refers to is labeled $Affected\ Fiscal\ Period$ in the figure. During this period, the firm is exposed to a certain number of *Extreme Temperature Days*. The financial performance of the firm is then announced at the *Announcement Date*, which follows the affected financial quarter with a certain time lag. Precisely this time lag gives analysts time to update their projections toward the end or after the closing of the fiscal period when the realized number of *Extreme Temperature Days* is known. To implement our tests, we focus on predictions for the financial periods that are one period ahead (labeled 6 in IBES Summary Statistics), and restrict the IBES forecasts in the sample to the last updates available (labeled "statistical periods" in IBES) before the actual earnings are announced. Thereby, we only analyze the forecasts which could be updated by analysts in time to incorporate all available information on heat exposure. Equation 2.3 shows the regression specification:

$$Performance\ Surprise_{iskt} = \beta\ Extreme\ Temperature\ Days_{ist} + \theta_{mt} + \kappa_{is} + \epsilon_{ist} \tag{2.3}$$

where i stands for the firm, s stands for the season of each firm that is based on its financial reporting schedule and takes values from one to four for each of the four financial quarters, κ_{is} represents the firm $\times$ financial quarter-fixed effect to absorb firm-location and firm-season-specific levels of heat exposure. k stands for the forecast measure, either revenues or pre-tax income; n for the firm's industry; t for the observed time period and θ_{mt}) for industry $\times$ time fixed effects to absorb the average forecast errors that analysts make systematically due to industry-specific economic dynamics. We calculate the $Performance\ Surprise_{it}$ by deducting the expected from the actual revenue or pre-tax income (k) and scale the difference by firms' total assets. *Extreme Temperature Days* refers to the number of exposed days based on one out of the four threshold used to classify days as hot, and we count the number of these days during the affected financial period, for which earnings are announced with some delay, at the point in time labeled t. The timing of the test and the match of *Extreme Temperature Days* to the financial periods is illustrated in Figure 2.6. We cluster standard errors by firms and add the log book-to-market ratio following Edmans (2011) and industry $\times$ year fixed effects to the regression specification to control for potential confounding effects. To control for size, we scale the forecasts and actual revenues and operating income by total assets of the firm.

Table 2.7 shows the main results for this test. Panel A refers to revenue forecast surprises and Panel B to pre-tax income surprises. The table shows that in line with the hypothesis, analysts do not take heat into account in forecasting firm performance. Further, the negative coefficients indicate that increases in firms' extreme temperature exposure lead to more negative performance surprises compared to the average conditions. For the revenue forecasts in Panel A, the effect that surprises become more negative are statistically significant for the absolute temperature thresholds of 25° Celsius (column 1, coefficient -0.0053, significant at the 5% level) and 30° Celsius (column 2, coefficient -0.0050, significant at the 10% level). Therefore, lower temperature thresholds may be more relevant in this sample, as the average annual temperature of firms' locations in this second analysis is 4° Celsius lower than the average annual temperature of those in the first test. With regard to pre-tax income (Panel B), increases in the number of extremely warm days over time are significantly and negatively related to the surprise, and the coefficients range from -0.0022 for the 25° Celsius threshold (significant on the 10% level) to -0.0037 for the 30° Celsius threshold (significant on the 1% level).

In terms of the economic relevance, the estimated effects are sizeable. Relative to the mean surprise on quarterly revenues scaled by assets (0.076%), and the standard deviation of the number of days per quarter by which heat exposure varies over time (6.9 days for the 30° Celsius threshold), the forecast errors attributable to heat (6.9 days $\times$ -0.0049 = -0.033) can explain up to 44% of the average mean error of analysts. For the pre-tax income forecasts, the error attributable to *Extreme Temperature Days* can explain up to 25% of the average error (30° Celsius threshold, 6.9 days $\times$ -0.0037 = -0.0255 of -0.104%). At the same time, these estimates are plausible. Due to sample changes, the results of the first and second part of the analysis are not directly comparable. However, the regressions are generally based on dependent variables with equal scaling. If the changes in the forecast accuracy are indeed induced by shocks in heat exposure that are not well understood by investors, the magnitude of the financial performance surprise should be of a similar magnitude as the effect of *Extreme Temperature Days* on actual performance. This proportion holds particularly for the estimates on pre-tax income surprises. The coefficients are very close to those for the general financial performance effect (coefficient for the 30° Celsius threshold in Table 2.2 : -0.0031, coefficient for the 30° Celsius threshold in Table 2.7: -0.0037). The revenue-related estimates, however, are on average smaller than the effects estimated in the first part of the analysis.

2.5 Heat Exposure and Announcement Returns

As we study small, local firms, the attention that analysts can devote to assessing the performance of each individual firm is likely to be limited[2.15]. In this section, we test whether the conclusion that market participants do not anticipate the repercussions of heat for performance holds beyond the case of analysts. As another common[2.16] and more general test on market surprises, we study whether investors react more negatively to earnings announcements in periods when firms have been exposed to a high number of *Extreme Temperature Days*. Again, we align our approach with the first and second parts of our the study and construct the test as illustrated in Figure 2.6. We again rely on exogenous year-to-year variation in the number of *Extreme Temperature Days* at firms' locations. If investors do not anticipate the relation between heat and earnings, then the announcement returns should systematically decrease with random increases in heat exposure.

To conduct this test, we obtain daily share prices from Compustat Global, convert the time series into U.S. dollars, and calculate the daily returns. As a proxy for the expected returns and as the benchmark used to estimate the market model, we calculate the equal and market capitalization-weighted returns of all firms in the sample. We trim the returns below the 1^{st} and above the 99^{th} percentile. Both 3-day and 5-day announcement returns are calculated based on the announcement date subsequent to the affected fiscal period. The summary statistics are shown in Panel C of Table 2.1, and equation 2.4 and 2.5 show the regression specification:

$$c(a)r_{ist_{-1,+1}} = \beta \ Extreme\ Temperature\ Days_{ist} + \gamma_{mt} + \kappa_{is} + \epsilon_{ist} \tag{2.4}$$

$$c(a)r_{ist_{-2,+2}} = \beta \ Extreme\ Temperature\ Days_{ist} + \gamma_{mt} + \kappa_{is} + \epsilon_{ist} \tag{2.5}$$

where i stands for the firm, s stands for the season for each firm that is based on its financial reporting schedule and takes values from one to four for each of the four financial quarters. t stands for the observed announcement date; γ_{mt} for industry-year, and κ_{is} for firm×season fixed effects. We calculate the cumulative announcement returns cr as the cumulative raw returns over 3- (Equation 2.4) and a 5-day event windows

[2.15] In line with this expectation, Panel B in Table 2.1 shows that on average, there are only 2.8 estimates per revenue or income forecast.

[2.16] For instance, see La Porta, Lakonishok, Shleifer, and Vishny (1997), Core, Guay, and Rusticus (2006), and Edmans (2011).

(Equation 2.5). As the choice of a benchmark can induce noise and bias if firms in different countries load differently on the benchmark returns, we choose the raw return-specification for the main test, but also estimate the results using benchmark-adjusted returns – using equal and market-capitalization weighted returns of all firms in our sample – and abnormal returns over the expected returns based on the market model to estimate the cumulative abnormal returns (car) for robustness tests[2.17]. The timing of the test and the matching of fiscal periods and *Extreme Temperature Days* are analogous to the second analysis, as illustrated in Figure 2.6. Standard errors are clustered at the firm level.

Panel A of Table 2.8 shows the main result for this test based on the raw returns for the 3-day event window. In line with the previous analysis on analyst forecasts, there is a consistent negative relation between increases in extreme temperature days during the financial period and announcement returns at the respective announcement date. For every additional day with temperatures exceeding the 90^{th} percentiles, the announcement returns become 0.0142 percentage points more negative over the 3-day window around the announcement date (Panel A, column 3, significant at the 5% level). For the 30° Celsius and 95^{th} percentile threshold, our estimates indicate a stronger magnitude of -0.0497 percentage points (30° Celsius threshold, significant at the 1% level) and -0.0251 percentage points (95^{th} percentile threshold, significant at the 5% level). Given the standard deviation in the number of days per quarter by which heat exposure varies over time (6.9 days for the 30° Celsius threshold), the effect of a one standard deviation increase in heat exposure would induce a 0.033 percentage point more negative announcement return. Compared to the sample average cumulative 3-day return of 0.142, the magnitude of the estimates is economically relevant. In an international sample, the choice of a benchmark can induce bias if firms in different countries load differently on the benchmark returns. Hence, we choose the raw return-specification for our main tests, but conduct additional tests to verify the robustness of the results and to understand the sensitivity of the results to using common benchmarks. Panel B of Table 2.8 shows the estimates based on the benchmark-adjusted returns, and Appendix Table A.3 shows the results for the 5-day window and the raw, benchmark-adjusted, and abnormal returns over the expected returns using the market model. The results remain similar both in magnitude and statistical significance.

[2.17] For the expected returns, we estimate the market model out of sample based on a maximum of 365 days ending 46 days before the announcement date

Altogether, our results do not only indicate that the exposure to *Extreme Temperature Days* negatively affects firms' financial performance, but also that investors and analysts do not fully anticipate this relation which is manifested in more negative revenue and operating income surprises and announcement returns.

2.6 Alternative Climate and Economic Explanations

We interpret the relations we have found so far causally. Location-specific intertemporal variation in heat exposure cannot be actively influenced by a firm's choice or predicted with precision beyond a horizon of several days. In other words, the variation cannot be predicted in time to affect the usual planning horizon of firm operations. Thereby, firm-specific characteristics can be ruled out as a driver of both the outcome and the measure of heat exposure. However, the measure of extreme temperatures could arguably be systematically correlated with other climate conditions. If these climate conditions also prove to influence firm performance, the estimates could be biased, or pick up phenomena beyond exposure to heat. To rule out such alternative causes, we conduct additional tests.

First, a plausible case in this context would be that quarters with more extremely high temperature days also come with fewer extreme low temperature days. Further, if cold spells are detrimental to firm performance, the measured effect of heat could be a combination of heat and cold effects. Supporting this view, Brown et al. (2017) illustrate that cold temperatures can affect cash flows. Therefore, we run additional tests that control for the number of cold days. We measure cold days consistent with hot days using 0° Celsius as an absolute and the 5^{th} and 10^{th} percentile as relative thresholds. Table 2.9 shows that the magnitude and significance of the coefficient for *Extreme Temperature Days* remain unchanged by this inclusion. In line with Brown et al. (2017), cold days are also negatively related to firm performance at the quarterly level, and the effect is statistically significant when using absolute thresholds (e.g. Panel A, column (1) and (2), coefficients -0.0284 and -0.0297, significant at the 10% level; or Panel B, column (1) and (2), coefficients -0.0100 and -0.0102, significant at the 1% level). However, the negative annual effect of cold days on revenues (operating income) is insignificant when both extremely high and low temperatures are classified as absolute thresholds, and the coefficients on the effect of extremely high days remain unchanged by including other temperature controls.

Beyond these potentially confounding effects related to the climate, another concern could be related to general economic trends. As extreme temperature exposure is arguably strongly clustered within countries, and as this clustering is reinforced due to our geographic identification strategy, an alternative explanation for observing the outlined effects could be a coincidental correlation of broader economic developments over time with variation in heat exposure. To address this concern in our baseline tests, we consistently estimate all coefficients with quarter and industry × quarter fixed effects to absorb the variation that is driven by industry-wide technological change and global economic developments. In addition to these controls, a time-varying control for country fixed effects is desirable but is empirically unfeasible due to the clustering of variation in the heat exposure at the country level.

However, we conduct two additional sets of tests to ensure that the observed effects are not driven by simultaneous economic developments. First, we conduct four placebo tests. If the driver of the negative relation of heat exposure and earnings is the general economic momentum, we expect to also find a systematic relation between shocks in heat exposure, investments, financing activities, and cash' holdings. As Table 2.10 shows, there is no evidence of a significant relation between changes in the number of days of heat exposure on cash holdings (Panel A); plant, property, and equipment sales or investment (Panel B); investments (Panel C); and working capital (Panel D). The only exception is the statistically significant effect (10% level) of additional days warmer than 25° Celsius on firms' cash holdings. All other coefficients for the effect on cash holdings are indistinguishable from zero, and unstable in their signs. Second, to rule out that a correlation between hot years and global economic shocks drives the results, we re-estimate the regressions and exclude 2008 and 2009 as the years of the financial crisis. As Table A.4 shows, the results are not weakened by excluding these years.

2.7 Extrapolation and Adaptive Capacity

Our results indicate that short-term increases in the number of extreme temperature days prove to be financially material for firms but that analysts and investors do not anticipate this short-run performance sensitivity. These findings raise two closely related questions: First, why do firms remain sensitive to shocks in extreme temperature exposure if these shocks prove to be costly? And second, what do these estimates mean for climate change projections?

First, our finding that firms are not yet fully resilient to temperature fluctuations does not necessarily indicate irrational behaviour or an ignorance of the problem. Under a scenario without climate change in which temperature distributions remain unchanged, firms might find not investing in adaptation to be optimal, accepting that some years are more productive than others depending on environmental conditions - as long as the *average conditions* allow the firm to maximize the value of its production or services. However, once temperature distributions shift persistently due to climate change, firms' production and adaptation might no longer be optimally matched to the environment, given the new average exposure to heat. Still, such a shift in temperature distributions would have to be large enough to financially incentivize firms to make costly adjustments. For instance, these investments could require firms to consistently use cooling technology, and potentially require substantial renovations of plant, property and equipment.

Whether the temperature changes in the past (or going forward) were (will be) strong enough to justify such investment is an empirical question that our study leaves open. However, our estimates allow for a back-of-the-envelope calculation of the costs that persistent temperature shifts could cause at the firm level – holding the current levels of adaptation fixed. Depending on firms' current adaptation and remaining potential to develop financial resilience, the adverse effect of one additional day of heat exposure on performance will be attenuated going forward. Hence, the back-of-the-envelope calculation produces an upper boundary of the expected effect. We use the projections of the number of extreme temperature days provided by the 5^{th} IPCC Assessment report, that are measured as days that exceed the 90^{th} percentile threshold. The IPCC report estimates that the temperature exceeded the 90^{th} percentile threshold on approximately 15% of the days in the year in 2000. In line with this estimate, we find an average exceedance rate of 16.3% in our sample from 1987 to 2016. Depending on the assumed climate change trajectory (termed Representative Concentration Pathways, RCPs), the IPCC estimates that by 2050, the exceedance rate will rise to 28% (RCP 2.5), 33% (RCP 4.5) or 38% (RCP 8.5). These scenarios mean 42.6, 60.9, or 79.1 additional extreme temperature days, on average. Financially, given our quarterly estimates of a decrease in sales turnover of 0.0182 percentage points and operating profit of 0.0027 percentage points, these scenarios indicate a decrease of sales turnover of 0.775% and operating income of 0.115% under the RCP 2.5, to 1.44% and 0.214% under the RCP 8.5. Given that we find that extreme temperature days affect firms' financial performance beyond the concurrent financial quarter in Panel C and D of Table 2.2, we also estimate the results on an annual basis in Table A.1. Based on the annual estimates, we find a stronger effect of extreme temperature days on annual sales turnover and a constant effect on operating income, that shows a performance reduction of 1.66% on sales turnover and 0.115% on operating income under the RCP 2.5 scenario.

However, we also find that the annual effect for extreme temperature days on operating income is attenuated compared to the quarterly estimates, whereas the effect on revenues becomes even stronger on the annual level. This attenuation is puzzling, and might be due to (at least) three different reasons. First, it could indicate the actual adjustment by the firm. If firms are capable of adjusting expense structures in the short run, income could remain unaffected by drops in revenue. The firms' adjustment to climate change has received very limited attention until now, but in a study of a large American automobile manufacturer, Cachon, Gallino, and Olivares (2012) find that operational adjustment to extreme temperatures is surprisingly very limited. Also, firms' short-term adjustment is unlikely to go without cost. As a second and alternative reason, the attenuated effect could be driven by statistical reasons. For instance, the signal-to-noise ratio in our measure of extreme temperature days is presumably high and could lead to the marginal insignificance of the results. As the r-squared shows, the within variation in operating income is generally harder to predict than the variation in revenues, where we do find statistically unambiguous evidence of a relation between heat and performance. As a third alternative explanation, the attenuated effect could be related to accounting choices. If extreme temperature exposure represents a performance shock which motivates firms to manage their earnings more aggressively, the attenuation could come from firms' ambitions to meet performance targets and to adjust their cost accounting. Particularly, the first and third explanations merit more attention, and the relation of climate-related shocks to the firms' performance, adaptation, and earnings management leave room for future study.

Beyond firms' financial incentives to adapt, another open question is to what extent firms are able to adapt. If the documented negative effect is indeed mainly production-related and stems from factors that are under the firms' control, firms are also largely in control of their degree of adaptation. In case the main driving channel proves to be employee performance, the financial incentives to adapt could strongly accelerate the demand for air conditioning and electricity demand and thereby represent a negative feedback loop between the physical effects of climate change and efforts to achieve a comprehensive economic transformation towards a low carbon economy. However, if the performance reduction under extreme temperatures is only partially due to the factors that firms can control, firms might have their hands tied and might not be in the position to choose new levels of adaptation individually.

2.8 Conclusion

In this study, we use an international sample of 4,400 listed firms with regionally concentrated assets in the period from 1995 to 2017 to test if firm-specific variation in heat exposure has a negative effect on financial performance. Previous studies argue that heat exposure reduces input supply and productivity to an extent that manifest itself on the aggregate economic level. In line with these studies, we find that exogenous increases in the number of extremely hot days per financial quarter represent negative shocks to revenues and operating income. The negative relation holds when we classify extremely high temperature days based on an absolute threshold of 30° Celsius as well as when we use two different place- and time-contingent thresholds derived from historical temperature distributions to classify days as normal or extremely hot. The documented negative effect is both statistically and economically significant: A one standard deviation increase in the number of extreme temperature days per quarter results in an average quarterly reduction in revenue of 9.9 million (31.15 million) U.S. dollars and a reduction of 811,500 (2.57 million) U.S. dollars in operating income given the median (75^{th} percentile) total assets of the firms in the sample. In a series of cross-sectional tests, we show that the negative relation between the number of days with extremely high temperatures and firm performance is mainly driven by reductions in asset turnover and to a lesser extent by changes in the cost margin. Moreover, we find evidence that the observed effect is at least partially supply-driven, as both firms with and without geographically separate asset and sales locations are subject to the negative effect. Also, firms' labor intensity is strongly related to how sensitive firms are to extremely high temperatures.

Based on these results, we conduct two tests to understand whether analysts and investors anticipate this negative financial effect of heat exposure at the firm level. First, we use analyst forecasts as a proxy for investors' expectations for revenue and operating income. Second, we calculate the abnormal returns around earnings announcements as a proxy for investors' expectations of future revenues and operating income. If extremely high temperature days are financially material and investors do not anticipate this effect, expectations on revenue and operating income should be systematically too high in periods when firms are exposed to more extremely warm days than usual. Moreover, expectations on firm performance should similarly be systematically higher than the actual performance and lead to negative announcement returns. Indeed, we find that both revenue and operating income surprises and (abnormal) announcement returns become more negative with increasing heat exposure at the firms' locations, which indicates that analysts and investors do not fully take into account information on high temperatures. In a nutshell, our results thereby contribute to the growing economic and financial evidence that climate factors matter for firm performance, and to the studies that investigate whether environmental and particularly climate-related factors are priced in financial markets. Moreover, our study closely connects to the recent central bank and investor debates driven by the threat that climate change poses to financial stability, and to legislative initiatives on the firm- and investor-level disclosures of climate-related risk exposure.

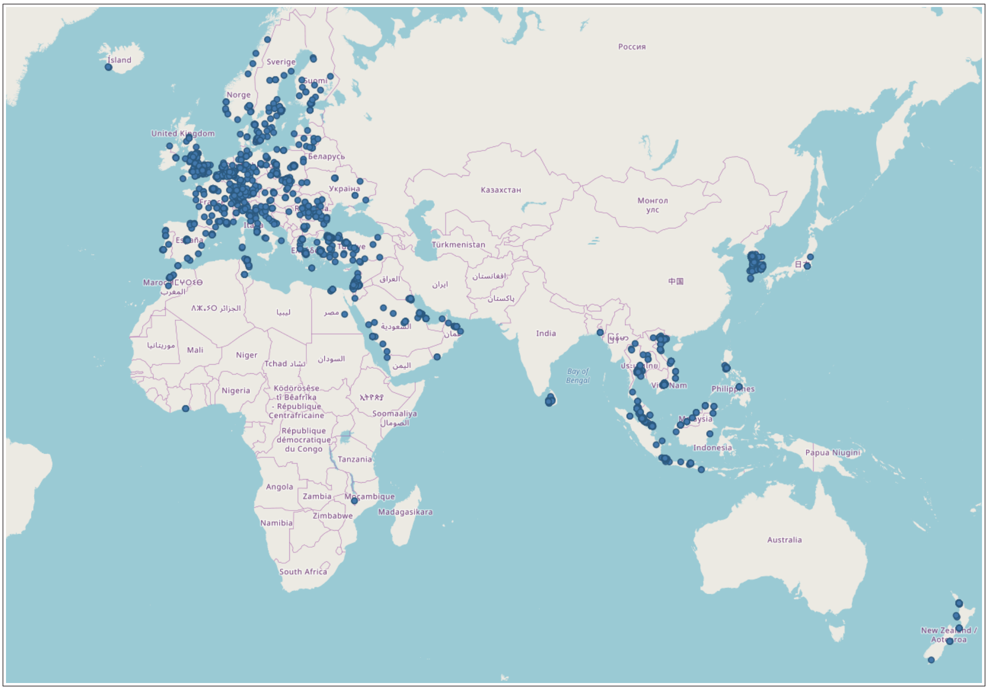

Figure 2.1: Geographic Distribution of the Sample

Notes: This figure shows the geographic distribution of the firms in the sample. To determine a firm-specific measure of heat exposure, we identify the location of firms' headquarters based on addresses and information on asset concentration from FactSet Revere records on geographic segments. We classify firms' assets as regionally concentrated if they report to hold at least 80% of assets in their home country. Furthermore, we restrict the sample to countries with a limited variation in climate zones. This way, we ensure that assets located further away from the headquarters are still likely to be exposed to similar variation in heat exposure. The country choice is based on a qualitative assessment of the similarity of the climate zones of the firms' home countries using the Koppen Climate Classification (Chen & Chen, 2017).

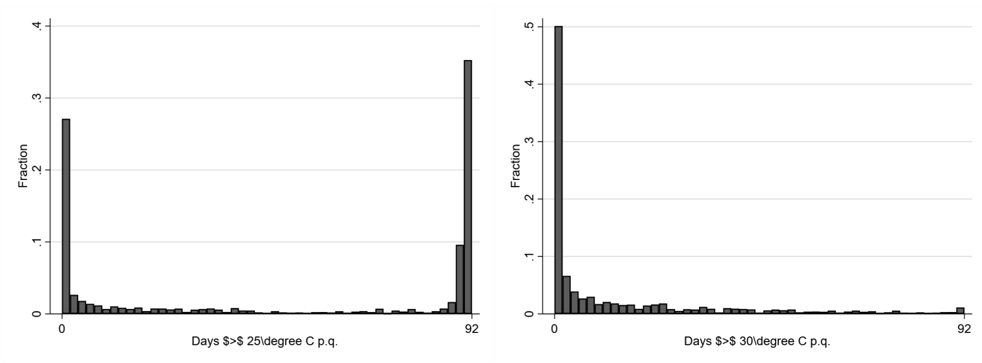

Figure 2.2: Levels of Heat Exposure in Days (Absolute Thresholds)

Notes: This figure shows the cross-sectional variation in quarterly heat exposure. Using absolute temperature thresholds to classify days as extremely warm (25 and 30°C), some firms are either never or always "treated", or in other words, located in climate zones were the thresholds are always or never crossed.

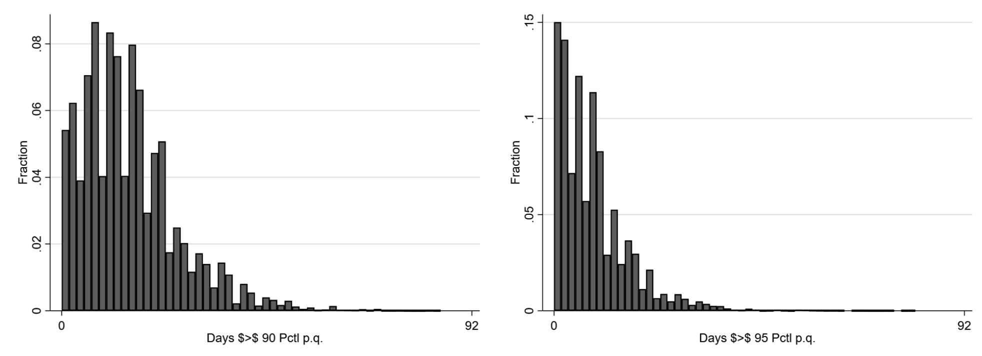

Figure 2.3: Levels of Heat Exposure in Days (Relative Thresholds)

Notes: This figure shows the distribution of quarterly heat exposure when thresholds are location- and time-contingent from classifying days as extreme temperature days when temperatures cross the 90^{th} or 95^{th} percentile of the distribution of temperatures in a given location between 1980 to 1999, based on temperatures on the same day as well as the five preceding and following days.

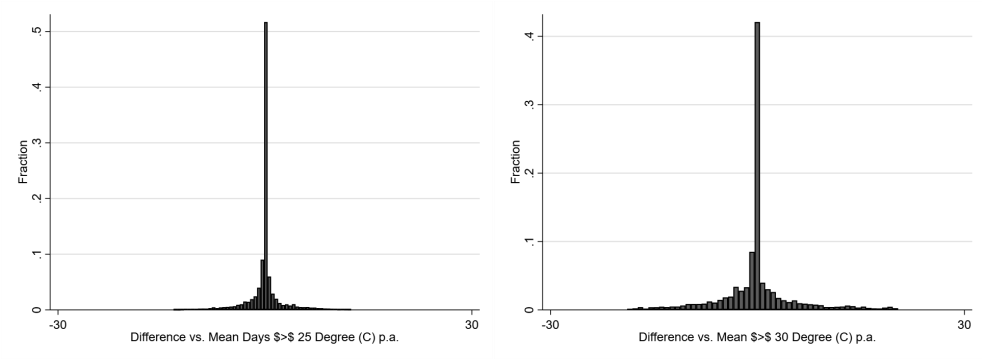

Figure 2.4: Within Variation of Heat Exposure (Absolute Thesholds)

Notes: This figure shows *within variation* in quarterly heat exposure. This variation is the number of days in a fiscal quarter on which firms were exposed to extreme temperatures minus the average number of days of heat exposure in the same fiscal quarter over the years in the sample period. Using absolute temperature thresholds, a substantial share of firms is never (always) exposed to temperatures over 25 and 30°C.

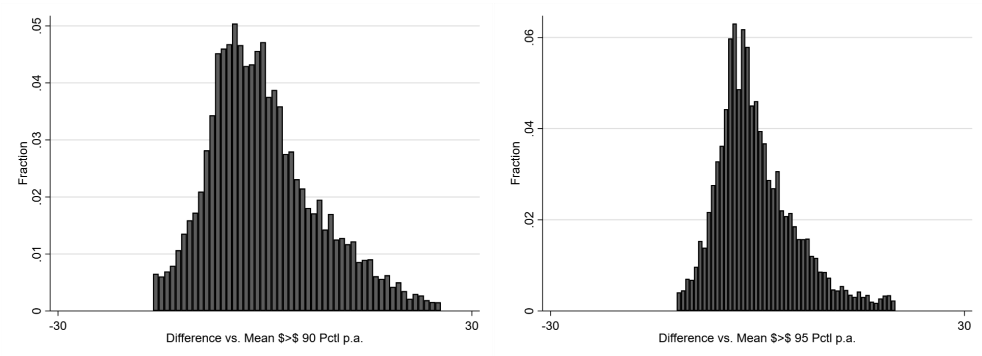

Figure 2.5: Within Variation of Heat Exposure (Relative Thresholds)

Notes: This figure shows *within variation* in quarterly heat exposure. This variation is the number of days in a fiscal quarter on which firms were exposed to extreme temperatures minus the average number of days of heat exposure in the same quarter over the years in the sample period. Days are classified as extremely warm based on the location- and time-specific thresholds, that are calculated using the historical temperature distributions from 1980 to 1999.

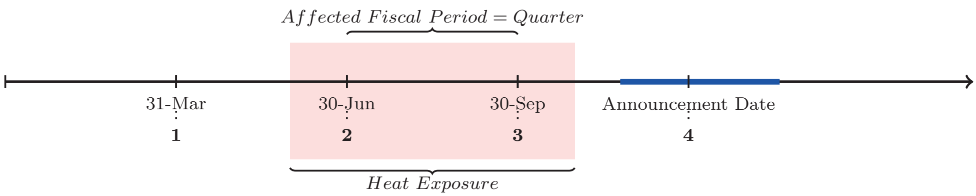

Figure 2.6: Construction of the Analyst Forecast & Announcement Returns Test

Notes: This figure shows the construction of the test on the accuracy of analyst forecasts and the test for the announcement returns. The measure of heat exposure *Extreme Temperature Days* is determined based on daily maximum temperatures in the months included in the quarterly fiscal period labeled *Affected Fiscal Period*. Investor reactions in terms of abnormal returns and analyst forecast errors on revenues and operating income are calculated for the announcement date on which the firms' earnings over the affected fiscal period are made public, after the realized extreme temperature exposure of the firm is known.

Table 2.1: Summary Statistics

Notes. This table shows descriptive statistics for all sub-samples of the analyses. N refers to firm-quarters in Panel A, earnings announcements in Panels B and C, and firm years in Panel D. Days $> \times$ refers to the number of *Extreme Temperature Days* defined by two absolute (25°C, 30°C) and two relative (90^{th} and 95^{th}) thresholds, that reflect that the 90^{th} or 95^{th} percentile of the location- and day-of-the-year-specific temperature distribution from 1980-1999 was exceeded. $Difference\ in\ Days\ > x$ measures heat exposure in a given quarter compared to the firm location-specific average over previous years in the same financial quarter. All variables are trimmed at the 1^{st} and 99^{th} percentiles, and all values converted to U.S. dollars. All values are scaled by assets and are displayed in %.

Panel (A) *Heat Exposure and Financial Performance – Quarterly Statistics*

	N	**Mean**	**Sd**	**P25**	**P50**	**P75**
Days > 25°C p.q.	153,127	50.664	41.583	0.000	71.000	91.000
Difference in Days > 25°C p.q.	153,127	-0.005	3.268	-0.214	0.000	0.167
Days > 30°C p.q.	153,127	13.417	21.904	0.000	1.000	19.000
Difference in Days > 30°C p.q.	153,127	-0.058	6.878	-1.250	0.000	0.438
Days > 90 Pctl p.q.	153,127	14.957	10.798	7.000	13.000	21.000
Difference in Days > 90 Pctl p.q.	153,127	0.003	8.815	-5.889	-1.333	4.417
Days > 95 Pctl p.q.	153,127	8.604	7.820	3.000	7.000	12.000
Difference in Days > 95 Pctl p.q.	153,127	-0.011	6.532	-4.000	-1.333	2.875
Annual Average Temperature	153,127	22.203	7.387	14.890	25.637	28.482
Revenue/Assets p.q.	153,127	23.229	17.237	10.739	19.504	31.095
Operating Income/Assets p.q.	153,127	2.026	3.057	0.632	2.003	3.596
Total Assets mUSD	152,863	984.645	28,269.009	19.226	61.916	196.277
Revenues mUSD p.q.	150,953	59.239	156.265	3.090	11.382	40.344
Operating Income mUSD p.q.	152,863	21.739	744.749	0.081	1.010	4.501

Panel (B) *Heat Exposure and Analyst Forecast Accuracy*

	N	Mean	Sd	P25	P50	P75
Revenue Mean Surprise/Assets	32,789	-0.081	1.696	-0.005	-0.000	0.002
Revenue Median Surprise/Assets	32,789	-0.076	1.682	-0.005	-0.000	0.002
Revenue Mean Surprise (%)	32,876	-2.494	13.393	-5.412	-0.491	3.193
Revenue Median Surprise (%)	32,876	-2.357	13.107	-5.228	-0.430	3.167
PreTax Income Mean Surprise/Assets	24,668	-0.104	0.831	-0.003	-0.000	0.001
PreTax Income Median Surprise/Assets	24,667	-0.104	0.830	-0.003	-0.000	0.001
PreTax Income Mean Surprise (%)	24,724	-2.740	124.277	-21.481	2.236	24.126
PreTax Income Median Surprise (%)	24,723	-2.392	124.061	-21.056	2.208	24.152
BooktoMarket Ratio	32,368	0.716	0.492	0.355	0.607	0.951
Annual Average Temperature	33,784	17.677	5.256	15.744	17.379	18.715
Number of Estimates	33,784	2.793	3.669	1.000	1.000	3.000

Panel (C) *Heat Exposure and Announcement Returns*

	N	Mean	Sd	P25	P50	P75
Cum. Return 3 Days	25,397	-0.142	6.979	-4.055	-0.151	3.612
Cum. BenchmarkAdj. Return (EW) 3 Days	25,406	0.044	6.622	-3.662	-0.051	3.545
Cum. Abnormal Return (MM EW) 3 Days	25,370	-0.125	6.547	-3.774	-0.068	3.337
Cum. Return 5 Days	25,377	-0.318	7.844	-4.987	-0.373	4.219
Cum. BenchmarkAdj. Return (EW) 5 Days	25,390	-0.033	7.490	-4.455	-0.210	4.259
Cum. Abnormal Return (MM EW) 5 Days	25,361	-0.198	7.441	-4.593	-0.225	4.072
Annual Average Temperature	25,767	17.789	5.457	15.741	17.416	19.029

Panel (D) *Heat Exposure and Financial Performance – Annual Statistics*

	N	Mean	Sd	P25	P50	P75
Days > 25°C p.a.	37,507	201.849	154.010	38.000	206.000	364.000
Difference in Days > 25°C p.a.	37,507	-0.007	7.237	-2.143	-0.111	1.875
Days > 30°C p.a.	37,507	54.100	71.303	1.000	18.000	90.000
Difference in Days > 30°C p.a.	37,507	-0.555	18.090	-4.333	-0.176	3.353
Days > 90 Pctl p.a.	37,507	59.574	28.803	40.000	55.000	73.000
Difference in Days > 90 Pctl p.a.	37,507	-0.298	22.173	-13.833	-2.500	10.857
Days > 95 Pctl p.a.	37,507	34.289	20.560	21.000	31.000	44.000
Difference in Days > 95 Pctl p.a.	37,507	-0.240	16.491	-10.000	-2.333	7.000
Revenue/Assets p.a.	36,857	86.860	58.209	42.820	76.363	118.161
Operating Income/Assets p.a.	36,254	8.148	8.508	3.528	8.119	13.222
Revenues mUSD p.a.	37,008	236.031	648.675	11.981	43.748	154.092
Operating Income mUSD p.a.	37,436	83.018	2,746.998	0.548	4.170	17.501

Table 2.2: Heat Exposure and Firm Performance

Notes. This table shows the effect of high temperatures on quarterly revenues (Rev-Assets) and operating income over total assets (OpInc-Assets). The dependent variables are expressed in %. *Extreme Temperature Days* refers to the number of high temperature days defined by two absolute (25°C, 30°C) and two relative (90^{th} and 95^{th}) thresholds, that reflect that the 90^{th} or 95^{th} percentile of the location- and day-of-the-year-specific temperature distribution from 1980-1999 was exceeded. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. Panels A and B show the results for financial performance and concurrent (same quarter) extreme temperature days. In Panels C and D, extremes temperature days lagged by one quarter are included in addition to the concurrent count of *Extreme Temperature Days*. The number of observations refers to firm quarters. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Concurrent Heat Exposure and Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0004	-0.0226***	-0.0182***	-0.0190***
	(0.0098)	(0.0073)	(0.0055)	(0.0069)
Observations	153,127	153,127	153,127	153,127
R-squared	0.841	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Concurrent Heat Exposure and Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0016	-0.0031*	-0.0027**	-0.0031*
	(0.0026)	(0.0018)	(0.0013)	(0.0018)
Observations	153,127	153,127	153,127	153,127
R-squared	0.593	0.593	0.593	0.593
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Lagged Heat Exposure and Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	-0.0007	-0.0142*	-0.0130**	-0.0137**
	(0.0098)	(0.0074)	(0.0056)	(0.0068)
L.Extr. Temperature Days	-0.0050	-0.0200***	-0.0185***	-0.0194**
	(0.0077)	(0.0074)	(0.0060)	(0.0077)
Observations	151,319	151,319	151,319	151,319
R-squared	0.841	0.842	0.842	0.842
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel D: *Lagged Heat Exposure and Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0017	-0.0019	-0.0024*	-0.0028
	(0.0026)	(0.0017)	(0.0014)	(0.0018)
L.Extr. Temperature Days	-0.0017	-0.0048***	-0.0030**	-0.0036**
	(0.0019)	(0.0015)	(0.0013)	(0.0016)
Observations	151,319	151,319	151,319	151,319
R-squared	0.594	0.594	0.594	0.594
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.3: Heat Exposure and Expenses

Notes. This table shows the effect of extreme temperatures on expense structures. Panel A shows regressions with the quarterly cost of goods sold over revenues as dependent variable, in Panel B, the dependent variable is the ratio of sales, general, and administrative expenses over assets. The dependent variables are expressed in %. *Extreme Temperature Days* is the number of days when a firm was exposed to high temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Cost of Goods Sold over Revenue*

	25°C COGS/Rev	30°C COGS/Rev	90^{th} P COGS/Rev	95^{th} P COGS/Rev
Extreme Temperature Days	0.01736	-0.00058	0.00786	0.01587**
	(0.0129)	(0.0066)	(0.0057)	(0.0079)
Observations	138,857	138,857	138,857	138,857
R-squared	0.754	0.754	0.754	0.754
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Sales, General, and Administrative Expenses over Revenue*

	25°C SGA/Rev	30°C SGA/Rev	90^{th} P SGA/Rev	95^{th} P SGA/Rev
Extreme Temperature Days	0.01449	0.02344**	0.01899**	0.02352*
	(0.0163)	(0.0106)	(0.0088)	(0.0118)
Observations	128,666	128,666	128,666	128,666
R-squared	0.677	0.677	0.677	0.677
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.4: Heat Exposure and Firm Performance – Geographic Sales-Assets-Separation

Notes. This table shows the effect of heat exposure on quarterly revenues (Panel A, Rev/Assets) as well as operating income over total assets (Panel B, OpI/Assets) in interaction with a dummy variable for firms with a geographic separation of assets and sales (top geographic revenue country is not the headquarters country) and is labeled (*Revenue Abroad*). The dependent variables are expressed in %. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. The number of observations refers to firm quarters. All regressions include firm- financial quarter and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Geographic Sales-Assets-Separation, Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	-0.0001	-0.0346***	-0.0245***	-0.0296***
	(0.0108)	(0.0108)	(0.0067)	(0.0084)
ETD x Revenue Abroad	0.0009	0.0186**	0.0112	0.0187*
	(0.0130)	(0.0090)	(0.0071)	(0.0098)
Observations	153,127	153,127	153,127	153,127
R-squared	0.841	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes
T-Test (p-stat)	0.951	0.022	0.043	0.200

Panel B: *Heat Exposure and Geographic Sales-Assets-Separation, Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	0.0001	-0.0050**	-0.0037**	-0.0045**
	(0.0027)	(0.0023)	(0.0015)	(0.0019)
ETD x Revenue Abroad	-0.0033	0.0030	0.0018	0.0024
	(0.0037)	(0.0024)	(0.0019)	(0.0024)
Observations	153,127	153,127	153,127	153,127
R-squared	0.593	0.593	0.593	0.593
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes
T-Test (p-stat)	0.381	0.318	0.278	0.369

Table 2.5: Heat Exposure and Firm Performance – Labor Intensity

Notes. This table shows the effect of heat exposure on quarterly revenues (Panels A and C, Rev/Assets) as well as operating income over assets (Panels B and D, OpInc/Assets) in interaction with two different measures of firms' labor intensity. The dependent variables are expressed in %. For both measures, we assign firms into terciles based on their labor expenses over total expenses (data from Factset and Compustat) In Panels A and B, firms are assigned to terciles by their absolute labor intensity regardless of industry averages. In Panels C and D, the assignement into terciles is based on firms' labor intensity compared to industry averages. *Extreme Temperature Days* stands for extreme temperature days (absolute thresholds 25°C, 30°C; relative thresholds 90^{th} pctl., 95^{th}). The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. The number of observations refers to firm quarters. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Labor Intensity, Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0283**	0.0157*	0.0440***	0.0516***
	(0.0119)	(0.0092)	(0.0106)	(0.0138)
ETD x (Absolute) Labor Intensity Tercile 2	-0.0397***	-0.0581***	-0.0807***	-0.0967***
	(0.0035)	(0.0072)	(0.0099)	(0.0136)
ETD x (Absolute) Labor Intensity Tercile 3	-0.0634***	-0.0830***	-0.1140***	-0.1304***
	(0.0051)	(0.0096)	(0.0143)	(0.0194)
Observations	114,973	114,973	114,973	114,973
R-squared	0.848	0.847	0.847	0.846
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Labor Intensity, Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0002	0.0001	0.0024	0.0030
	(0.0032)	(0.0021)	(0.0021)	(0.0029)
ETD x (Absolute) Labor Intensity Tercile 2	-0.0020***	-0.0030*	-0.0060***	-0.0087***
	(0.0007)	(0.0015)	(0.0019)	(0.0026)
ETD x (Absolute) Labor Intensity Tercile 3	-0.0038***	-0.0073***	-0.0085***	-0.0099***
	(0.0011)	(0.0022)	(0.0026)	(0.0035)
Observations	114,973	114,973	114,973	114,973
R-squared	0.600	0.600	0.600	0.600
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Heat Exposure and Labor Intensity by Industry, Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0273**	0.0063	0.0344***	0.0427***
	(0.0103)	(0.0085)	(0.0106)	(0.0142)
ETD x (Relative) Labor Intensity Tercile 2	-0.0313***	-0.0442***	-0.0647***	-0.0786***
	(0.0030)	(0.0061)	(0.0102)	(0.0150)
ETD x (Relative) Labor Intensity Tercile 3	-0.0374***	-0.0439***	-0.0775***	-0.0897***
	(0.0037)	(0.0068)	(0.0119)	(0.0166)
Observations	149,765	149,765	149,765	149,765
R-squared	0.842	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel D: *Heat Exposure and Labor Intensity by Industry, Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0002	-0.0017	-0.0001	-0.0001
	(0.0027)	(0.0020)	(0.0020)	(0.0028)
ETD x (Relative) Labor Intensity Tercile 2	-0.0009	-0.0012	-0.0020	-0.0031
	(0.0006)	(0.0013)	(0.0019)	(0.0027)
ETD x (Relative) Labor Intensity Tercile 3	-0.0020***	-0.0028*	-0.0043**	-0.0047*
	(0.0007)	(0.0015)	(0.0019)	(0.0027)
Observations	149,765	149,765	149,765	149,765
R-squared	0.594	0.594	0.594	0.594
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.6: Heat Exposure and Firm Performance – Heterogeneity

Notes. This table shows the heterogeneity of the effect of heat exposure on quarterly revenues (Panels A, C & E, Rev/Assets) as well as operating income over assets (Panels B, D & F, OpI/Assets). The dependent variables are expressed in %. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures, which is defined based on two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. First, we illustrate the effect of *Extreme Temperature Days* on firm performance when we exclude the agricultural industry ($SIC\ 1^{st}\ digit = 0$) in Panels A and B. Second, Panels C and D show the interaction of the effect with an indicator that takes a value of one if firms operate in the utility industries. Panels E and F shows the results estimated for an interaction term on the effect of heat exposure and an indicator for firms which are located in Scandinavia. The number of observations refers to firm quarters. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Firm Performance Outside of Agriculture, Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	-0.0006	-0.0225***	-0.0187***	-0.0194***
	(0.0099)	(0.0075)	(0.0056)	(0.0069)
Observations	149,765	149,765	149,765	149,765
R-squared	0.841	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Firm Performance Outside of Agriculture, Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0015	-0.0030*	-0.0026*	-0.0031*
	(0.0026)	(0.0018)	(0.0013)	(0.0018)
Observations	149,765	149,765	149,765	149,765
R-squared	0.594	0.594	0.594	0.594
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Heat Exposure and Firm Performance in Utilities, Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0006	-0.0231***	-0.0189***	-0.0198***
	(0.0103)	(0.0074)	(0.0057)	(0.0071)
ETD x Utilities	-0.0035	0.0163	0.0170	0.0239
	(0.0150)	(0.0185)	(0.0134)	(0.0177)
Observations	153,127	153,127	153,127	153,127
R-squared	0.841	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes
T-Test (p-stat)	0.820	0.710	0.879	0.808

Panel D: *Heat Exposure and Firm Performance in Utilities, Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0017	-0.0031*	-0.0028**	-0.0033*
	(0.0028)	(0.0018)	(0.0014)	(0.0019)
ETD x Utilities	0.0021	0.0020	0.0029	0.0028
	(0.0058)	(0.0043)	(0.0030)	(0.0039)
Observations	153,127	153,127	153,127	153,127
R-squared	0.593	0.593	0.593	0.593
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes
T-Test (p-stat)	0.943	0.784	0.978	0.905

Panel E: *Heat Exposure and Firm Performance in Scandinavia, Revenue*

	25°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0024	-0.0206***	-0.0220***
	(0.0096)	(0.0055)	(0.0070)
ETD x Scandinavia	-0.0971	0.0360*	0.0506
	(0.0928)	(0.0207)	(0.0323)
Observations	153,127	153,127	153,127
R-squared	0.841	0.841	0.841
Firm × Season FE	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes
T-Test (p-stat)	0.313	0.454	0.366

Panel F: *Heat Exposure and Firm Performance in Scandinavia, Operating Income*

	25°C OpI/Assets	90^{th} P C OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0019	-0.0039***	-0.0047**
	(0.0026)	(0.0014)	(0.0019)
ETD x Scandinavia	0.0161	0.0181***	0.0261***
	(0.0165)	(0.0042)	(0.0058)
Observations	153,127	153,127	153,127
R-squared	0.593	0.593	0.593
Firm × Season FE	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes
T-Test (p-stat)	0.503	0.001	0.000

Table 2.7: Heat Exposure and Firm Performance – Analyst Forecasts

Notes. This table shows the effect of *Extreme Temperature Days* on the accuracy of quarterly analyst forecasts of quarterly revenues (Panel A) and pre-tax income (Panel B). The dependent variable is the financial performance surprise, measured as the actual value of revenues (Panel A) or pre-tax income (Panel B) minus the median analyst estimate, that are scaled by the total assets of the firm lagged by one year. The ratios are expressed in %. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds is used for the measure of *Extreme Temperature Days* in the regression. All regressions include firm financial quarter fixed effects (to control for firm location and firm-specific seasonal effects) and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered at the firm level.

Panel A: *Heat Exposure and Revenue Analyst Forecasts*

	25°C Median Surprise	30°C Median Surprise	90^{th} P Median Surprise	95^{th} P Median Surprise
Extreme Temperature Days	-0.0053**	-0.0050*	-0.0026	-0.0019
	(0.0023)	(0.0026)	(0.0020)	(0.0027)
Ln Book-to-Market Ratio	0.0548*	0.0562*	0.0560*	0.0558*
	(0.0302)	(0.0302)	(0.0302)	(0.0302)
Observations	28,580	28,580	28,580	28,580
R-squared	0.321	0.321	0.321	0.321
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Pre-Tax Income Analyst Forecasts*

	25°C Median Surprise	30°C Median Surprise	90^{th} P Median Surprise	95^{th} P Median Surprise
Extreme Temperature Days	-0.0022*	-0.0037***	-0.0026**	-0.0029*
	(0.0012)	(0.0014)	(0.0012)	(0.0016)
Ln Book-to-Market Ratio	0.0992***	0.1002***	0.1002***	0.1003***
	(0.0193)	(0.0194)	(0.0193)	(0.0193)
Observations	21,426	21,426	21,426	21,426
R-squared	0.352	0.352	0.352	0.352
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.8: Heat Exposure and Announcement Returns

Notes. This table shows the effect of heat exposure on announcement returns. In the main specification which we show in this table, we use the raw returns (Panel A) and returns over the equal weighted return of all firms in the sample (Panel B) during a 3-day event window (-1 to +1) around earnings announcements as the dependent variable. All returns are expressed in %. Tests based on other specifications are shown in the Appendix Table A.3. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds is used for the measure of *Extreme Temperature Days* in the regression. All regressions include firm financial quarter fixed effects (to control for firm location and firm-specific seasonal effects) and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered at the firm level.

Panel A: *Heat Exposure and 3-Day Raw Announcement Returns*

	25°C 3 Day	30°C 3 Day	90^{th} P 3 Day	95^{th} P 3 Day
Extreme Temperature Days	-0.0088	-0.0497***	-0.0142**	-0.0251**
	(0.0139)	(0.0130)	(0.0072)	(0.0100)
Observations	22,433	22,532	22,831	22,696
R-squared	0.238	0.238	0.235	0.233
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and 3-Day Benchmark-Adjusted Announcement Returns*

	25°C 3 Day EW	30°C 3 Day EW	90^{th} P 3 Day EW	95^{th} P 3 Day EW
Extreme Temperature Days	-0.0199	-0.0253**	-0.0214***	-0.0304***
	(0.0132)	(0.0123)	(0.0069)	(0.0096)
Observations	22,448	22,545	22,843	22,710
R-squared	0.237	0.236	0.234	0.233
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.9: Alternative Climate-Related Explanations – Low Temperatures

Notes. This table shows the results of our main tests with additional control variables for the number of cold days in the financial quarters. Thereby, we ensure that the main results are driven by heat and not by simultaneous decreases in the number of cold days. The table shows the effect of heat exposure on quarterly revenues (Panel A, Rev-Assets) as well as operating income scaled by total assets (Panel B, OpInc-Assets), by controlling for the number of cold days. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds is used for the measure of *Extreme Temperature Days* in the regression. Cold days are classified by the absolute threshold of 0°C in column 1 and 2 and as days with temperatures below the 5^{th} (column 3) and 10^{th} (column 4) percentile of the historical distribution for the location and days of the year. All regressions include firm financial quarter fixed effects (to control for firm location and firm-specific seasonal effects) and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0021	-0.0235***	-0.0199***	-0.0195***
	(0.0096)	(0.0071)	(0.0056)	(0.0070)
Cold Days	-0.0284*	-0.0297*	-0.0102	-0.0072
	(0.0158)	(0.0160)	(0.0096)	(0.0135)
Observations	149,573	149,573	149,573	149,573
R-squared	0.838	0.838	0.838	0.838
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0013	-0.0035**	-0.0034**	-0.0037*
	(0.0026)	(0.0017)	(0.0014)	(0.0019)
Cold Days	-0.0100***	-0.0102***	-0.0027	-0.0022
	(0.0029)	(0.0029)	(0.0024)	(0.0037)
Observations	149,573	149,573	149,573	149,573
R-squared	0.575	0.575	0.575	0.575
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table 2.10: Alternative Economic Explanations – Placebo Tests

Notes. This table shows a series of placebo tests, which we use to ensure that the main results are not driven by simultaneous economic developments. If the driver of the negative relation of heat exposure and earnings is general economic momentum, we expect to also find a systematic relation between shocks in heat exposure, investments, financing activities, and cash holdings. This table shows the effect of heat exposure on working capital over assets (Panel A), plant, property & equipment over assets (Panel B), investments over assets (Panel C) and cash holdings over assets (Panel D) on a quarterly basis. The dependent variables are in %, the coefficients refer to percentage points. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds is used for the measure of *Extreme Temperature Days* in the regression. All regressions include firm financial quarter fixed effects (to control for firm location and firm-specific seasonal effects) and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Working Capital*

	25°C	30°C	90^{th} P	95^{th} P
Extreme Temperature Days	-0.0263*	0.0058	-0.0040	-0.0004
	(0.0143)	(0.0103)	(0.0070)	(0.0097)
Observations	146,464	146,464	146,464	146,464
R-squared	0.737	0.737	0.737	0.737
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Plant, Property & Equipment*

	25°C	30°C	90^{th} P	95^{th} P
Extreme Temperature Days	0.0039	0.0128	0.0083	0.0044
	(0.0086)	(0.0080)	(0.0053)	(0.0074)
Observations	145,158	145,158	145,158	145,158
R-squared	0.866	0.866	0.866	0.866
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Heat Exposure and Investments*

	25°C	30°C	90^{th} P	95^{th} P
Extreme Temperature Days	0.0005	0.0027	0.0034	0.0041
	(0.0061)	(0.0052)	(0.0040)	(0.0049)
Observations	103,882	103,882	103,882	103,882
R-squared	0.695	0.695	0.695	0.695
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel D: *Heat Exposure and Cash Holdings*

	25°C	30°C	90^{th} P	95^{th} P
Extreme Temperature Days	-0.0019	-0.0040	0.0009	0.0027
	(0.0088)	(0.0068)	(0.0054)	(0.0066)
Observations	144,934	144,934	144,934	144,934
R-squared	0.695	0.695	0.695	0.695
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Appendix – Additional Tables

Table A.1: Heat Exposure and Annual Firm Performance

Notes. This table shows the effect of high temperatures on annual revenues (Rev-Assets) and annual operating income over total assets (OpInc-Assets). The dependent variables are expressed in %. *Extreme Temperature Days* refers to the number of high temperature days defined by two absolute (25°C, 30°C) and two relative (90^{th} and 95^{th}) thresholds, that reflect that the 90^{th} or 95^{th} percentile of the location- and day-of-the-year-specific temperature distribution from 1980-1999 was exceeded. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. Panels A and B show the results for annual financial performance and the concurrent (same year) extreme temperature days. In Panels C and D, extremes temperature days lagged by one financial year are included in addition to the concurrent count of *Extreme Temperature Days*. The number of observations refers to firm years, and all regressions include firm and industry × calendar year fixed effects. Standard errors are clustered two-way at the firm and calendar year level.

Panel A: *Concurrent Heat Exposure and Revenue – Annual Results*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	-0.0073	-0.0418**	-0.0390***	-0.0382**
	(0.0371)	(0.0176)	(0.0132)	(0.0132)
Observations	36,835	36,835	36,835	36,835
R-squared	0.853	0.853	0.853	0.853
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Concurrent Heat Exposure and Operating Income – Annual Results*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0057	-0.0042	-0.0027	-0.0028
	(0.0057)	(0.0044)	(0.0027)	(0.0031)
Observations	36,180	36,180	36,180	36,180
R-squared	0.647	0.647	0.647	0.647
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Lagged Heat Exposure and Revenue – Annual Results*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	-0.0013	-0.0383*	-0.0355**	-0.0349**
	(0.0396)	(0.0185)	(0.0135)	(0.0136)
L.Extr. Temperature Days	-0.0033	-0.0074	-0.0192	-0.0264*
	(0.0342)	(0.0109)	(0.0111)	(0.0135)
Observations	34,398	34,398	34,398	34,398
R-squared	0.858	0.858	0.858	0.858
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel D: *Lagged Heat Exposure and Operating Income – Annual Results*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	-0.0061	-0.0055	-0.0046**	-0.0046
	(0.0056)	(0.0038)	(0.0022)	(0.0027)
L.Extr. Temperature Days	-0.0006	-0.0014	-0.0002	-0.0003
	(0.0053)	(0.0026)	(0.0024)	(0.0034)
Observations	33,793	33,793	33,793	33,793
R-squared	0.654	0.655	0.655	0.655
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table A.2: Robustness – Analyst Forecasts

Notes. This table shows the effect of *Extreme Temperature Days* on the accuracy of quarterly analyst forecasts of revenues (Panel A) and pre-tax income (Panel B). The dependent variable is the financial performance surprise, measured as the actual value of revenues (Panel A) or pre-tax income (Panel B) minus the *mean* analyst estimate, scaled by the total assets of the firm lagged by one year. The ratios are expressed in %. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds is used for the measure of *Extreme Temperature Days* in the regression. All regressions include firm financial quarter fixed effects (to control for firm location and firm-specific seasonal effects) and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered at the firm level.

Panel A: *Heat Exposure and Revenue Analyst Forecasts*

	25°C Mean Surprise	30°C Mean Surprise	90^{th} P Mean Surprise	95^{th} P Mean Surprise
Extreme Temperature Days	-0.0042*	-0.0042	-0.0017	-0.0008
	(0.0023)	(0.0026)	(0.0021)	(0.0027)
Ln Book-to-Market Ratio	0.0636**	0.0648**	0.0645**	0.0643**
	(0.0304)	(0.0304)	(0.0304)	(0.0304)
Observations	28,578	28,578	28,578	28,578
R-squared	0.325	0.325	0.325	0.325
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Pre-Tax Income Analyst Forecasts*

	25°C Mean Surprise	30°C Mean Surprise	90^{th} P Mean Surprise	95^{th} P Mean Surprise
Extreme Temperature Days	-0.0024*	-0.0036**	-0.0027**	-0.0032*
	(0.0013)	(0.0014)	(0.0012)	(0.0017)
Ln Book-to-Market Ratio	0.1065***	0.1075***	0.1076***	0.1077***
	(0.0202)	(0.0202)	(0.0201)	(0.0201)
Observations	21,431	21,431	21,431	21,431
R-squared	0.348	0.348	0.348	0.348
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table A.3: Robustness – Announcement Returns

Notes. This table shows additional specifications of the tests on the effect of heat exposure on announcement returns, which we express in %. As the dependent variable, we use the raw returns (Panel A), returns over the equal weighted return of all firms in the sample (Panel B), returns over the expected return of the market model using equal weighted returns of the full sample as the benchmark (Panel C) and over the expected return of the market model using the market capitalization weighted returns of the full sample as the benchmark (Panel D). Betas in the market model are estimated out of sample based on up to 365 days until t=-46, with the earnings announcement in t=0. All returns are summed over a 5- (-2 to +2) instead of the 3-day event window (-1 to +1) around the earnings announcements, which we use in the main tests. *Extreme Temperature Days* is the number of days when a firm was exposed to extreme temperatures and is defined by two absolute (25°C, 30°C) and two relative (90^{th} pctl., 95^{th} pctl. of the location- and day-of-the-year-specific temperature distribution, 1980-1999) thresholds. The column headers indicate which of the four thresholds are used for the measure of *Extreme Temperature Days* in the regression. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered at the firm level.

Panel A: *Heat Exposure and 5-Day Raw Announcement Returns*

	25°C 5 Day	30°C 5 Day	90^{th} P 5 Day	95^{th} P 5 Day
Extreme Temperature Days	-0.0149	-0.0771***	-0.0217***	-0.0394***
	(0.0164)	(0.0149)	(0.0084)	(0.0117)
Observations	22,416	22,510	22,803	22,669
R-squared	0.238	0.235	0.232	0.231
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and 5-Day Benchmark-Adjusted Announcement Returns*

	25°C 5 Day EW	30°C 5 Day EW	90^{th} P 5 Day EW	95^{th} P 5 Day EW
Extreme Temperature Days	-0.0198	-0.0478***	-0.0252***	-0.0375***
	(0.0156)	(0.0144)	(0.0080)	(0.0112)
Observations	22,426	22,526	22,817	22,682
R-squared	0.237	0.232	0.231	0.230
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel C: *Heat Exposure and 5-Day Abnormal Returns (Market Model, Equal-Weighted Returns as Benchmark)*

	25°C 5 Day EW	30°C 5 Day EW	90^{th} P 5 Day EW	95^{th} P 5 Day EW
Extreme Temperature Days	-0.0101	-0.0030	-0.0192**	-0.0257**
	(0.0152)	(0.0143)	(0.0080)	(0.0112)
Observations	22,403	22,507	22,799	22,663
R-squared	0.233	0.229	0.228	0.227
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel D: *Heat Exposure and 5-Day Abnormal Returns (Market Model, Market Capitalization-Weighted Returns as Benchmark)*

	25°C 5 Day MW	30°C 5 Day MW	90^{th} P 5 Day MW	95^{th} P 5 Day MW
Extreme Temperature Days	0.0026	-0.0139	-0.0138*	-0.0191*
	(0.0152)	(0.0143)	(0.0080)	(0.0112)
Observations	22,417	22,519	22,809	22,675
R-squared	0.229	0.226	0.224	0.223
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Table A.4: Robustness – Firm Performance Excluding Financial Crisis Years

Notes. As a robustness test, we exclude the years of the financial crisis from the sample (2008, 2009, 2010). The table shows the effect of high temperatures on revenues (Rev-Assets) and operating income over total assets (OpInc-Assets) for this adjusted time period. The dependent variables are expressed in %. *Extreme Temperature Days* refers to the number of high temperature days defined by two absolute (25°C, 30°C) and two relative (90^{th} and 95^{th}) thresholds, that reflect that the 90^{th} or 95^{th} percentile of the location- and day-of-the-year-specific temperature distribution from 1980-1999 was exceeded. The column headers indicate which threshold the count of *Extreme Temperature Days* refers to. Panels A and B show the results for financial performance and concurrent (same quarter) extreme temperature days. In Panels C and D, extremes temperature days lagged by one quarter are included in addition to the concurrent count of *Extreme Temperature Days*. The number of observations refers to firm quarters. All regressions include firm-financial quarter fixed effects (Firm × Season) to control for firm location and firm-specific seasonal effects and industry-calendar quarter fixed effects (Industry × Qtr). Standard errors are clustered two-way at the firm and calendar quarter level.

Panel A: *Heat Exposure and Revenue*

	25°C Rev/Assets	30°C Rev/Assets	90^{th} P Rev/Assets	95^{th} P Rev/Assets
Extreme Temperature Days	0.0009 (0.0118)	-0.0328*** (0.0073)	-0.0231*** (0.0053)	-0.0241*** (0.0072)
Observations	120,717	120,717	120,717	120,717
R-squared	0.847	0.847	0.847	0.847
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

Panel B: *Heat Exposure and Operating Income*

	25°C OpI/Assets	30°C OpI/Assets	90^{th} P OpI/Assets	95^{th} P OpI/Assets
Extreme Temperature Days	0.0009 (0.0027)	-0.0040** (0.0018)	-0.0022* (0.0011)	-0.0021 (0.0015)
Observations	120,717	120,717	120,717	120,717
R-squared	0.615	0.615	0.615	0.615
Firm × Season FE	Yes	Yes	Yes	Yes
Industry × Qtr FE	Yes	Yes	Yes	Yes

3

Climate Change and Adaptation in Global Supply-Chain Networks

3.1 Introduction

Climate change is one of the greatest challenges of our time. The average global surface temperature has increased by 0.85° Celsius (1.5° F) since the industrial revolution, leading to more frequent extreme weather events such as heatwaves, forest fires, and catastrophic floods, with dramatic effects for society and economic activity (Carleton and Hsiang, 2016). According to the 2017 U.S. Climate Science Special Report, the cost of extreme climate-related events for the United States alone has exceeded \$1.1 trillion since 1980 (CSSR, 2017).[3.1] By the end of the century, temperatures are expected to increase even further by 0.9 to 5.4° C (1.6 – 9.7° F) (IPCC, 2013b).

This chapter is based on a working paper co-authored with Christoph Schiller (Arizona State University, W.P. Carey School of Business).

[3.1] See for example Dell et al. (2014) and Auffhammer (2018) for a summary of the literature on the economic effects of climate change.

While the academic literature in finance and economics has provided broad evidence on the adverse effects of climate change, including corporate earnings (Addoum et al., 2019), labor productivity (Graff-Zivin, Hsiang, and Neidell, 2018), stock returns (Kumar, Xin, and Zhang, 2019), and capital structure (Ginglinger and Moreau, 2019), much less is known about how firms and market participants can adapt to climate change. In contrast, Managers and investors are increasingly looking for ways to mitigate climate change risks, for example by adapting their operations and investments (Lin et al., 2018).[3.2]

In the age of globalization, most firms operate in extensive global production and supply-chain networks. Supply-chains often move through parts of the world that are most vulnerable to climate impacts. As a result, adapting to climate change is a complex task, as firms might be indirectly exposed to climate change risks due to their suppliers and customers.[3.3] Indeed, Barrot and Sauvagnat (2016) and Seetharam (2018), among others, show that the impact of extreme weather events can propagate through firm-level production networks. Consequently, in a recent survey, over 50% of CEOs mentioned risks posed to their global supply chains by climate change as one of their primary concerns (PWC, 2015).

Hence, the aim of this paper is twofold. First, we investigate if firms are affected by climate change risk due to their global supply-chain network. Specifically, we estimate the firm performance effects of climate change related extreme weather events on supplier firms around the world and the propagation of climate-related performance shocks to their corporate customers. Second, we study how firms adapt their supply-chain organizations in response to climate change risks. In particular, we examine if customers optimize and diversify their supplier network by replacing high-risk with low-risk supplier firms.

We combine detailed global, firm-level supply-chain data from FactSet Revere with geographic location data from FactSet Fundamentals and granular climate data on heatwaves from the European Center for Medium-term Weather Forecasts and floods from the Darthmouth Flood Observatory. Our supply-chain dataset includes 4,289 (4,568) unique supplier (customer) firms, comprising over 200,000 quarterly supplier-customer observations across 51 countries around the world, over the period from

[3.2] Krüger, Sautner, and Starks (2018) document that institutional investors consider engagement and risk management strategies to address the financial implications of climate change risks for their portfolio firms.

[3.3] For example, during the 2011 flooding disaster in Thailand, more than 14,500 firms reliant on Thai suppliers experienced business disruptions worldwide (BSR, 2018).

2003 to 2017.[3.4] We focus on two types of climate change risks – extreme heatwaves and flooding – for the following reasons. First, the literature in physiology and economics has pointed to several direct and indirect channels through which heatwaves can affect firm productivity. For example, extreme heat reduces human capital (Graff-Zivin et al., 2018), labor provision (Graff-Zivin and Neidell, 2014), and productivity (Zhang et al., 2018), with sharp declines typically observed at temperatures over 30° C.[3.5] Given current global carbon emissions, the number of heat days (i.e. days that exceed 100° F) is projected to rise dramatically, from currently 1% of days to more than 15% of days by 2099 (Graff-Zivin and Neidell, 2014), making extreme heatwaves a common and impactful phenomenon in the future. Second, flooding incidents can cause enormous economic damage to the affected region. According to FEMA, the United States suffered more than $260 billion in flood-related damages between 1980 and 2013. As a result of climate change, both both inland and coastal floods are expected to become more frequent and severe in the coming years (CSSR, 2017).

While Addoum et al. (2019) and Pankratz, Bauer, and Derwall (2019) show that exposure to local heatwaves affects the profitability of listed firms in many industries, both the question if climate change related shocks propagate along firm-level links and how customer firms can potentially mitigate such risks are unclear. First, the implications of climate shocks for suppliers and customers might differ. While extreme temperatures and floods might be costly to supplier firms, for example by increasing energy consumption for air conditioning or clean-up costs, customer firms would be unaffected by such shocks if suppliers cannot pass on the incurred costs downstream. In this case, neither heat nor flood related shocks would propagate from suppliers to customers. On the other hand, if heatwaves or floods lead to lower production output, such disruptions could propagate along the supply-chain and affect customer firms, potentially with a delay.

Second, if managers understand the risks of climate change, they plausibly organize operations to absorb climate risks and minimize disruptions due to shocks to their suppliers. Again, we would not expect climate shocks to propagate from suppliers to customer in this case. On the other hand, frictions such as relationship-specific investments or a high degree of input specialization might prevent customer firms

[3.4] In contrast to previous research on supply-chains in finance, which has mostly relied on data from Compustat Segment Files, this dataset allows us to study the initiation and termination of customer-supplier relationships. See Section 3.2 for details.

[3.5] High temperatures are also associated with higher civil conflict risk (Burke, Hsiang, and Miguel, 2015a) and immigration (Feng, Krüger, and Oppenheimer, 2010), which might indirectly impact firms in the affected areas.

from making such adjustments or from switching to alternative suppliers. Further, the risks of climate change have become much more salient over the past decades, as the frequency of extreme weather events and scientific evidence of future risks and public awareness both have increased. If managers are increasingly considering climate change risks when making operational and investment decisions, we would expect that customers become more likely to switch suppliers when observed climate change risks exceed previous expectations.

Our first set of tests focuses on the effect of climate change related weather events on the operating performance of affected supplier firms. Following the climate science literature (Carleton and Hsiang, 2016), we construct a location specific measure of heatwaves for our sample supplier firms based on the daily temperatures over a given quarter in the location of the firm's production facilities. Consistent with Addoum et al. (2019), we document that the occurrence of a heatwave during one of the three previous firm-quarters is associated with a subsequent reduction in revenue (operating income) by 3.9% (9.7%) relative to the sample median. Focusing on flooding incidents, we document a decrease by 3.9% (10.2%) relative to the sample median. These results hold after controlling for firm-fixed effects, firm-specific seasonal trends, industry-specific time trends, as well as a host of firm- and industry characteristics and trends.

Next, we provide evidence that firms are indeed exposed to climate change risks due to their global supply-chain network. Our findings show that climate change related shocks to supplier firms have a negative effect on the performance of their customers. Following the occurrence of a heatwave in a given firm-quarter at a single supplier, customer revenues decrease by 0.2% relative to the sample median. When suppliers are affected by a local flooding incident, customer revenue and operating income are reduced by 1.8% and 2.2%, respectively. Consistent with Barrot and Sauvagnat (2016), these effects hold with a lag of up to four quarters.

We conduct a number of robustness tests. First, we employ counting measures of heatwaves and flood incidents instead of using dummy variables and find similar result. Second, we implement our experiments both at the supplier-customer-quarter observation level as well as in a collapsed sample of customer-quarter-level observations, aggregating across suppliers for each sample customer. The results are similar in both settings. Third, we implement a placebo test by studying time periods in which our supplier-customer pairs were *not yet* or *no longer* in a supply-chain relationship. We find no evidence of climate risk propagation during these placebo periods.

Our main tests focus on the adaptation of supply-chains to climate change risks. We first examine how climate change risk affects the likelihood that customers terminate the relationship with their customers. Assuming that managers trade off potential climate-related risks with other firm characteristics (product quality, costs, delivery times, etc.) when entering a supply-chain relationship, we hypothesize that a customer firm is more likely to terminate an existing supplier-relation when the climate shocks observed over the course of a supply-chain relationship exceed the ex-ante anticipated risks. We therefore construct a measure of *realized vs. expected climate risk* by comparing heatwaves and flood incidents after the establishment of a supply-chain link to the observed climate shocks in the years before as a benchmark.

We document a large, positive effect of realized vs. expected climate risk on supplier termination. Our results show that a supply-chain relationship is 1.0 (3.7) percentage points more likely to be terminated in a given year, if the realized number of heatwaves (floods) exceeds the ex-ante expected number. This effect is economically meaningful given the unconditional expectation that a supply-chain relationship ends in any given year of 15.1% in our sample. The results are robust to using several alternative ways of constructing our climate risk measure, and significant at the 1%-level, controlling for any time-invariant supplier-by-customer characteristics, various time-variant financial supplier and customer characteristics, industry-by-time fixed effects, and country-by-time fixed effects. Importantly, when we solely consider the occurrence of heatwaves and floods throughout the supply-chain relationship (without comparing it to ex-ante expected climate shocks), we find a much smaller, statistically insignificant impact on the likelihood of supply-chain relationship termination. This is consistent with the notion that managers are taking climate risks into consideration when entering a supply-chain relationship.

Last, we examine how firms optimize their supply-chain climate risk by analyzing if customers switch from high climate-risk to low climate-risk suppliers. For this purpose, we consider all instances of ending supply-chain relationships in our sample and match each 'dropped' supplier with the 'replacement' suppliers, i.e. firms with the same 4-digit SIC code which newly became suppliers to the same customer within the next two years. We then compare the realized climate risk of the dropped and replacement suppliers based on the number of heatwaves and flooding incidents over the same time period. We find that replacement suppliers on average have 0.83 fewer heatwaves and 0.03 fewer floods than terminated suppliers, measured over the duration of the relation with the terminated supplier. The result is statically significant at the 1% level (t-statistics of 17.9 and 4.2), and robust to alternative comparison periods and climate risk measures.

Our paper contributes to the literature on the economic effects of climate change along several dimensions. To the best of our knowledge, we present the first evidence of operational adaptation to climate change-risk at the firm level. Our main result shows that managers respond to climate risks resulting from their supply-chain network by switching from high-risk to low-risk suppliers, indicating that climate risks can drive the formation of global firm-level production networks. This finding has important potential implications. As the climate science literature has shown (e.g. Burke et al., 2015b and Carleton and Hsiang, 2016), developing countries around the world are more severely affected by the outcomes of global climate change than developed countries in North America and Western Europe. However, as particularly the largest corporations traded on international stock exchanges rely on extensive, worldwide production networks, it is important for managers and policymakers to be aware of the extent to which the economic implications of climate change are shared through supply chain links. Moreover, if firms further shift economic activity from 'southern' to 'northern' countries due to heterogeneity in climate change risk, this effect could contribute to widening global inequality and economically weaken the areas most vulnerable to climate change. Lin et al. (2018) also study climate change adaptation, focusing on the investments of electricity generating firms in more flexible power generation technologies.

This paper also provides novel evidence on the implications of climate change for firms and investors. Previous research in the finance literature has studied the direct effects of climate shocks on firm profitability (Zhang et al., 2018; Addoum et al., 2019; Pankratz et al., 2019), housing prices (Baldauf, Garlappi, and Yannelis, 2019), stock returns (Kumar et al., 2019), financial markets (Bansal et al., 2016; Hong et al., 2019; Schlenker and Taylor, 2019), and capital structure (Ginglinger and Moreau, 2019). Our paper is the first to show that firms can be indirectly exposed to climate shocks due to their global supplier network. This aspect of our findings is most closely related to Barrot and Sauvagnat (2016), Seetharam (2018), and Boehm et al. (2019), who document the propagation of natural disasters along input-output linkages. The fundamental difference between our study and these papers is that we focus on the effects of temperature exposure and flood incidents, allowing us to assess the potential impact of climate change risk propagation along supply-chain links.

3.2 Data Sources and Descriptive Statistics

To conduct our empirical analysis, we combine data on global supply-chain relationships, firm financial performance, and granular data on local climate exposure from four main sources. In the following sections we describe the data sources in detail, explain how we link the individual datasets, and provide summary statistics for our main sample. The final sample used for the empirical tests in Sections 3.3 and 3.5 varies, as we merge supplier-customer relationship data with different climate change-related databases. For example, in Section 3.3 we focus on the propagation of climate shocks along existing supply-chain links, while Section 3.5 explores the determinants of customers switching suppliers. The following summary statistics therefore refer to our main sample used to examine climate shock propagation in Section 3.3. For this purpose, we retain each supplier- and customer-quarter in our main sample for which a complete record of supply-chain data, financial information, and climate exposure data is available. Throughout the rest of the paper, we provide relevant summary statistics and details in the context of the respective empirical tests.

3.2.1 Global Supply-Chains

We start by obtaining information on customer-supplier relationships from the recently available FactSet Revere database. Previous research on supply-chains in finance (e.g. Hertzel, Li, Officer, and Rodgers, 2008; Cohen and Frazzini, 2008; Banerjee, Dasgupta, and Kim, 2008) has relied primarily on the SEC's regulation S-K, which requires U.S. firms to disclose the existence and names of customer firms representing at least 10% of their total sales, to identify customer-supplier links. In contrast, the Revere supply-chain data has two important advantages that are particularly important in the context of this paper. First, while the SEC regulation does not apply in other countries, hence limiting existing research mostly to U.S. firms, Factset Revere supply-chain data includes both U.S. and foreign supplier and customer firms. This is important because many of the regions most vulnerable to climate change around the world are located outside of the United States. Second, and more importantly, previous research relying on the SEC regulation has been unable to study the initiation and termination of supplier-customer relationships, since the appearance and disappearance of a given supply-chain link in the data might either be due to a customer starting/ending a relationship with a given supplier, or because a customer firm was above/below the 10% reporting threshold in a given year. In contrast, the Revere supply-chain data is hand-collected, verified, and updated by FactSet analysts relying on a range of primary sources of information, including companies' annual reports and 10-K filings, investor presentations, company websites and press releases, corporate actions, and 10-Q and 8-K filings. This is crucial for our analysis of supply-chain formation and climate change adaptation, as it provides us with precise information on the beginning and end of a given supplier-customer relationship.

In total, our sample includes 4,568 unique customer firms and 4,289 unique supplier firms across 51 different countries, comprising approximately 220,000 supplier-customer pair-year-quarter observations over the sample period from 2003 to 2017. The geographical and industry distribution of the suppliers and customers in our sample is summarized in Table 3.1 and visually illustrated in Figures 3.1 and 3.2. As documented in Table 3.1, most of the suppliers and customers in our sample operate in manufacturing (SIC 1st digits 2 and 3) or transport and utilities (SIC 1st digit 4). Geographically, the majority of suppliers are located in North America (41%), East Asia and Pacific (30.6%) and Europe or Central Asia (18.4%). The regional distribution of customers is similar to the geographic distribution of the suppliers.

Table 3.2a (Panel C) presents relationship-level summary statistics for the firms in our sample. As documented, the average supply-chain relationship in the sample lasts 13.83 quarters. Similar to previous research on supply-chains in finance (e.g. Cen, Dasgupta, Elkamhi, and Pungaliya, 2015; Cen, Maydew, Zhang, and Zuo, 2017; Cen, Chen, Hou, and Richardson, 2018), we document an asymmetric mutual importance between customers and their suppliers in our sample. First, sample customer firms are typically much larger than their suppliers. The median sample customer holds 29 times the assets of the median supplier firm (book value of assets). Second, for firm-pairs where detailed sales data from supplier to customer is available (9.39% of the sample), the average proportion of sales the sample customers represent to their suppliers is 17.87%, while the average proportion of cost-of-goods-sold (COGS) suppliers represent to customers is only 1.82%. This relationship asymmetry suggests that customers on average have higher bargaining power in the relationship with their suppliers.

3.2.2 Accounting Performance and Firm Characteristics

Next, we obtain quarterly financial performance records for the firms in our sample from 2000 to 2017 from Compustat North America and Compustat Global.[3.6] Our main variables of interest for measuring operating firm performance in Section 3.3 are quarterly revenues and operating income, scaled by asset size. In addition to financial performance data, we obtain information on firms' financial reporting schedules to ensure that we correctly match climate records and performance records when financial quarters deviate from calendar quarters. To ensure that international financial records comparable, we convert all variables into U.S. dollars using the WRDS currency conversion tables, and deflate the values using the consumer price index information provided by the International Financial Statistics of the International Monetary Fund.

We further collect data on several additional firm characteristics from FactSet as control variables. These characteristics include firm controls such as the date of the first trade of the firms' shares to construct a proxy for firm age, the price-to-book ratio as well as the debt-to-assets ratio. To remove outliers, we trim all variables above (below) the 99th (1st) percentile. We further drop firms with incomplete records of financial information and exclude firms in the financial industry (SIC code between 6000 and 6999).

Panels A and B of Table 3.2a report summary statistics for customer and supplier financial performance and firm characteristics after applying the data filters outlined above. In line with the expectation that suppliers are on average smaller than their customers, the average book value of assets is is 6,354 million USD for customer firms, and 5,097 million USD for suppliers. Customers (Panel A) and suppliers (Panel B) have similar operating performance in our sample. The average quarterly (median) customer *Revenue/Assets* is 23.99% (19.91%) for customers and 21.96% (18.77%) for suppliers. The average quarterly (median) customer *Operating Income/Assets* is 2.47% (2.57%) for customers and 1.92% (2.31%) for suppliers.

[3.6] Compared to our sample of supply-chain relationships from FactSet Revere, we extend the financial performance sample by three years for later placebo tests, see Table 3.5.

3.2.3 Firm Locations

A crucial requirement for our empirical analysis of the impact of climate shocks on downstream propagation and the formation of supply-chain relationships is identifying the location of our sample firms. In this paper, we obtain information on the location of firms' operations from the FactSet Fundamentals database. Specifically, as our primary measure for firm location we use the addresses (City, Zip Code, Street Name) of firm headquarters as obtained from FactSet Fundamentals.

Of course, firms' plants and establishments are not always located in the same location as firms' headquarters. However, this measurement error is likely to bias our estimates in Sections 3.3 and 3.5 against finding any effect of climate shocks on firm performance and supply-chain formation. In addition, we use FactSet Revere information on firms' geographical concentration of assets to determine in which locations firms operate. These records are collected based on firms' public reporting of assets, sales, and income by geographic and product segments. Specifically, publicly listed firms are required to disclose these concentrations for all segments which represent more than 10% of total assets, sales, or income. In our main analysis, we limit our sample to firms with more than 50% of their assets in their home country to ensure that climate shocks affect a substantial part of firms' assets and operations. To match firms with the local information on climate hazards, we geocode the addresses of their headquarters using the Bing Maps API.

We apply two additional location-based data filters to our main sample: First, we remove decentralized firms with $< 50\%$ of assets in their primary geographic segment. Second, we drop all supplier-customer firm-pairs for which the headquarters of the two firms are located within 500km of each other in the analyses of Section 3.5, to rule out that both firms are affected simultaneously by the same climate shocks. As reported in Panel A and B of Table 3.2a, both customers and suppliers hold a substantially larger share of their assets in their home country than imposed by our 50% threshold: the average asset home-country concentration of customers is 79.4%, and the concentration of suppliers' assets is 80.5%.

3.2.4 Climate Data

In this paper we focus on two types of climate change related shocks – extreme heatwaves and flooding incidents – for the following reasons. First, heatwaves and floods are regionally concentrated events, allowing us to exploit the high granularity of climate data and the resulting geographic variation in climate exposure across our sample firms in our empirical tests. Second, climate science research widely agrees that heatwaves and floods are expected to become significantly more frequent and severe in the coming years (CSSR, 2017), making these climate shocks a particularly important subject of study for assessing the future economic costs of climate change. This is different from other type of natural disasters previously studied in the literature, e.g. earthquakes, as their occurance cannot be unambiguously linked to climate change. Third, while both extreme heat and floods can cause significant economic damage (see e.g. Graff-Zivin et al., 2018; Graff-Zivin and Neidell, 2014; Zhang et al., 2018), the two types of climate shocks possibly affect firms' operating performance and the results propagation effects through different channels. This allows us to further study the way climate shocks affect supply-chain formation by comparing similarities and differences between the effects of heatwaves and floods.

Heatwaves

First, we construct indicators capturing the occurrence of heatwaves at the firm-quarter-level from daily, location-specific information on maximum temperatures. The global coverage of weather station-based temperature records varies substantially across time and across different regions around the world. The resulting data gaps can cause substantial issues for empirical analysis, as weather station coverage can for example be correlated with other economic characteristics of a given region. To alleviate this concern, we use 're-analysis' temperature data[3.7] from the European Center for Medium-term Weather Forecasts (ECMWF), which is available at a significantly higher geographical and temporal granularity than the temperature data used in previous research (see e.g. Lin et al., 2018). Specifically, we use the ERA-Interim reanalysis data set with global, daily coverage of a $0.75 \times 0.75°$ latitude-longitude grid. The data is available starting in 1979.[3.8]

To construct our sample of local heatwave shocks, we begin by matching daily maximum temperatures to customer and supplier firms by based on the closest ERA-interim latitude-longitude grid nodes for the geocoded addresses of our sample firms. Next, we convert the temperatures from Kelvin to ° Celsius and identify the start and end dates of heatwaves. Following the heatwave definition of the National Weather Service, we label spells of three or more days with daily maximum temperatures over 30° Celsius by firm location as the occurrence of a heatwave (National Weather Ser-

[3.7] Re-analysis temperatures are generated by interpolating local temperatures based on data from existing weather stations and a number of other atmospheric data sources based on scientifically established climate models.

[3.8] Dee et al. 2011 provide a detailed description of the data set.

vice, 2019)[3.9]. Additionally, we compute the duration of the heatwaves by location and heatwave, and aggregate the number of heatwave days on the monthly, and later on the firm-quarter level.

Table 3.2b reports summary statistics on climate shocks affecting the customers and suppliers in our sample. As Panel A (customers) and B (supplier) of Table 3.2b show, the firms in our sample are regularly exposed to heatwaves, 29.8% of customer-firm-quarters and 36% of supplier-firm-quarters are affected by at least one heatwave in our sample. The average length of the heatwaves (consecutive days over 30° C) is substantial with an average of 23.8 heatwave days per financial quarter for suppliers, conditional on the occurrence of a heatwave, and 24.2 days for customers. On average, suppliers and customers are exposed to similar temperatures, with a sample average temperature of 18.6° Celsius (18.5° Celsius) for the customers (suppliers).

Floods

Second, we obtain data on global surface water levels to determine whether firms are affected by flooding incidents in a given quarter. While surface temperatures are the most commonly cited consequence of global climate change, the scientific literature widely agrees that flooding incidents will also increase significantly in frequency and severity in the future as a direct result of climate change, i.e. due to heavy rainfall, rapid melting of snow and ice, and parched soil (CSSR, 2017). At the same time, flooding can cause significant economic damage, providing us with a second type of climate shock that potentially affects firms in a different way than heatwaves.

We gather information on surface water levels from the Dartmouth Flood Observatory. To compile this data, the Dartmouth Observatory models the earth surface as a set of highly granular polygons and uses on satellite images and remote sensing sources to identify flooding of inundated ares. In addition, the observatory collects information on floods from news and governmental sources. The dataset includes start and end dates for each flood and detailed geographical information on the inundated areas polygons, from 1984 until today. The dataset further provides additional information on the floods such as the associated damages, size of the affected area, and deaths. We rely on the flood polygons used by the Dartmouth Observatory to spatially match the coordinates of our sample firms to the areas affected by the floods

[3.9] Precisely, the National Weather Services defines heatwaves as "three or more consecutive days with the temperature reaching or exceeding 90 degrees *(Fahrenheit)*".

using the software QGIS. Compared to the country-level flooding data used in previous research, this approach allows us to determine more precisely if a given firm location was inundated at a given point in time.

Equivalent to the procedure outlined in Section 3.2.4 for the heatwave records, we compute the number of days for which a firm was exposed to a given flood, and aggregate the count of floods on a monthly basis. Panel A and B of Table 3.2b illustrate the aggregate flooding summary statistics at the firm-quarter level. On average, suppliers and customers experience floods in 6.0% and 6.1% of all firm-quarters. The average number of 26.7 (30.8) casualties conditional on the occurrence of a flood suggests that we observe flood events with a substantial magnitude.

EM-DAT Disaster Data

For additional robustness tests in Section 3.3 we also include climate shock data from the international disaster database *EM-DAT* provided by the Centre for Research on the Epidemiology of Disasters (CRED, 2011). EM-DAT is one of the most commonly used datasets in the literature on the economic cost of climate hazards.[3.10] To compare our heatwave and flood data with the country-level EM-DAT disaster, we first distinguish if the temperature-related EM-DAT events are heatwaves or cold spells. Subsequently, we aggregate flood and heat events on a monthly basis based on the start and end dates, and combine the disaster data with our local records from the ECMWF and the Darthmouth Flood Observatory. Table 3.2b provides the EM-DAT summary statistics.

We conjecture that our high-granularity heatwave and flood incidents data and the country-level data from EM-DAT differ along two dimensions. First, using country-level information naturally overstates the extent to which firms have been affected by natural disasters. In that case, the EM-DAT shocks would overstate firms' exposure to both floods and heatwaves. Second, the salience of the two hazard types and the probability that events are registered should differ across data sources. Both heat and flood events are recorded by EM-DAT only if they either caused ten or more associated casualties, affected more than 100 people, lead to the declaration of a state of emergency, or resulted in a call for international assistance. While floods are highly visible, the relevance of extreme temperatures and heatwaves can be contingent on the

[3.10] See for example: Strömberg, 2007; Noy, 2009; Lesk, Rowhani, and Ramankutty, 2016 context, and hence more difficult to identify. Therefore, we expect that the disaster data only captures a subset of both floods and heatwaves that we can detect locally, particularly in the case of heatwaves.

In line with this reasoning, the average number of flood-affected firm-quarter observations is significantly higher based on the country-level match compared to the EM-DAT match. For instance, suppliers are physically exposed to floods only 6.1% of the time according to the local data, compared to 49% if we match based on EM-DAT country-level records. The opposite holds for heatwaves. While our local data suggests that heatwaves occur frequently, the disaster statistics yield a much lower affected numbers of firm-quarters - despite the geographic overestimation.

3.3 Direct Exposure to Climate Shocks

We begin our analysis by studying the direct effects of climate shocks on the supplier firms in our sample. This exercise is important to verify that the shocks we study in this paper indeed have an economically significant effect on firm operating performance. Many of the regions most severely affected by climate change are located outside of the developed countries of North America and Western Europe. Hence, our analysis complements the results in Somanathan et al. (2015); Zhang et al. (2018); Addoum et al. (2019), as we study the effect of heatwaves on firm earnings and performance in a global setting. Further, by also studying flooding incidents – in addition to local heatwaves – we are able to compare the economic effects of different climate change related risks. In our main analysis we focus on heatwave and flooding data from ECMWF and the Dartmouth Observatory, as the EM-DAT disaster data is less granular for floods and too restrictive for heatwaves, as documented in Section 3.2.4.

One important consideration for our tests is that firms likely adjust to the average climate hazard exposure in production locations. If managers understand climate risks and organize production to maximize profits, they might choose (not) to produce in certain places if adjustment potential is (in)sufficient, or they adjust the production equipment to match the expected climate exposure – contingent on the firm's financial capacity to do so. Hence, it the cross-sectional relationship between climate exposure variables and firm financial performance is likely endogenous.

However, while managers can base their decisions on expected climate exposure, they do not have power over the weather variation over time and the exact timing of climate shocks. Moreover, both floods and heatwaves can only be predicted with precision on short horizons, which are unlikely to allow for substantial adjustment in the production planning. Therefore, the variation in climate shocks over time is an exogenous source of variation and randomly distributed once we condition on fixed firm locations. This allows us to identify the causal impact of floods and heatwaves on firm operating performance.

We isolate the effect of time-series variation in climate shocks for a given firm on firm operating performance by estimating OLS regressions with firm-by-quarter fixed effects. By interacting firm-fixed effects and quarter fixed effects, our model absorbs both any time-invariant firm-level characteristics, as well as firm-specific seasonal effects during the four quarters of the year. This is important because firm operating performance varies seasonally throughout the year, and this seasonal variation might be correlated with the occurrence of climate shocks. Further, we include industry-by-year-by-quarter fixed effects to absorb any industry-specific time trends.

Our two main variables for measuring firm operating performance in the following regression models are sales turnover and profitability. Specifically, we use quarterly revenues and operating income, divided by assets. We specifically focus on these two measures – as opposed to for example earnings – since revenues and operating income are harder to manipulate by firms' strategic accounting - and the incentive to smooth earnings might be particularly high following adverse financial shocks.

In principle, the location-specific variation in flood and heat shocks over time cannot be actively influenced by firm choices. However, as climate shocks could randomly coincide with changes in firm characteristics over time, we additionally introduce size, age, and profitability specific time fixed effects. For this purpose, we sort all firms into size, age, and profitability terciles and interact the grouping variables with year-quarter fixed effects in our main specification, following Barrot and Sauvagnat (2016). Specifically, we estimate models of the following form, clustering robust standard errors on the firm level in line with Barrot and Sauvagnat (2016):

$$y_{iqt} = \sum_{k=q}^{K} \beta_k \times Climate\ Shocks_{iqt} + \mu_{iq} + \gamma_{mqt} + \delta_{BS2016_{iqt}} + \epsilon_{iqt} \tag{3.1}$$

where y_{iqt} is either *Revenue/Assets* (Rev/AT) or *Operating Income/Assets* (OpI/AT) of firm i in quarter q of year t (with $q = 1, ..., 4$), $Climate\ Shocks_{iqt}$ is a dummy variable indicating the occurrence of a heatwave or flood in the location of firm i in quarter q in year t. μ_{iq} are firm $\times$ quarter fixed effects. γ_{mqt} are year $\times$ quarter $\times$ industry fixed effects based on 2-digit SIC codes, the index m for $m = 1, ..., M$ industries is for notational convenience only, and $m = f(i)$. $\delta_{BS2016_{iqt}}$ are firm size, age, and profitability $\times$ year $\times$ quarter fixed effects as in Barrot and Sauvagnat (2016). In robustness tests, we also use the count of climate events by financial quarter as an alternative specification. As it is ex-ante unclear if the financial impact of climate shocks manifests immediately or with some delay throughout the financial year, we estimate two different specification of the outline model. First, we limit the climate shock observations to the current financial quarter and second, i.e. we restrict the specification to $q = 0$, second, we additionally include three lags, $q = -3, ..., 0$.

Table 3.3 reports the regression results for Equation (3.1). In Panel A we estimate regressions without climate shock lags, in Panel B we additionally include three lags of climate shock events. The results in both panels indicate that heatwaves and floods adversely impact the bottom line of our supplier firms. However, the results also show that the full financial impact only becomes visible over the course of the financial year. On the one hand, we find a very small contemporaneous impact of heat events on firm operating performance, as both the effect on sales turnover and profitability is statistically indistinguishable from zero in Panel A. At the same time, the occurrence of a flood is associated with an average decrease in *Revenue/Assets* of 0.19 percentage points, and a decrease in operating income over assets between 0.095 to 0.1 percentage points.

On the other hand, Panel B indicates that the financial impact of heatwaves and floods is in fact much larger than the simple analysis of contemporaneous climate shocks suggests, in line with the findings of Barrot and Sauvagnat (2016). When we include three lags of climate shocks in Equation (3.1) while holding the sample fixed, we find a material impact of heatwaves on both Rev/AT and OpI/AT between one to three financial firm quarters after the occurrence of a heatwave. The coefficient estimate for the effect of heatwaves on sales turnover in columns (1) and (2) is between -0.25 to -0.26 (statistically significant at the 5 and 10% level), and between -0.09 to -0.12 for operating margin in columns (3) and (4) for the coefficients with a lag of two to three quarters. Floods similarly decrease sales turnover (between -0.25 and -0.29 percentage points, statistically significant on the 5% and 10% level) and profitability (-0.11 to -0.12 percentage points, significant on the 1% level) in the contemporaneous and the previous two financial quarters. Given the average operating margin (OpI/AT) of 2% and sales turnover (Rev/AT) of 22% in our supplier sample, the mean effects are economically meaningful, representing approximately a 1% reduction in sales turnover and a 5.5% reduction in operating income over assets, relative to the sample mean. The documented difference in how quickly financial performance measures reflect the occurrence of climate shocks could have important implications for market participants. If heatwaves are reflected by accounting measures of firm performance with a delay, it becomes more difficult for investors to understand the link between the such temperature events and firm performance. Hence, this delay could help explain the underreaction of investors to firms' exposure to extreme temperatures, documented in the recent literature (Addoum et al., 2019; Pankratz et al., 2019).

Our results naturally raise questions regarding the economic mechanisms driving the observed effects. In the context of heatwaves, a large literature in economics has focused on the channels through which extreme temperatures can cause aggregate economic losses[3.11]. With regard to floods, these channels have been studied less explicitly, but the observed net effect could be caused by damages to assets, equipment and infrastructure, as well as production distortions during the floods, e.g. if worker safety is endangered and production thereby constrained throughout the duration of the floods. As the focus of our analysis lies on the direct and indirect performance implications of climate shocks and the adaptation of supply-chain managers, we remain agnostic about the precise mechanics of the directly observable effects in this paper.

We conduct several robustness tests for the direct effects of climate shocks on firm operating performance. First, we estimate the impact of the climate shocks on supplier performance after replacing heatwave and flood dummies with counting variables indicating the number of climate events per financial quarter. The results are reported in Appendix Table B.1 and show that the statistical significance and overall pattern remain similar for this alternative specification. Moreover, the statistically strongest effects of heatwaves again appear to occur with a delay of two quarters after the firm was exposed to the heatwaves. Similarly, and in line with our main test in Table 3.3, contemporaneous floods have a significant immediate as well as a two-quarter delayed impact on sales turnover and operating income. When we use

[3.11]Previous research documents that electricity prices increase with heat exposure (Pechan and Eisenack, 2014), while water supply tightens (Mishra and Singh, 2010) and both cognitive and physical worker performance are compromised (Sepannen et al., 2006; Xiang, Bi, Pisaniello, and Hansen, 2014).

the count of heatwaves and floods per quarter for our estimations, the magnitude of the coefficient estimates is naturally smaller than the aggregate effect for all events in a financial quarter estimated in Table 3.3.

As our final robustness test on the direct impact of climate shocks, we estimate the impact of heatwave and flooding disasters on supplier performance using the country-level data from EM-DAT. Overall, the results reported in Appendix Table B.2 confirm our conjecture from Section 3.2.4: for evaluating the financial impact of climate shocks on the firm level the use of climate data with high geographical granularity is essential. While heatwaves identified as disasters in the EM-DAT database are negatively correlated with supplier performance only in the specifications in columns (1) and (2) and with a delay of one financial quarter, the coefficient estimates are statistically indistinguishable from zero, or even *positive* in all other specifications.

3.4 Indirect Exposure to Climate Shocks

Based on our result from the previous Section 3.3, showing that heatwaves and floods significantly decrease supplier operating performance, we next test if climate hazards propagate downstream along supply-chain links. Since particularly the largest corporations traded on international stock exchanges rely on extensive, worldwide production networks, it is important to better understand if even firms which are not located in areas with a high climate risk exposure can indirectly be harmed by increases in the intensity of climate hazards due to their (remote) suppliers.

Analogous to our previous tests, we use sales turnover and profitability, measured by revenue over assets and operating income over assets, as our two main dependent variables for assessing whether climate risk is indeed propagated along supply-chains are. Despite the adverse direct effect on suppliers documented above, the implications of climate shocks for supplier and customer performance might differ. On the one hand, customer firms could be unaffected by shocks to supplying firms if suppliers cannot pass on the incurred costs downstream. At the same time, customers could also include climate factors in their contingency management, enabling them switch suppliers without incurring large costs if a specific supplier is hit by a heatwave or flooding. In both cases, neither heat nor flood related shocks would propagate from suppliers to customer along the supply-chain, and we should not be able to document a significant impact of climate shocks to suppliers on customer financial performance.

On the other hand, environmental shocks such as heatwaves or floods can cause supply-chain glitches and lower production output at the supplier and customer level. These disruptions are particularly likely if the provided inputs have a high level of specificity (Barrot and Sauvagnat, 2016). If climate shocks to suppliers on average cause distortions, we would expect to find a negative relation between customer financial performance and supplier exposure to climate risk.

To test these competing hypotheses, we require two identifying assumptions. As in the previous analysis, it is problematic to study this question in the cross-section, as the exposure of customer firms to climate shocks through suppliers might be endogenous. For instance, if certain industries systematically depend on specific inputs from suppliers clustered in risky areas, climate shocks and customer firm performance might be endogenously correlated. In contrast, it is reasonable to assume that the variation in supplier exposure to climate shocks over time is unrelated to time invariant firm characteristics such as industry associations.[3.12] Therefore, analogous to our model in Equation (3.1), all our results in this section are due to within-firm-pair variation over time.

Second, customer firms could experience similar performance effects as their suppliers when they themselves are hit by climate shocks. Therefore, to ensure that our results are not due climate shocks affecting customer firms directly, we exclude all customers-supplier pairs with customers located within a 500 kilometer radius of the affected supplier from our analysis.

Based on these considerations, we estimate two different models. In our first set of tests we estimate pooled OLS regressions of the following form,

$$y_{csqt} = \sum_{k=q}^{K} \beta_k \times Climate\ Shocks_{sqt} + \mu_{csq} + \gamma_{mqt} + \delta_{BS2016_{cqt}} + \epsilon_{csqt} \qquad (3.2)$$

where y_{csqt} is either $Revenue/Assets$ or $Operating\ Income/Assets$ of customer c in quarter q of year t, $Climate\ Shocks_{sqt}$ is a dummy variable indicating the occurrence of a heatwave or flood in the location of supplier s in year-quarter qt, μ_{csq} are supplier-customer pair $\times$ quarter ($q = 1, ..., 4$) fixed effects, γ_{mqt} are industry $\times$ quarter $\times$ year fixed effects based on 2-digit SIC codes with m determined by c, and $\delta_{BS2016_{cqt}}$ are

[3.12] In our later analyses, we find that firms tend to terminate relationships with suppliers that face increases in climate shock exposure compared to historical, expected levels of climate risk. However, the tendency of customers to cut off suppliers that are particularly exposed to climate risk should only bias our effects downward.

customer firm size, age, and profitability $\times$ year-quarter fixed effects similar to Equation (3.1). The unit of observation in these test is the customer-supplier-quarter. By including pair-by-quarter fixed effects (γ_{mqt}), our model subsumes all time-invariant relationship characteristics (e.g. supplier and customer country characteristics, languages, geographical distance, average input specificity, average relationship strength, and firm fixed effects) as well as relationship-specific seasonal patterns. Our results are therefore obtained from time-series variation in the observations for the same quarter over the years in the sample.

In our second set of tests, we collapse our panel observations at the customer level by aggregating over all suppliers of a given customer, and estimate regressions of the following form,

$$y_{cqt} = \sum_{k=q}^{K} \beta_k \times Climate\ Shocks_{cqt} + \mu_{cq} + \gamma_{mqt} + \delta_{BS2016_{cqt}} + \epsilon_{cqt} \tag{3.3}$$

where y_{cqt} again captures customer firm *Revenue/Assets* or *Operating Income/Assets*, and μ_{cq}, γ_{mqt}, and $\delta_{BS2016_{cqt}}$ are fixed effects at the customer-by-quarter ($q = 1, ..., 4$), industry-by-year-by-quarter, and size/age/ROA $\times$ year-quarter level.
$Climate\ Shocks_{cqt}$ is obtained as the maximum of $Climate\ Shocks_{csqt}$ over all suppliers s of customer c in period qt. The unit of observation in these tests as at the customer-year-quarter level.

Based on our findings in Section 3.3, we include lags of $k = 3$ periods for the climate shocks in both Model (3.2) and (3.3). In line with our identifying assumptions that the variation over time in flood and heat shocks on suppliers are exogenous and that the supplier shocks only affect customers through the supply chain link, other characteristics of the customer firms should not be systematically correlated with both the outcome and the flood and heatwave occurrence. Hence, we do not include firm-level controls in our main specification, but again add size, age, and profitability times quarter fixed effects to control for different firm profiles, analogous to Equation 3.2. In line with Barrot and Sauvagnat (2016), we cluster robust standard errors on the relationship and on the customer firm level in Equations (3.2) and (3.3), respectively.

3.4.1 Climate Shock Propagation – Results

Table 3.4 reports the results for our first test on customers' sensitivity to supplier climate risk exposure, as detailed in Equation (3.2). The unit of observation in Panel A is at the supplier-customer-year-quarter level. The first four columns show the impact of supplier heatwaves, columns (5) to (8) report the effect of supplier floods. With regard to heatwaves, we find tentative evidence that the climate shocks on suppliers propagate along the supply chain. Specifically, we find a negative impact (coefficient -0.044) of heatwaves at the supplier locations on customer revenues in column (2), statistically significant at the 10% level. All other coefficient estimates for the propagation effect of heatwaves lagged by one to three quarters are marginally not statistically significant. However, all coefficient estimates carry negative signs, and the difference in the magnitude between the impact of heatwaves on revenues and operating income is in line with the estimations of the direct impact of heat on supplier firms. Hence, while the observed effect is small in our sample, our finding is still economically meaningful, given that the frequency of heatwaves is projected to increase substantially in the future due to ongoing climate change.

In comparison, the shock propagation of floods is unambiguous and both statistically and economically large. According to our estimates, customer revenue over assets decreases between 0.10 to 0.16 percentage points in three quarters after the supplier has initially been exposed to a flood. Moreover, customers' operating income is reduced by 0.02 up to 0.04 percentage points (all effects significant on the 1% level). These magnitudes are economically meaningful even at low climate shock frequencies: Compared to the sample median, the occurrence of a flood at the supplier firm reduces customer revenue and operating income by 1.8% and 2.2%, respectively.

In Panel B of Table 3.4, we show the results for the sample collapsed on the customer level, implementing the model in Equation (3.3). Again, we find evidence that the climate shocks on supplier firms propagate along the supply chain with a tentative, statistically negative impact of heatwaves at the supplier locations on operating income (column (3), coefficient estimate of -0.052, significant at the 5% level). For floods, the results are similar in magnitude to our first set of tests using the full panel. The impact of floods at one of a given customer's supplier firms reduces revenues over assets between -0.15 and -0.16 percentage points (statistically significant at the 10% and 5% level), with a lag of two calendar quarters. Further, floods have a significant negative effect on operating income (coefficient estimates between -0.053 and -0.045 percentage points, significant at the 5% and 10% level), with a lag of one quarter.

Taken together, our results provide evidence that climate change related shocks can propagate downstream along the supply-chain. This finding indicates that climate change could affect even firms in relatively 'climate-safe' parts of the world as supply-chains span the globe. On average, the results also suggest that suppliers can pass some of the cost caused by climate shocks on to customers, or that not all customers in our sample are fully hedged against idiosyncratic shocks to their suppliers through their contingency management. while the evidence on the side of heatwaves is tentative[3.13], the flood-related effects are pronounced both in a statistical and economic sense. Our results are consistent with Barrot and Sauvagnat (2016), who document that the financial shocks imposed by natural disasters propagate along the supply chain when inputs are specific.

3.4.2 Climate Shock Propagation – Robustness

We conduct a number of robustness with respect to our findings on the propagation of climate shocks. First, to verify that the effects we observe are indeed attributable to climate shock transmission through supply-chain linkages, we implement a placebo test based on the start and end dates of our sample supply-chain relationships. Specifically, we re-estimate our regressions models specified in Equations (3.2) and (3.3) using the same sample of supplier-customer relationships. However, in our placebo tests we use only the periods before and after a given supplier-customer pair was engaged in a supply-chain relationship.

If the supply-chain data from FactSet Revere correctly identifies the beginning and end of our sample supplier-customer relations, and our results in Section 3.4.1 are indeed due to the propagation of climate shocks, we should not find a negative effect of supplier climate shocks on customer firm operating performance in the placebo sample. Indeed, as reported in Table 3.5, we do not find a negative relation between supplier climate shocks and customer firm performance, neither when conducting the tests on the full customer-supplier pair level sample (Panel A), nor on the collapsed sample at the customer level (Panel B).

[3.13]Given the marginally insignificant results for the heatwave-based tests, it is important to bear in mind that the empirical setting biases the results downwards. First, if a share of the customers in the sample has a strong contingency management with several alternative suppliers, and second, if managers respond to operational distortions caused by troubled suppliers, and replace suppliers that are particularly exposed, so that affected supply-chain links systematically drop out of the sample.

As an additional robustness test, we estimate the shock propagation based on a count measure of heatwaves and floods instead of an indicator variable. The results are reported in Appendix Table B.3. Again, we find weak evidence for a propagation of heatwave-related shocks on the supplier to the customer operating income (column 2, coefficient estimate of -0.015, significant at the 5% level) and strong evidence for the propagation of flood related shocks. Last, we repeat our tests using the country-level climate shock data from EM-DAT, analogously to Section 3.3. The results are reported in Appendix Table B.4. In line with our results focusing on the direct effect of climate shocks, we cannot document a consistent relation between customer performance and the climate disaster measures from EM-DAT.

3.5 Supply-Chain Adaptation

Our results in the previous sections show that climate-related shocks matter for firm financial performance, both directly and indirectly through supply chain links. Hence, managers have an incentive to monitor the climate-change related risk imposed by their suppliers. In this section, we empirically test if managers indeed take climate-risk considerations into account by adapting their to supply-chain relationships.

3.5.1 Climate Trends and Supplier Termination

We first test if climate-change risk increases the likelihood that a supplier-customer relationship is terminated. On the one hand, costly climate-related shocks could cause operational issues at a given supplier, making the firm a less attractive supply chain partner going forward. On the other hand, customer and supplier firms often make substantial relationship-specific investments to set up and maintain a supply chain relationship. It is unclear if the adverse financial consequences of climate risk exposure are sufficiently high to result in the termination of an existing customer-supplier relationship.

We use the FactSet Revere information on the start and end dates of customer-supplier relationships to test these hypotheses. To construct the main outcome variable, we generate a panel of firm years in which the customer-supplier relationships are active, and set the dummy variable $\mathbb{1}(End)$ to take the value of one in the last year a given supply-chain relationship is reported in FactSet Revere. To avoid mechanical issues in the last year of our sample we drop observations from 2017.

To construct our main variable of interest capturing supplier climate risk exposure, we start with the assumption that managers trade off potential climate-related risks with other firm characteristics such as product quality, costs and delivery times when entering a supply-chain relationship. Under this scenario, a customer firm is generally aware of climate risks associated with a given supplier and continuously weighs the costs and benefits of remaining in the relationship. As long as the costs of leaving a given relationship exceed the costs of staying, the customer will continue the relationship with a supplier. If this assumption holds, realized climate shocks over the course of a supply-chain relationship that fall within the normal, ex-ante anticipated range of events given a supplier's location and climate risk will not substantially influence the likelihood that the supplier is dropped, all else equal. However, if realized climate risks increase beyond the anticipated levels, and in ways that firms are not prepared for or hedged against, it would reduce the economic viability of a supplier-customer relationship and increase the profitability that the relationship ends.

To test this conjecture, we construct the measure
$\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\ \ (t)$, as illustrated in Figure 3.3. We first estimate the expected number of climate shocks per year in the supplier location over a benchmark period of five[3.14] years*before* the establishment of any given supplier-customer relationship.
$\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\ \ (t)$ then takes the value of one in year t, if the difference between the realized number of climate shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of shocks, and zero otherwise.

In econometric terms, our following test again relies on two identifying assumptions. First, we exploit the fact that climate trends, besides the timing of climate shocks, are to a large extent random over time and cannot be predicted with precision. Hence, managers can incorporate expected levels of climate risk exposure, but not deviations from the expectation into their decision making. Second, to be able to assume that the estimated effect is not caused by the direct impact of changing climate risk on the customer, we again exclude all customers-supplier pairs with customers located within a 500 kilometer radius of the affected supplier. Based on these assumptions, our measure of realized vs. expected climate risk is orthogonal to other firm decisions, and our corresponding estimate reflects the impact of the change in supplier climate shock exposure. We estimate the following linear probability model,

[3.14] In robustness tests, we use seven, ten, and fifteen years, respectively.

$$\mathbb{1}\left(End\right)_{cst} = \beta \times \mathbb{1}\left(Realized > Expected\ Climate\ Shocks\right)_{cst} + \mu_{cs} + \gamma_{mnt} + \rho_{lt} + \epsilon_{cst} \tag{3.4}$$

where $\mathbb{1}\left(End\right)_{sct}$ is an indicator taking the value of one in year t if it is the last year on record of the relation between supplier s and customer c.

To control for potential confounding effects, we estimate the regressions with several dimensions of fixed effects. First, we include relationship fixed-effects μ_{cs} in all specification to account for supplier $\times$ customer characteristics that impact the probability of a relationship to end, but do not vary over time. For instance, suppliers could face a fixed probability of termination based on their industry association. Further, we include supplier industry-by-year fixed effects γ_{mt} to account for industry trends, for example related to the extent to which customers switch from buying inputs to manufacturing inputs. For notational convenience, the index $m = 1, ..., M$ represents the respective supplier industry (determined by s). We also add supplier country-year fixed effects ρ_{lt} to account for changing macroeconomic risks that impact whether customer firms maintain supplier-relationships (index l determined by s). In addition, we estimate the model with supplier country- $\times$ customer country $\times$ year fixed effects (index l determined by s and c) to account for changes in international trade dynamics, such as changing barriers or import-related costs. We cluster robust standard errors on the relationship level cs.

Table 3.6 reports the results. Across all specifications, we find a robust, positive impact of high realized vs. expected climate exposure on the likelihood of supply-chain relationship termination. In line with the results on the financial impact of the climate hazards as well as the financial propagation of the shocks in the supply chains, the results suggest that increases in flood exposure increase the probability a supply-chain relationship ends on average by 3.7 percentage points (column 8, coefficient significant at the 1%-level). The impact of heatwave exposure increases is equally strong in terms of its statistical significance but economically smaller at percentage points (column 4, coefficient statistically significant at the 1%-level). The difference in the magnitude between floods and heatwaves is in line with the stronger direct and indirect impact of floods compared to heatwaves documented in Sections 3.3 and

3.4. Both the estimate for heatwaves and floods are economically meaningful, given the unconditional expectation of 15.12% that a supply chain relationship ends in any given year in our sample.

To test the robustness of this result, we change the horizon over which we compute the expected number of floods or heatwaves per year. Appendix Table B.5 indicates that the results are robust when we extend the period from 5 to 7, 10, or 15 years, as both the estimates for heatwaves and floods remain very similar in magnitude and significance. Moreover, we test whether the results remain stable when we include additional time-variant financial control variables for both the supplier and customer firms. Thereby, we control for changes in the financial health of the firms which could otherwise influence the probability of the continuation of the relationship. As Appendix Table B.6 shows, the results again remain very similar both in magnitude and significance when we control for changes in the debt-to-assets ratio, the log price-to-book ratio, and firm size proxied by the natural logarithm of the market value of equity.

3.5.2 Climate Shocks and Supplier Termination

To validate our assumption that managers take climate risks into account when establishing supply-chain relations, we next replace our measure of realized vs. expected climate risk with a simple measure of realized climate shocks since the beginning of the supplier relationship. If the general level of climate risk exposure is taken into consideration before forming supply chain relationships, climate shocks per se should not be a strong determinant of supplier termination. We again estimate the model in Equation (3.4), replacing $\mathbb{1}\left(Realized > Expected\ Climate\ Shocks\right)$ with $Climate\ Shocks\ (t)$ of the supplier firm.

The results, reported in table Table 3.7 show the sensitivity of supply-chain relationship continuation to realized climate shocks. Depending on the dimension of fixed effects, we find a small, positive impact of heatwave and flood occurrence on the probability that a supply-chain relationship ends for some specifications. However, the economic magnitude of this effect is small: For heatwaves, the probability of termination is increases by 0.16 to 0.17 percentage points (columns 3 and 4, coefficients significant at the 5% level), for floods, there is some evidence of an increase by 0.29

to 0.33 percentage points (columns 5 and 6, coefficients significant at the 1%-level). This effect is an order of magnitude smaller and insignificant compared to the tests based on realized vs. expected climate risk.

Taken together, our results are consistent with the notion that managers are taking climate risks into consideration when entering a supply-chain relation. Also, the results suggest that increases in climate risk exposure can be an important determinant of the probability of the continuation of the relationships. If this effect holds globally, it could have important implications for international development. According to Burke et al., 2015b and Carleton and Hsiang, 2016, developing countries around the world are most severely affected by the outcomes of global climate change. If financial incentives from supply-chain disruptions motivate 'Northern' firms to further shift economic activity from 'Southern' to 'Northern' countries, the effect could contribute to widening global economic inequality.

3.5.3 Climate Risk Exposure of Old and New Suppliers

To shed further light on the question how firms adapt their supply-chains to climate change, and to examine if climate risks are indeed driving the formation of production networks, we next study if customers switch from high risk to low risk suppliers based on climate exposure. As we showed in the previous section, realized climate shocks in exceedance of previously anticipated levels can increase the likelihood that a given supplier relationship ends. However, it is unclear if managers understand the link between climate risk exposure and financial performance, and hence mitigate these risks by switching to different suppliers with lower climate exposure. Instead, customer managers might simply observe the adverse financial effects of (indirect) climate shocks without considering climate risk as an underlying driver of financial performance effects. Under this scenario, we would not expect to find a difference in climate risk exposure between 'old' suppliers whose supply-chain relationships are terminated and 'new' replacement suppliers.

To test this conjecture, we limit our dataset to supplier-customer links with a known end date, retaining approximately 60,000 observations.[3.15] Of course, not all supplier-customer relationships in our sample end because of climate risk considerations. However, the noise introduced by this measurement error would bias us against finding significant results. For each supplier whose relationship with a customer ends throughout our sample period (i.e. 'old' supplier), we then identify (likely) replace-

[3.15]Note that in contrast to the performance-related tests, in this setting we do not condition on the availability of performance information for customer and supplier firms.

ment suppliers who entered a new supply-chain relationship with the same customer within the next two years, as reported in FactSet Revere. We require replacement candidates to have the same four-digit SIC code as the 'old' supplier, and consider only supply-chain relationships recorded by FactSet analysts for the first time in the two years after the 'old' supply-chain relationship ended. After applying these constraints, we identify 100,000 combinations of terminated and replacement suppliers.

Next, we compare the climate hazard exposure of actual supplier firms during the active years of the initial ('old') supply-chain relationship and their respective, likely, replacements. Figure 3.4 illustrates the construction of the test. First, we compare the number of climate shocks of the actual, replaced supplier to the exposure that a replacement supplier would have had during the time period in which the original relationship was active. Second, we estimate and compare the number of climate shocks that actual and replacement suppliers were exposed to throughout the whole sample period from 1984 to 2017. Third, we compare the time period after which the original supply-chain relationship has ended. In all tests, we keep the observed years between the actual, original, and hypothetical replacement suppliers constant. This requirement is important to ensure that year-specific climate trends do not confound the comparison.

Table 3.8 reports the mean differences and t-statistics of the comparison of the exposure of all replaced suppliers and replacement suppliers. We conduct three tests per climate hazard: first, based on the realized shocks throughout the entire sample period, second, based on the duration of the supply-chain relationship, and third, based on the time thereafter until 2017. Focusing on heatwaves, we find that replacement suppliers are on average less exposed during the original, terminated relationship period, experiencing 0.83 fewer heatwaves on average. In the period after the termination and during the time in which the new relationships are active, this difference further increases to 2.0 fewer heatwaves (all differences are significantly different from zero at the 1% level). The same pattern holds with regards to floods. Whereas potential replacement suppliers are slightly less exposed to floods during the original relationship period (difference of -0.031, significant at the 1% level), the difference becomes more pronounced after the termination of the original link (difference of -0.33, significant at the 1% level).

Hence, our results are consistent with the notion that climate risks can drive the formation of supply-chain relations. If suppliers are negatively impacted by climate shocks and the cost of these shocks are shared in supply chains, managers face a financial incentive to manage the extent to which they are indirectly exposed to climate risk. Moreover, we observe that supplier climate risk exposure beyond expected levels increases the probability that customers switch suppliers. In line with the notion that these switches are climate related, managers appear to identify less sensitive supplier firms as alternatives to the original supply-chain partner.

3.6 Conclusion

In this paper, we combine temporally and spatially granular data on heatwaves and flooding from the European Center for Medium-term Weather Forecasts (ECMWF) and the Darthmouth Flood Observatory with a detailed dataset on global supply chain relationships from FactSet Revere. We obtain a climate-supply-chain database with 4,289 (4,568) suppliers (customers) across 51 countries around the world from 2003 to 2017, and investigate two questions: First, do climate shocks matter financially, and do they propagate along supply chains? And second, if so, how do firms respond to changing climate risk exposure in their supply chain networks?

We present two main insights. First, we test if climate change exposure has direct and indirect firm performance effects due to supply chain networks. We find that the financial performance of suppliers is negatively associated with heatwaves and flooding incidents, and show that the financial consequences of these climate shocks propagate to customers through supply chain links. Second, we study how firms adapt their supply-chain organizations in response to climate change risks. We find that firms are more likely to end relationships with suppliers which experience an unexpectedly high number of climate shocks compared to expectations formed at the beginning of the supply-chain relationship. Moreover, in substituting these suppliers, firms diversify their supplier network and replace high-climate-risk with lower-climate-risk suppliers.

Our results both on climate shock transmission and supply chain adaptation are economically meaningful. For instance, we find that heatwaves and floods are associated with a subsequent reduction of 4% in sales turnover and 10% in profitability at the directly affect firm, relative to the sample median. In terms of the adaptation effects, unexpectedly high numbers of floods and heatwaves increase the probability that customers abandon their suppliers by 4% and 1% compared to the unconditional sample probability of a customer-supplier relationship termination of 15%.

Our finding have two important, potential implications with regard to the impact of climate change on internationally diversified firms, and the impact of the adaptation efforts of these firms on international economic development. First, while developing countries are likely to experience the most pronounced increases in climate shocks, the results on the indirect impact of climate shocks suggest that economic impact of climate change is likely to be – at least partially – shared through economic links in global production networks. Second, if firms in high-climate risk countries are more likely to be substituted by customers in favor of suppliers in less vulnerable locations, the outlined effects could further economically weaken the areas most vulnerable to climate change.

Our study contributes to the rapidly growing academic literature on the financial impact of climate change, and is among the first studies to provide evidence on how firms adapt to climate change.

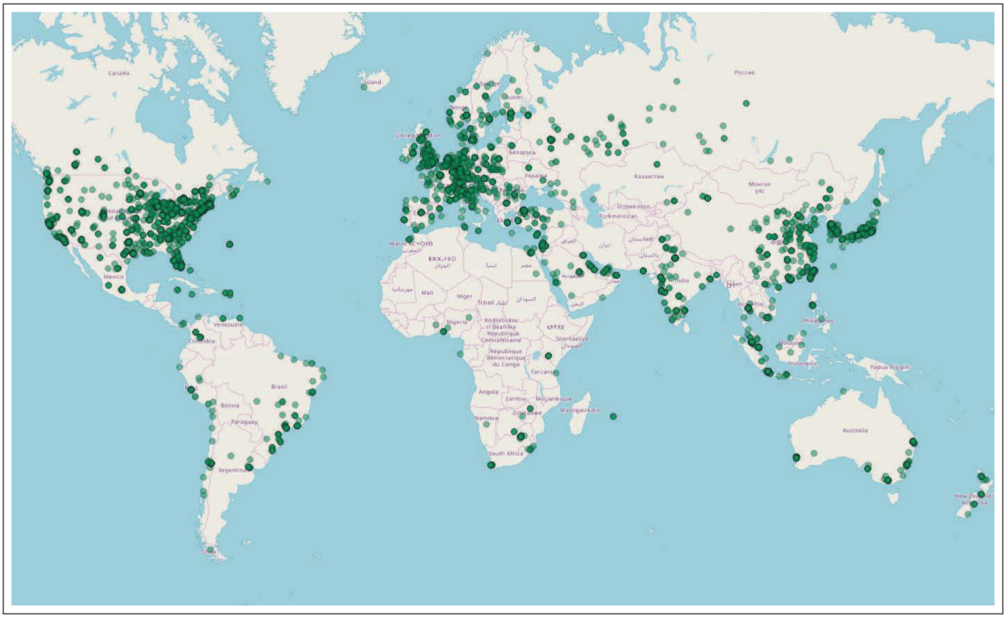

Figure 3.1: Geographic Distribution of Customers

Notes. This figure illustrates the geographic distribution of the customers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 3.1 reports the number of customers by regions of the world.

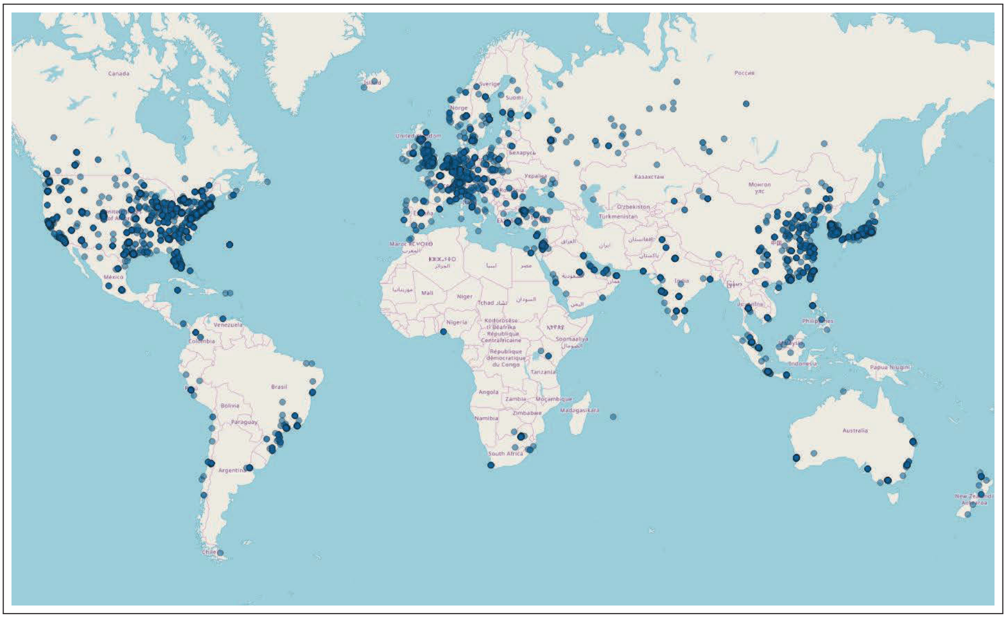

Figure 3.2: Geographic Distribution of Suppliers

Notes. This figure illustrates the geographical distribution of the suppliers in our sample. Supply-chain relationships and firm locations are obtained from FactSet Revere and FactSet Fundamentals, respectively. The corresponding Table 3.1 reports the number of customers by regions of the world.

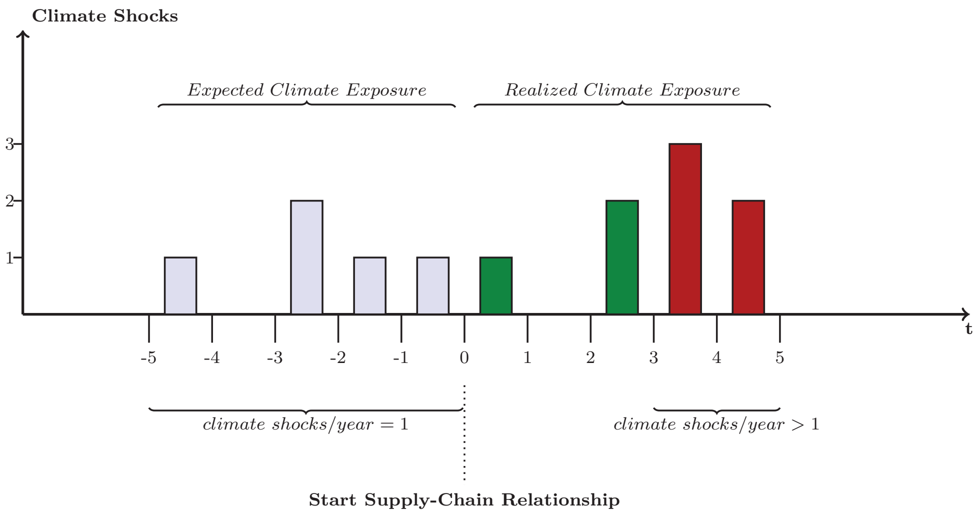

Figure 3.3: Variable Construction: Realized & Expected Climate Shocks

Notes. This figure illustrates the construction of $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\ (t)$, an indicator variable capturing the discrepancy between realized and expected climate risk based on the exposure of a hypothetical supplier to climate shocks over time. It is constructed by first estimating the expected number of climate shocks per year in the supplier location over a benchmark period of five (in robustness tests seven, ten, and fifteen) years *before* the establishment a given supplier-customer relationship. $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\ (t)$ then takes the value of one in year t if the difference between the realized number of climate shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of shocks *(illustrated in red)*, and zero otherwise *(illustrated in green)*.

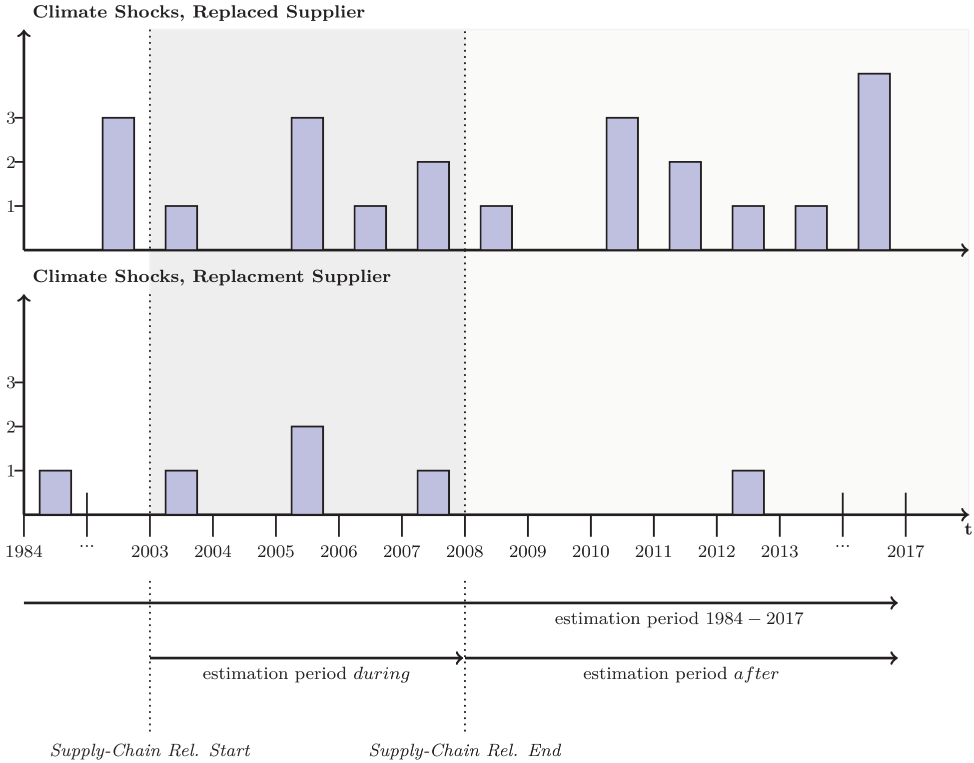

Figure 3.4: Variable Construction: Climate Exposure of the Suppliers

Notes. This figure illustrates the construction of the comparison of the climate exposure of replaced and replacement suppliers, based on an example of a hypothetical replaced supplier and the replacement. We compare the climate exposure of old and new suppliers based on three time periods. First, we compute the exposure to climate shocks for actual and replacement suppliers throughout the whole sample period from 1984 to 2017. Second, we estimate and compare the climate shock exposure of the replaced and replacement supplier based on the years (*illustrated in dark grey*) during which the initial supply-chain relationship was active. Third, we compare the exposure of both suppliers during the years (*illustrated in light grey*) after the initial supplier has been replaced.

Table 3.1: Sample Composition

Notes. This table shows the industry and geographic distribution of customers and suppliers in our sample. We retain supplier and customer firms from the FactSet Revere universe of supply chain relationships if more than 50% of their assets are in their home country and at least one complete record of financial performance data and climate hazard records is available during the period from 2000 to 2017. We drop firms that operate in the financial industry (one-digit SIC code of 6). The number of observations refers to firms.

Customers

SIC Code	No.	%
1	460	10.1
2	863	18.9
3	1,147	25.1
4	721	15.8
5	646	14.1
7	518	11.3
8	195	4.3
9	18	0.4
Total	4,568	100.0

Suppliers

SIC Code	No.	%
1	482	11.2
2	803	18.7
3	1,226	28.6
4	637	14.9
5	313	7.3
7	606	14.1
8	212	4.9
9	10	0.2
Total	4,289	100.0

Customers

Region	No.	%
East Asia & Pacific	1,397	30.6
Europe & Central Asia	838	18.4
Latin America & Caribbean	183	4.0
Middle East & North Africa	135	3.0
North America	1,852	40.6
South Asia	99	2.2
Sub-Saharan Africa	54	1.2
Total	4,558	100.0

Suppliers

Region	No.	%
East Asia & Pacific	1,457	34.0
Europe & Central Asia	775	18.1
Latin America & Caribbean	135	3.2
Middle East & North Africa	96	2.2
North America	1,756	41.0
South Asia	27	0.6
Sub-Saharan Africa	36	0.8
Total	4,282	100.0

Table 3.2a: Summary Statistics – Firm and Relationship Characteristics

Notes. This table presents summary statistics of the financial performance of the customer firms (Panel A) and supplier firms (Panel B) in our sample, as well as the characteristics of the customer-supplier pairs (Panel C). The sample period is 2000 to 2017 and the number of observations refers to firm-quarters (pair year) in Panel A and B (Panel C). The percentage of assets, price-book ratio, and debt-asset ratio are obtained from Factset, and total assets, revenues and operating income over total assets are from Compustat Global and Compustat North America. The sample excludes firms with less than 50% of their assets in their home country, observations with missing records on revenue and/or operating income, missing lagged climate exposure records, as well as records of firms that operate in the financial industry (one-digit SIC code of 6).

Panel A: Customers

Variables	N	Mean	SD	p25	p50	p75
Pct. Assets Home Country	93,076.000	88.825	12,374.838	77.018	95.888	100.000
Price-Book Ratio	77,938.000	4.386	69.987	1.245	1.991	3.318
Debt-Assets Ratio	81,532.000	25.921	58.712	7.998	23.106	37.155
Total Assets mUSD	93,076.000	6,353.646	22,195.190	381.761	1,296.504	4,250.391
Revenue/Assets (Quarter)	93,076.000	23.988	17.143	11.630	19.914	32.019
Op. Income/Assets (Quarter)	93,076.000	2.474	2.941	1.214	2.565	3.959

Panel B: Suppliers

Variables	N	Mean	SD	p25	p50	p75
Pct. Assets Home Country	86,615.000	88.338	17.919	78.192	96.616	100.000
Price-Book Ratio	72,695.000	3.749	20.676	1.258	2.025	3.368
Debt-Assets Ratio	75,939.000	23.447	24.425	4.898	20.115	35.377
Total Assets mUSD	86,615.000	5,096.686	21,595.702	194.664	690.095	2,612.214
Revenue/Assets (Quarter)	86,615.000	21.958	15.482	10.871	18.769	29.542
Op. Income/Assets (Quarter)	86,615.000	1.932	3.653	0.781	2.310	3.758

Panel C: Customer-Supplier Pairs

Variables	N	Mean	SD	p25	p50	p75
Suppl. Sales/Total Suppl. Sales	2,439	17.873	17.363	8.667	13.000	20.400
Suppl. Sales/Cust. Cost Goods Sold	1,848	1.815	5.085	0.058	0.274	1.171
Customer/Supplier Assets	25,954	342.489	1,036.583	4.908	29.036	172.786
Customer/Supplier Sales	25,954	1.336	1.437	0.542	0.902	1.522
Customer/Supplier Op. Income	25,954	1.022	1.584	0.429	0.917	1.566
Distance Customer-Supplier (km)	25,954	4,043.456	3,894.813	699.792	2,593.262	6,904.968
Customer-Supplier Active (Quarters)	25,954	13.828	10.612	8.000	12.000	16.000

Table 3.2b: Summary Statistics – Climate Exposure

Notes. This Table presents summary statistics of the climate exposure measures of the customers (Panel A) and suppliers (Panel B) in our sample. The sample period is 2000 to 2017 and the number of observations refers to firm-quarters. We apply similar data filters as in Table 3.2a. The variables *heatwave days*, *flood days*, and *flood deaths* are constructed conditional on the respective occurrence of a heatwave of flood incident, lowering the respective number of observations. Heatwave occurrence and characteristics are constructed using daily temperature data from the ERA-Interim database of the European Center for Medium-term Weather Forecasts, flood-related variables are obtained from the Darthmouth Flood Observatory, and EM-DAT indicators are from the Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED).

Panel A: Customers

Variables	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Heatwave in Financial Quarter	93,076.000	0.301	0.459	0.000	0.000	1.000
Number Heatwaves in Financial Quarter	93,076.000	0.534	0.918	0.000	0.000	1.000
Heatwave Days	28,041.000	23.881	26.243	7.000	16.000	32.000
Average Temperature	93,076.000	18.843	8.920	11.468	20.379	26.426
Flood in Financial Quarter	93,076.000	0.062	0.241	0.000	0.000	0.000
Number Floods in Financial Quarter	93,076.000	0.082	0.347	0.000	0.000	0.000
Flood Deaths	5,774.000	29.338	147.970	0.000	4.000	18.000
EM-DAT Flood	93,076.000	0.503	0.500	0.000	1.000	1.000
EM-DAT Heatwave	93,076.000	0.054	0.226	0.000	0.000	0.000

Panel B: Suppliers

Variables	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Heatwave in Financial Quarter	86,615.000	0.373	0.484	0.000	0.000	1.000
Number Heatwaves in Financial Quarter	86,615.000	0.676	0.996	0.000	0.000	1.000
Heatwave Days	32,315.000	24.499	25.613	7.000	17.000	33.000
Average Temperature	86,615.000	18.723	8.797	11.370	20.204	26.177
Flood in Financial Quarter	86,615.000	0.063	0.243	0.000	0.000	0.000
Number Floods in Financial Quarter	86,615.000	0.084	0.351	0.000	0.000	0.000
Flood Deaths	5,476.000	33.801	166.491	1.000	5.000	22.000
EM-DAT Flood	86,615.000	0.511	0.500	0.000	1.000	1.000
EM-DAT Heatwave	86,615.000	0.055	0.228	0.000	0.000	0.000

Table 3.3: Climate Shocks and Supplier Firm Performance

Notes. This Table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets. *Heatwave* (t) and *Flood* (t) are dummy variables indicating the occurrence of a climate shock in quarter t, respectively. Panel A shows the results for contemporaneous climate shocks observed during financial quarter t, Panel B includes three additional climate lags. The number of observations refers to supplier firm-quarters, and the sample period is 2000 to 2017. We apply similar data filters as in Table 3.2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwave (t)	0.03166	0.02241	-0.01930	-0.01513				
	(0.1065)	(0.1071)	(0.0360)	(0.0363)				
Flood (t)					-0.18854*	-0.15404	-0.09460***	-0.09774***
					(0.1112)	(0.1111)	(0.0361)	(0.0364)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwave (t)	-0.05987	-0.06485	-0.04328	-0.03768				
	(0.1253)	(0.1252)	(0.0393)	(0.0398)				
Heatwave (t-1)	-0.26467**	-0.26323**	-0.01000	-0.00882				
	(0.1316)	(0.1298)	(0.0428)	(0.0431)				
Heatwave (t-2)	-0.26348**	-0.23965*	-0.13313***	-0.12375***				
	(0.1326)	(0.1311)	(0.0402)	(0.0405)				
Heatwave (t-3)	-0.25308**	-0.23141*	-0.10326***	-0.09929**				
	(0.1201)	(0.1186)	(0.0388)	(0.0391)				
Flood (t)					-0.26743**	-0.22553*	-0.11412***	-0.11614***
					(0.1288)	(0.1286)	(0.0403)	(0.0406)
Flood (t-1)					-0.25238**	-0.21675*	-0.02420	-0.02420
					(0.1237)	(0.1238)	(0.0416)	(0.0419)
Flood (t-2)					-0.29058**	-0.28779**	-0.12465***	-0.11980***
					(0.1266)	(0.1280)	(0.0414)	(0.0413)
Flood (t-3)					-0.07022	-0.04943	0.00359	0.00740
					(0.1188)	(0.1197)	(0.0376)	(0.0374)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 3.4: Downstream Propagation of Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. In Panel A the unit of observation is at the supplier-customer pair-quarter level. In Panel B we collapse the data at the customer level by aggregating across suppliers. The climate shock dummy variables take the value of one if at least one supplier has been affected by a heatwave or a flood, respectively. Hence, the number of observations in Panel B refers to customer firm-quarters. The sample period in both panels is from 2003 to 2017. *Sup Heatwave* (t) and *Sup Flood* (t) are dummy variables indicating the occurrence of a climate shock at the location of the supplier firm. We apply similar data filters as in Table 3.3. All regressions include relationship-by-quarter fixed effects (Panel A) and customer-by-quarter fixed effects (Panel B), respectively, as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 3.3. Standard errors are clustered on the customer-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Supplier-Customer Pair-Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	0.02786	0.02672	-0.01790	-0.01912				
	(0.0470)	(0.0465)	(0.0137)	(0.0132)				
Sup Heatwave (t-1)	-0.01464	-0.01745	-0.00962	-0.00987				
	(0.0221)	(0.0213)	(0.0068)	(0.0066)				
Sup Heatwave (t-2)	-0.03825	-0.04398*	-0.00806	-0.00803				
	(0.0245)	(0.0238)	(0.0074)	(0.0071)				
Sup Heatwave (t-3)	-0.02819	-0.02662	-0.00956	-0.00805				
	(0.0258)	(0.0251)	(0.0072)	(0.0070)				
Sup Flood (t)					-0.08335	-0.06364	-0.01944	-0.01096
					(0.0569)	(0.0544)	(0.0161)	(0.0154)
Sup Flood (t-1)					-0.11191***	-0.09930**	-0.03034**	-0.02220*
					(0.0418)	(0.0411)	(0.0122)	(0.0117)
Sup Flood (t-2)					-0.11857***	-0.12130***	-0.03792***	-0.03555***
					(0.0416)	(0.0406)	(0.0120)	(0.0115)
Sup Flood (t-3)					-0.15530***	-0.14299***	-0.03110***	-0.02366**
					(0.0430)	(0.0418)	(0.0120)	(0.0117)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Customer Firm-Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.04554	-0.02099	-0.03659	-0.02541				
	(0.1113)	(0.1114)	(0.0294)	(0.0290)				
Sup Heatwave (t-1)	-0.12701	-0.10292	-0.05150**	-0.03996				
	(0.0836)	(0.0838)	(0.0258)	(0.0259)				
Sup Heatwave (t-2)	-0.05269	-0.06724	0.00114	0.00398				
	(0.0748)	(0.0747)	(0.0258)	(0.0258)				
Sup Heatwave (t-3)	-0.05443	-0.04173	-0.00864	-0.00528				
	(0.0784)	(0.0785)	(0.0251)	(0.0251)				
Sup Flood (t)					0.02105	0.03538	0.00680	0.02062
					(0.0892)	(0.0889)	(0.0250)	(0.0255)
Sup Flood (t-1)					-0.10328	-0.09463	-0.05304**	-0.04528*
					(0.0818)	(0.0816)	(0.0248)	(0.0247)
Sup Flood (t-2)					-0.15035*	-0.16157**	-0.03007	-0.03828
					(0.0786)	(0.0781)	(0.0243)	(0.0240)
Sup Flood (t-3)					-0.07456	-0.08922	0.00754	0.00636
					(0.0857)	(0.0874)	(0.0258)	(0.0255)
Observations	44,566	44,565	44,566	44,565	44,566	44,565	44,566	44,565
R-squared	0.888	0.891	0.671	0.679	0.888	0.891	0.671	0.679
Firm-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 3.5: Downstream Propagation – Placebo Tests

Notes. This table presents the results of placebo tests on the impact of climate shocks at the supplier location on customer revenues over assets (Rev) and operating income over assets (OpI). We construct the placebo sample by restricting the observations to *real* customer-supplier pairs during periods in which the relationship was *not yet* or *no longer* active. We apply similar data filters as in Table 3.4. *Heatwave* (t) and *Flood* (t) are dummies indicating the occurrence of a climate shock in period t. In Panel A, the number of observations refers to supplier-customer pair-quarters. In Panel B, we collapse the data in a similar way as in Panel B of Table 3.4. The sample period in both panels is from 2003 to 2017. All regressions include relationship-by-quarter fixed effects (Panel A) and customer-by-quarter fixed effects (Panel B), respectively, as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 3.4. Standard errors are clustered on the customer-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Supplier-Customer Pair Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.02492	-0.02748	-0.01388	-0.00968				
	(0.0395)	(0.0383)	(0.0105)	(0.0099)				
Sup Heatwave (t-1)	0.02350	0.01697	0.00199	0.00006				
	(0.0200)	(0.0196)	(0.0055)	(0.0054)				
Sup Heatwave (t-2)	0.03437*	0.02456	0.00914*	0.00623				
	(0.0189)	(0.0185)	(0.0054)	(0.0053)				
Sup Heatwave (t-3)	0.01116	0.00337	0.00062	-0.00202				
	(0.0204)	(0.0199)	(0.0053)	(0.0052)				
Sup Flood (t)					0.07029*	0.05970	0.01540	0.01676
					(0.0383)	(0.0375)	(0.0111)	(0.0105)
Sup Flood (t-1)					-0.00240	-0.01806	0.01524*	0.01616*
					(0.0315)	(0.0306)	(0.0087)	(0.0083)
Sup Flood (t-2)					0.01146	0.01105	0.01409*	0.01733**
					(0.0317)	(0.0307)	(0.0085)	(0.0081)
Sup Flood (t-3)					0.01051	0.00328	0.00825	0.00849
					(0.0311)	(0.0304)	(0.0084)	(0.0082)
Observations	542,962	542,961	542,962	542,961	542,962	542,961	542,962	542,961
R-squared	0.887	0.891	0.685	0.703	0.887	0.891	0.685	0.703
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Customer Firm Level

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwave (t)	-0.11981	-0.11738	-0.02767	-0.02955				
	(0.0882)	(0.0878)	(0.0267)	(0.0265)				
Sup Heatwave (t-1)	0.15363**	0.16255**	0.00044	-0.00175				
	(0.0743)	(0.0745)	(0.0234)	(0.0234)				
Sup Heatwave (t-2)	0.01662	0.03214	0.01570	0.01661				
	(0.0727)	(0.0729)	(0.0226)	(0.0229)				
Sup Heatwave (t-3)	-0.02077	-0.00569	0.04261**	0.04308**				
	(0.0739)	(0.0741)	(0.0216)	(0.0215)				
Sup Flood (t)				0.10892	0.08744	0.01090	0.00010	
					(0.0740)	(0.0747)	(0.0217)	(0.0217)
Sup Flood (t-1)					0.13973*	0.12288	0.06497***	0.06359***
					(0.0784)	(0.0782)	(0.0203)	(0.0202)
Sup Flood (t-2)					0.00940	0.00138	0.03121	0.02713
					(0.0733)	(0.0731)	(0.0219)	(0.0219)
Sup Flood (t-3)					0.08090	0.07144	0.02089	0.01358
					(0.0718)	(0.0718)	(0.0211)	(0.0212)
Observations	77,342	77,339	77,342	77,339	77,342	77,339	77,342	77,339
R-squared	0.839	0.842	0.587	0.596	0.839	0.842	0.587	0.596
Firm-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 3.6: Expected vs. Realized Climate Risk and Relationship Termination

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination. Panel A reports the results for heatwaves, Panel B reports the results for flooding incidents. The unit of observation in all regressions is at the supplier-customer pair-year level, the dependent variable is a dummy variable taking the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. The regressions include only pair-years in which the relationship was active. Our main variable of interest is the indicator variable $\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\,(t)$, capturing the deviation of realized from expected supplier climate. It is constructed by first estimating the expected number of climate shocks per year in the supplier location over a benchmark period of five years *before* the establishment a given supplier-customer relationship. $\mathbb{1}\,(Realized > Expected\ Climate\ Shocks)\,(t)$ then takes the value of one in year t if the difference between the realized number of climate shocks per year since the beginning of the supplier-customer relationship exceeds the corresponding expected number of shocks, and zero otherwise. We exclude customers headquartered within a 500 kilometer radius of the supplier and apply similar data filters as in Table 3.4. The regressions include relationship fixed effects, year fixed effects, supplier-industry-by-year, supplier-country-by-year, and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Heatwaves

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(Realized > Expected\ Heatwaves)\,(t)$	0.02320***	0.02309***	0.01422***	0.01045***
	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Panel B: Flooding Incidents

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
$\mathbb{1}\,(Realized > Expected\ Floods)\,(t)$	0.04707***	0.04770***	0.03982***	0.03681***
	(0.0021)	(0.0022)	(0.0022)	(0.0022)
Observations	299,718	298,053	297,998	294,330
R-squared	0.354	0.379	0.413	0.416
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Table 3.7: Robustness – Realized Climate Risk and Relationship Termination

Notes. This table presents linear probability model estimates on the of realized supplier-firm climate shocks on the likelihood of supply-chain relationship termination. Panel A reports the results for heatwaves, Panel B reports the results for flooding incidents. *Heatwave* (t) and *Flood* (t) are dummy variables indicating the occurrence of a climate shock in the location of the supplier firm in year t, respectively. The unit of observation is at the supplier-customer-year level. We include only active supply-chain relationship years. The dependent variable takes the value of one if a given supplier-customer relationship ends after the current year t, and zero otherwise. Similar to Table 3.6, we exclude all customers located within 500 kilometers of their supplier and apply similar data filters as in Table 3.6. The regressions include relationship fixed effects, year fixed effects, supplier-industry-by-year, supplier-country-by-year, and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Heatwaves

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
Heatwave (t)	0.00118	0.00104	0.00171**	0.00160**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Panel B: Flood Incidents

	Dependent Variable: Last Relationship Year (0/1)			
	(1)	(2)	(3)	(4)
Flood (t)	0.00285***	0.00331***	0.00106	0.00010
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Observations	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415
Relationship FE	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	No	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes

Table 3.8: Climate Change Risk and Supplier Substitution

Notes. This table reports the difference in climate change exposure between terminated suppliers and their subsequent replacements. To construct the sample for this table, we match each supplier firm for which the supplier-customer relationship is terminated during the sample period ("old suppliers") (as reported in Table 3.6) with their replacements ("new suppliers"). Replacement suppliers are identified as those firms with identical 4-digit SIC codes as the "old suppliers", which enter a new supply-chain relationship with a given customer within two years of the previous supply-chain relationship termination. Panel A shows the comparison for heatwave exposure, Panel B shows the results for flood exposure. The first line in each panel compares the number of climate shocks over the period from 1984 to 2017, the second line compares the exposure during the period in which the "old" supply-chain relationship was active, and the third line refers to the time period after the "old" relationship is abandoned. *t*-statistics are reported in brackets. *, ** and *** indicate statistical significance at the 5%, 1% and 0.1% level, respectively.

Panel A: Heatwaves

	(1) New vs. Old	
Heatwaves 1984-2017	-5.239***	[-17.569]
Heatwaves during Terminated Supply Chain Relationship	-0.829***	[-17.993]
Heatwaves after Termination of the Original Supply Chain Relationship	-2.065***	[-22.606]
Observations	100,172	

Panel B: Flood Incidents

	(1) New vs. Old	
Floods 1984-2017	-0.000	[-0.008]
Floods During Terminated Supply Chain Relationship	-0.031***	[-4.182]
Floods After Termination of the Original Supply Chain Relationship	-0.333***	[-23.340]
Observations	100,172	

Table B.1: Robustness – Climate Shocks and Supplier Firm Performance

Notes. This table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets. *Heatwaves* (t) and *Floods* (t) are continuous variables measuring the total number (count) of climate shocks in the supplier's location in quarter t. Panel A shows the results for contemporaneous climate shocks observed during financial quarter t, Panel B includes three additional climate lags. The number of observations refers to supplier firm-quarters, and the sample period is 2000 to 2017. We apply similar data filters as in Table 3.2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heatwaves	-0.00036	0.00942	0.00884	0.00969				
	(0.0621)	(0.0624)	(0.0190)	(0.0192)				
Heatwaves (t-1)	-0.09555	-0.09363	-0.00385	-0.00613				
	(0.0696)	(0.0686)	(0.0209)	(0.0211)				
Heatwaves (t-2)	-0.14765**	-0.14069**	-0.06833***	-0.06902***				
	(0.0715)	(0.0709)	(0.0207)	(0.0208)				
Heatwaves (t-3)	-0.20294***	-0.18615***	-0.05274**	-0.05239**				
	(0.0660)	(0.0659)	(0.0206)	(0.0207)				
Floods					-0.22041**	-0.19408**	-0.09581***	-0.09614***
					(0.0885)	(0.0887)	(0.0283)	(0.0287)
Floods (t-1)					-0.17513*	-0.15295*	-0.02764	-0.02481
					(0.0924)	(0.0922)	(0.0286)	(0.0288)
Floods (t-2)					-0.18122**	-0.18212**	-0.07107**	-0.06623**
					(0.0912)	(0.0923)	(0.0297)	(0.0296)
Floods (t-3)					-0.06639	-0.05708	-0.01064	-0.00673
					(0.0853)	(0.0860)	(0.0272)	(0.0271)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table B.2: Robustness – EM-DAT Climate Shocks and Supplier Performance

Notes. This table presents OLS regression estimates on the impact of climate shocks in the location of the sample supplier firms on supplier firm revenues (Rev) and operating income (OpI), both scaled by assets. $EM - DAT\ Heatwave\ (t)$ and $EM - DAT\ Flood(t)$ are dummy variables indicating the occurrence of a climate shock in the supplier's location in quarter t based on the EM-DAT international disaster database. The number of observations refers to supplier firm-quarters, and the sample period is 2003 to 2017. We apply similar data filters as in Table 3.2a. All regressions include firm-by-quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, and industry-by-year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered on the firm level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Sup Rev (t)		Sup OpI (t)		Sup Rev (t)		Sup OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EM-DAT Heatwave (t)	-0.05013	-0.22382	0.04729	0.02408				
	(0.1862)	(0.1977)	(0.0556)	(0.0669)				
EM-DAT Heatwave (t-1)	-0.34675**	-0.38940**	-0.12494***	-0.15618***				
	(0.1511)	(0.1602)	(0.0483)	(0.0560)				
EM-DAT Heatwave (t-2)	0.07203	-0.01361	0.07404	0.07325				
	(0.1546)	(0.1579)	(0.0559)	(0.0603)				
EM-DAT Heatwave (t-3)	0.16453	0.02850	0.07788	0.06295				
	(0.1547)	(0.1603)	(0.0569)	(0.0601)				
EM-DAT Flood (t)					-0.03392	-0.00332	0.00581	0.00484
					(0.0755)	(0.0797)	(0.0268)	(0.0285)
EM-DAT Flood (t-1)					-0.04415	0.02797	0.06244**	0.06291*
					(0.0822)	(0.0836)	(0.0303)	(0.0323)
EM-DAT Flood (t-2)					-0.03657	0.01128	0.04908	0.05400*
					(0.0759)	(0.0787)	(0.0300)	(0.0319)
EM-DAT Flood (t-3)					-0.07892	-0.02729	0.02255	0.02113
					(0.0703)	(0.0725)	(0.0264)	(0.0286)
Observations	86,615	86,615	86,615	86,615	86,615	86,615	86,615	86,615
R-squared	0.887	0.889	0.740	0.741	0.887	0.889	0.740	0.741
Firm-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Yr-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table B.3: Robustness – Downstream Propagation of Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. The unit of observation is at the supplier-customer pair-quarter level and the sample period is from 2003 to 2017. *Sup Heatwaves* (t) and *Sup Floods* (t) are continuous variables measuring the total number (count) of climate shocks in the supplier's location in quarter t. We apply similar data filters as in Table 3.4. All regressions include relationship-by-quarter fixed effects as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 3.4. Standard errors are clustered on the customer-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sup Heatwaves (t)	0.02938	0.03503	-0.01539**	-0.01081				
	(0.0257)	(0.0250)	(0.0072)	(0.0069)				
Sup Heatwaves (t-1)	0.00610	0.00773	-0.00487	-0.00314				
	(0.0120)	(0.0117)	(0.0033)	(0.0031)				
Sup Heatwaves (t-2)	0.00525	0.00278	-0.00061	-0.00052				
	(0.0123)	(0.0119)	(0.0035)	(0.0034)				
Sup Heatwaves (t-3)	0.00787	0.01075	-0.00344	-0.00183				
	(0.0129)	(0.0126)	(0.0033)	(0.0032)				
Sup Floods (t)					-0.11948***	-0.10698**	-0.03053**	-0.02331**
					(0.0451)	(0.0424)	(0.0123)	(0.0115)
Sup Floods (t-1)					-0.13504***	-0.13094***	-0.03392***	-0.02911***
					(0.0323)	(0.0315)	(0.0094)	(0.0088)
Sup Floods (t-2)					-0.15698***	-0.15939***	-0.03760***	-0.03565***
					(0.0318)	(0.0307)	(0.0083)	(0.0079)
Sup Floods (t-3)					-0.15580***	-0.14692***	-0.02846***	-0.02304***
					(0.0321)	(0.0315)	(0.0083)	(0.0080)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table B.4: Robustness – Downstream Propagation of EM-DAT Climate Shocks

Notes. This table presents OLS regression estimates on the impact of climate shocks at the supplier location on revenues over assets (Rev) and operating income over assets (OpI) of their respective customers. The unit of observation is at the supplier-customer pair-quarter level and the sample period is from 2003 to 2017. $EM-DAT\ Heatwave\ (t)$ and $EM-DAT\ Flood\ (t)$ are dummy variables indicating the occurrence of a climate shock in the supplier's location in quarter t based on the EM-DAT international disaster database. We apply similar data filters as in Table 3.4. All regressions include relationship-by-quarter fixed effects as well as year-by-quarter fixed effects. Columns (2), (4), (6), and (8) additionally include terciles of size, age, and ROA interacted with year-by-quarter fixed effects (BS2016 FE) as in Table 3.4. Standard errors are clustered on the customer-supplier relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable:							
	Cus Rev (t)		Cus OpI (t)		Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EM-DAT Heatwave (t)	-0.07784	-0.09911	0.04383*	0.04897**				
	(0.0831)	(0.0820)	(0.0264)	(0.0245)				
EM-DAT Heatwave (t-1)	0.08667*	0.06417	0.00409	0.00762				
	(0.0497)	(0.0486)	(0.0155)	(0.0149)				
EM-DAT Heatwave (t-2)	-0.11003**	-0.10010**	-0.01911	-0.01421				
	(0.0502)	(0.0499)	(0.0153)	(0.0148)				
EM-DAT Heatwave (t-3)	-0.04647	-0.04014	0.01404	0.01114				
	(0.0521)	(0.0516)	(0.0168)	(0.0163)				
EM-DAT Flood (t)					0.06421	0.04346	0.02854**	0.02195**
					(0.0408)	(0.0406)	(0.0117)	(0.0112)
EM-DAT Flood (t-1)					0.02745	0.01803	-0.00236	-0.00463
					(0.0225)	(0.0222)	(0.0070)	(0.0068)
EM-DAT Flood (t-2)					0.01866	0.01528	0.01159*	0.01082
					(0.0235)	(0.0228)	(0.0068)	(0.0066)
EM-DAT Flood (t-3)					0.04297*	0.05178**	-0.00326	-0.00228
					(0.0227)	(0.0229)	(0.0067)	(0.0063)
Observations	214,302	214,302	214,302	214,302	214,302	214,302	214,302	214,302
R-squared	0.948	0.951	0.807	0.820	0.948	0.951	0.807	0.820
Relationship-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes	No	Yes	No	Yes

Table B.5: Robustness – Expected vs. Realized Climate Risk

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination. The sample and variables are constructed similarly as in Table 3.6. In Panels A, B, and C we use benchmark periods of seven, ten, and fifteen years before the establishment of a supply-chain relationship to construct our main variables of interest, $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$, as illustrated in Figure 3.3. We apply similar data filters as in Table 3.6. The regressions include relationship fixed effects, year fixed effects, supplier-industry-by-year, supplier-country-by-year, and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: 7-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01340***	0.01259***	0.00744***	0.00564***				
	(0.0021)	(0.0021)	(0.0022)	(0.0022)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.07069***	0.07149***	0.06483***	0.06027***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.356	0.381	0.415	0.417
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel B: 10-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01452***	0.01203***	0.00671***	0.00662***				
	(0.0021)	(0.0021)	(0.0021)	(0.0021)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.07492***	0.07381***	0.07195***	0.06895***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.356	0.381	0.415	0.417
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel C: 15-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01984***	0.01691***	0.01286***	0.01414***				
	(0.0021)	(0.0021)	(0.0022)	(0.0022)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.06034***	0.05982***	0.05815***	0.05595***
					(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	299,718	298,053	297,998	294,330	299,718	298,053	297,998	294,330
R-squared	0.353	0.378	0.413	0.415	0.355	0.380	0.414	0.416
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sup-Industry-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Yr FE	No	Yes	Yes	No	No	Yes	Yes	No
Sup-Country-by-Cus-Country-by-Yr FE	No	No	No	Yes	No	No	No	Yes

Table B.6: Robustness – Expected vs. Realized Climate Risk with Control Variables

Notes. This table presents linear probability model estimates on the impact of realized vs. expected supplier-firm climate shocks on the likelihood of supply-chain relationship termination, controlling for supplier and customer firm characteristics. The sample and variables are constructed similarly as in Table 3.6. In Panels A, B, and C we use benchmark periods of seven, ten, and fifteen years before the establishment of a supply-chain relationship to construct our main variables of interest, $\mathbb{1}\,(\textit{Realized} > \textit{Expected Climate Shocks})\,(t)$, as illustrated in Figure 3.3. We apply similar data filters as in Table 3.6. The regressions include relationship fixed effects, year fixed effects, supplier-industry-by-year, supplier-country-by-year, and supplier-country-by-customer-country-by-year fixed effects as indicated. Robust standard errors are clustered on the relationship level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: 7-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01306***	0.01154***	0.00614*	0.00612*				
	(0.0032)	(0.0033)	(0.0034)	(0.0034)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.06411***	0.06738***	0.06050***	0.05226***
					(0.0035)	(0.0035)	(0.0036)	(0.0036)
Debt-Assets Ratio Supplier	-0.00035**	-0.00056***	-0.00004	0.00017	-0.00035**	-0.00055***	-0.00005	0.00016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt-Assets Ratio Customer	0.00014	0.00004	0.00001	0.00037*	0.00012	0.00002	-0.00001	0.00035*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Price-Book Ratio Customer	-0.02256***	-0.01471***	-0.01023***	-0.01515***	-0.02205***	-0.01425***	-0.00990***	-0.01517***
	(0.0034)	(0.0034)	(0.0033)	(0.0035)	(0.0034)	(0.0034)	(0.0033)	(0.0035)
Price-Book Ratio Supplier	-0.00089	0.00790**	0.00863***	0.00066	-0.00089	0.00783**	0.00882***	0.00080
	(0.0032)	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0032)
Ln(MV Equity) Supplier	-0.02108***	-0.02462***	-0.01757***	-0.01110***	-0.02106***	-0.02457***	-0.01739***	-0.01097***
	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
Ln(MV Equity) Customer	-0.00093	-0.00032	0.00018	-0.00039	-0.00106	-0.00043	0.00008	-0.00051
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Observations	137,239	137,171	137,099	133,519	137,239	137,171	137,099	133,519
R-squared	0.373	0.400	0.435	0.439	0.375	0.403	0.436	0.440
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SupIndustry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-CusCountry-Yr FE	No	No	No	Yes	No	No	No	Yes

Panel B: 10-year benchmark period

	Dependent Variable: Last Relationship Year (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Heatwaves})\,(t)$	0.01727***	0.01362***	0.00728**	0.00907***				
	(0.0032)	(0.0032)	(0.0033)	(0.0033)				
$\mathbb{1}\,(\textit{Realized} > \textit{Expected Floods})\,(t)$					0.06559***	0.06581***	0.06344***	0.05770***
					(0.0035)	(0.0035)	(0.0037)	(0.0037)
Debt-Assets Ratio Supplier	-0.00034**	-0.00055***	-0.00004	0.00017	-0.00035**	-0.00056***	-0.00005	0.00016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Debt-Assets Ratio Customer	0.00014	0.00005	0.00001	0.00037*	0.00011	0.00001	-0.00001	0.00034*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Price-Book Ratio Customer	-0.02254***	-0.01470***	-0.01022***	-0.01514***	-0.02211***	-0.01438***	-0.01001***	-0.01527***
	(0.0034)	(0.0034)	(0.0033)	(0.0035)	(0.0034)	(0.0034)	(0.0033)	(0.0035)
Price-Book Ratio Supplier	-0.00078	0.00796**	0.00866***	0.00069	-0.00082	0.00800**	0.00896***	0.00095
	(0.0032)	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0032)
Ln(MV Equity) Supplier	-0.02105***	-0.02456***	-0.01754***	-0.01112***	-0.02068***	-0.02420***	-0.01710***	-0.01070***
	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
Ln(MV Equity) Customer	-0.00093	-0.00032	0.00018	-0.00038	-0.00114	-0.00051	-0.00000	-0.00059
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Observations	137,239	137,171	137,099	133,519	137,239	137,171	137,099	133,519
R-squared	0.373	0.400	0.435	0.439	0.375	0.402	0.436	0.440
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SupIndustry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-Yr FE	No	No	Yes	No	No	No	Yes	No
SupCountry-CusCountry-Yr FE	No	No	No	Yes	No	No	No	Yes

4

Insider Ownership, Governance Mechanisms, and Global Corporate Bond Pricing

4.1 Introduction

A great deal of attention in the literature has been devoted to the diversity of ownership and corporate governance structures around the world and their consequences for the valuation of corporations. Many of these studies have investigated corporate ownership from a shareholder perspective. An important question to ask is whether ownership structures also play a role in the valuation of corporations' outstanding debt. This question is particularly relevant now that the bond market has become an even more prominent source of capital supply for companies in both developed and emerging markets. According to Tendulkar and Hancock (2014), the global corporate bond market has almost tripled since the early 2000s, and corporate bond financing – especially for the medium and long term - increased relative to other forms of financing.

This chapter is based on a working paper co-authored with Rob Bauer and Jeroen Derwall (Maastricht University).

In this study, we focus on bond pricing effects associated with owners that have not received much attention in the international corporate bond literature to date despite their prominent presence in ownership structures around the world: corporate insiders. We define insider ownership as the percentage of shares that directors, managers, and other individuals involved in the management of a firm hold directly, through private companies or obtained by exercising employee stock options. We exploit a rich, pooled cross section of 10,470 bonds from 48 countries over the period from 2003 to 2014, issued by over 1,200 firms that vary in terms of insider ownership.

On the theoretical front, a prevailing view is that with greater levels of ownership, insiders' interests become more closely aligned with those of outside shareholders because insiders' pay-offs are more directly linked to stock market performance (Jensen and Meckling, 1976). This reasoning implies that insiders who are directly involved in management or able to exert managerial influence in other ways engage in less self-serving behavior when they have larger personal stakes at risk. Bondholders may rationally anticipate that they also benefit from this *incentive-alignment* effect, which suggests there is a negative relation between insider ownership and corporate bond spreads.

However, on the empirical front, we provide evidence to the contrary. Our first main finding is that around the world yield spreads of corporate bonds increase significantly with higher levels of insider ownership, which is inconsistent with the incentive-alignment view. This positive relation is statistically significant across many regional sub-samples, and economically relevant: a one percentage-point increase in insider ownership is associated with an average 1.4 basis points increase in the yield spread, controlling for a host of fixed effects as well as firm- and issue-level variables.

The question why greater insider control exacerbates debt agency costs is the subsequent focus of this study. The first common explanation, which we dub the *risk-taking* view, is that increased insider ownership might cause managers to undertake more risky investments that benefit shareholders but reduce value for bondholders (Shleifer and Vishny, 1997; Ortiz-Molina, 2006). Although the risk preferences of insiders and outside shareholder are better aligned in firms with more insider ownership, bondholders may suffer from the higher levels of risk taking favoured by equity holders. The corporate bond market may consequently rationally anticipate riskier corporate decisions to emerge with greater insider ownership; (see, e.g., Ortiz-Molina (2006) for a discussion of managerial decisions reflective of future risk taking). However, we find that greater insider control continues to be associated with higher spread levels even after controlling for proxies of risk such as volatility and financial leverage. The risk-taking view also predicts that insiders become more risk-averse at high levels of ownership (e.g., Wright, Ferris, Sarin, and Awasthi, 1996; Ortiz-Molina, 2006), whereas in our sample spreads are higher even when insider ownership is over 20 percent. These results suggest that insider control matters for bond pricing, and for reasons beyond those implied by the risk-taking view.

In this paper, we therefore examine whether consumption of private benefits is an additional economic channel of concern to bondholders that underlies the relation between insider ownership and spreads of corporate bonds around the world, which we refer to hereafter as the *private-benefits* view. Specifically, insiders may enjoy greater control over the firm with an increase in ownership that could facilitate their consumption of private benefits (e.g., Fama, 1980; Fama and Jensen, 1983; Morck, Shleifer, and Vishny, 1988). Because the consumption of private benefits might diminish the value of corporate assets, we could expect that both bondholders and shareholders price-protect against insider ownership.

Given these alternative explanations, it is important for our empirical analysis that we distinguish between risk-taking incentives and consumption of private benefits stemming from insider ownership. To achieve this goal, we first introduce an interaction effect between insider ownership and firm-level shareholder-rights provisions as measured by a global shareholder-rights index we construct in a manner similar to Bebchuk, Cohen, and Ferrell (2008). Governance provisions affecting shareholder rights are useful here because of their dual impact on conflicts of interest between managers, shareholders, and debt capital suppliers: they affect shareholders' ability to not only (i) prevent and discipline self-serving managerial behaviour that would harm shareholder value as well as bondholder wealth, but also (ii) encourage management in taking risks that benefits shareholders at the expense of bondholders (Klock, Mansi, and Maxwell, 2005; Ashbaugh-Skaife, Collins, and LaFond, 2006). Hence, to the extent that insiders abuse corporate resources for personal benefit, bondholders and non-insider shareholders have a common interest in stronger shareholder rights. We therefore hypothesize under the private-benefits view that the positive effect of insider ownership on the spread is mitigated by shareholder-rights provisions. In contrast, under the risk-taking view, greater insider ownership fuels managerial risk taking that benefits shareholders but which raises the risk of default. Because shareholder rights on their own have been suggested to encourage managerial risk taking at the expense of bondholders (Klock et al., 2005; Ashbaugh-Skaife et al., 2006; Cremers, Nair, and Wei, 2007), we expect under the risk-taking view that more shareholder rights either amplify or at least do not mitigate the positive relation between insider ownership and the spread. The results indicate that the positive effect of insider ownership on yield spreads is weaker in firms with stronger shareholder rights, which we consider consistent with the private-benefits view.

We delve deeper into the private-benefits view by studying the specific channel through which insiders could use their ownership to expropriate outsiders: tunnelling. Tunnelling is defined as the "transfer of assets and profits out of firms for the benefit of their controlling shareholders" (Johnson, LaPorta, Lopez-di Silanes, and Shleifer, 2000). Whereas some forms of tunnelling, especially illegal ones such as theft and fraud, are hard to observe, other forms require disclosure. We focus on related-party transactions (RPTs). Disclosure rules on RPTs are nowadays widespread, but regulation is generally too weak to prevent transactions that could be harmful to outside shareholders and creditors (Atanasov, Black, and Ciccotello, 2011). We find that greater insider ownership is associated with a greater probability of RPTs, and that RPTs are also positively related to spreads.

We undertake various tests to address potential endogeneity, reverse causality and robustness issues. We account for the alternative interpretations that insiders take large stakes in the company when or before it experiences higher debt capital costs, either because of informed trading or in order to strengthen the financial firms' financial condition. Additionally, it is possible that firms with greater insider ownership exhibit deviations from the one-share-one-vote principle, given that the incentive to consume private benefits to the detriment of capital suppliers may arise when insiders have stronger voting rights relative to cash flow rights. Interestingly, the positive association between insider ownership and the spread remains after we drop firms from the sample that deviate from a one-share-one-vote principle and firms with cross-ownership, suggesting that a control-ownership wedge cannot fully account for this relation. Finally, the results are qualitatively similar when we change the unit of observation from bond-level spreads to firm-level spreads.

This study makes several contributions. First of all, we disentangle the nature of debt agency costs arising from insider ownership by distinguishing risk-taking from private-consumption channels. Ortiz-Molina (2006) hypothesizes that bondholders anticipate future risk-taking and risk-shifting incentives arising from managerial ownership. He reports that at-issue spreads on U.S corporate bonds were higher with greater top-management ownership and/or stock options, but less so at high ownership levels. Our global evidence on bond yields and related-party transactions suggests that, next to potential managerial risk-taking incentives, higher insider ownership heightens the risk that bondholder wealth is affected by consumption of private benefits.

Second, our study adds a new perspective on the relevance of shareholder rights mechanisms for the bond market. Literature has suggested that the bond market deems shareholder rights mechanisms harmful to bondholder wealth due to conflicts of interests between shareholders and bondholders (e.g., Klock et al., 2005; Ashbaugh-Skaife et al., 2006). We provide evidence that bondholders' consideration of shareholder rights is less straightforward: although shareholder rights mechanisms on their own could theoretically encourage management to take risks that benefits shareholders at the expense of bondholders, our results imply that bondholders deem shareholder rights mechanisms instrumental in reducing their risk of expropriation by powerful insiders. This moderating role of shareholder rights in the relation between insider ownership and bond spreads extends Cremers et al. (2007), who report that shareholder rights moderate the relation between concentrated institutional ownership and bond prices.

Furthermore, by linking insider ownership to spreads and related-party transactions (RPTs), this study not only contributes to the corporate bond literature but also extends studies that examine the effects of tunnelling on firm value. Although RPTs are not 'an evil by definition' (Pacces, 2011) and seldom prohibited, their potential abuse is an internationally widespread concern of policymakers. Empirical evidence suggests that the impact of RPTs on firm profitability and stock returns in specific Asian countries is negative, but bondholder' response to RPTs has not yet been documented. Anecdotal evidence from practice suggests that related party transactions matter for a company's creditworthiness. For example, in its assessment of an equipment-manufacturing company, a leading credit-rating agency commented that ''...ownership concentration may also result in a deterioration of its corporate governance standards, including an increase in risks related to excessive shareholder distributions, related-party transactions and prudent financial policy'' (Moody's Investor Service, 2013). This study documents beyond such anecdotes that RPTs reduce firm value through their association with higher bond yield spreads.

Finally, despite the rapid growth of the market for traded debt outside the U.S., the vast majority of studies on the role of ownership and corporate governance in bond valuation to date have revolved around U.S. corporate bonds whereas much less is known about their influence on corporate bond dynamics around the world.

Next to literature on managerial ownership, Anderson et al. (2003) find that family ownership is negatively associated with the cost of debt of U.S. firms. Bhojraj and Sengupta (2003) document a negative relation between institutional ownership (as well as stronger control by outside directors) and at issue-spreads of U.S. bonds, but higher spreads in the presence of concentrated institutional ownership. Huang and Petkevich (2016) suggest that institutional ownership negatively relates to the yield spread provided that institutions are long-term oriented. Among the scarce body of evidence on bonds issued outside the U.S., Ellul et al. (2009) report that family ownership exhibits a positive (negative) relation to the issue yield when county-level investor protection is relatively weak (strong). Borisova et al. (2015) report that government ownership causes higher spreads, but a lower spread in times of crisis or greater likelihood of financial distress. We investigate the cross section of traded corporate bond yields for firms based on a considerably larger bond universe matched with data on insider ownership and firm-level governance mechanisms.

4.2 Data Description

4.2.1 Main Dependent and Independent Variables

Our unique global dataset on corporate bonds leans on a number of different data providers. Our initial universe of companies is defined by GMI Ratings, which provides corporate governance ratings and indicators for listed firms worldwide over the period from 2003 to 2014, including indicators about shareholder rights provisions and related-party transactions. For each firm in the GMI universe, we use Factset Research ("Factset") to obtain all identifiers on debt securities outstanding in a given year[4.1]. The resulting bond-ISIN identifiers serve as inputs to Datastream and Factset for the collection of issue-level bond data. We drop index-inked, inflation-linked, floating and convertible bonds. In line with prior research, we exclude firms from the financial industry (Anderson, Mansi, and Reeb, 2004; Klock et al., 2005; Cremers et al., 2007). Our main dependent variable is the yield spread on corporate bonds at the end of each calendar year provided by Datastream. The spread is defined as the difference between the bond's yield to maturity and that of a risk-free benchmark with matching currency and the closest maturity possible. Since the yield spreads are skewed by outliers, we trim the variable at the top and bottom 1%.

[4.1] Using Datastream, bonds would have to be matched manually to issuing firms in order to achieve a panel dataset. However, Datastream appears to have the largest coverage of yield spread data. For this reason, in our study, Factset serves as an intermediate step in matching issue-specific data with firm-specific data.

To determine how insider ownership relates to the yield spread, we obtain annual data on insider ownership for each bond issuer from Factset Ownership (also known as Factset/LionShares).[4.2] Factset contains international ownership information for equities with detailed insight into owner classifications. For instance, different types of insiders can be distinguished and the percentage of their ownership can be accessed separately. We define insider ownership as the percentage of shares that directors, managers, and other individuals involved in the management of a firm hold directly, through private companies or obtained by exercising employee stock options.

We introduce an annual shareholder-rights index for each firm in our dataset in order to investigate whether bondholders value insider ownership conditional on governance mechanisms that strengthen shareholder control. We construct the shareholder-rights index based on annual data on shareholder-rights limitations from Governance Metrics International (GMI). GMI (now part of MSCI) assesses small, mid and large cap companies' corporate governance based on macro data from academic, government and NGO datasets, company disclosures, and media reports (MSCI, 2016). The index we construct using a selection of GMI data is similar to the Entrenchment Index (E-Index) of Bebchuk et al. (2008) but is converted to a shareholder-rights measure in the spirit of Cremers et al. (2007).

An important issue in our research design is whether firms with different levels of insider ownership have fundamentally different characteristics that may also affect spreads, which would need to be taken into account. We consider as controls a battery of variables that drive spreads according to prior related empirical studies. Firm-level control variables taken from Datastream include the market value of equity, total debt-to-assets, profitability (*Return on Assets*), stock return volatility, and the dividend yield. As for issue level controls, we include a Moody's Rating from Factset and an indicator of investment-grade bonds (*Investment Grade Rating*). We consider a Split Rating dummy, which equals 1 whenever a Moody's rating differs from a S&P credit rating from Datastream, and Second Rating dummy that equals 1 whenever an issuer in our sample receives a rating from both Moody's and S&P. We transform the ordinal credit ratings from Moody's and S&P to numerical variables that range from 1 (D Rating) to 9 (AAA Rating). Other issue-specific controls are issue volume, measured by the logarithm of the amount issued in million U.S. dollars (*ln Amount Issued*), the remaining time to maturity from observation to redemption date (*Time to Maturity*), and a dummy that equals 1 if the bond is issued not only

[4.2] Factset data is available directly from Factset Research Systems, and indirectly via alternative platforms. We obtained ownership data directly from Factset.

domestically both also elsewhere (*Globally Issued Bond*). We also use dummies to indicate whether a bond is senior (*Senior*) and secured (*Secured*), and dummies for identifying put (Put Option) and call (*Call Option*) features, similar to Cremers et al. (2007) and Boubakri and Ghouma (2010).

We study whether insider ownership is associated with the risk of tunnelling using GMI's records on companies' related party transactions (RPTs). Specifically, GMI indicates whether it has become public in given year that a firm has been involved in a RPT in the past two years. The transactions are defined as events involving executive and non-executive directors, managers, controlling shareholders, and relatives of any of these individuals. For modelling the probability of RPTs, we use from Datastream debt-assets and market value of equity as proxies of cash-flow restrictions and firm visibility, and both analyst coverage and the number of stock indexes the issuer is part of as proxies of firm opacity. We also collect the contract enforcement score from the World Bank Doing Business (World World Bank, 2016) report as a proxy for the strength of legal frameworks.

Appendix Table C.1 summarizes the variables and their underlying sources.

4.2.2 Summary Statistics

Our sample covers 50,134 bond-year observations, which pertain to 10,470 corporate bonds from 1,222 non-financial firms. The GMI universe is the most restrictive and limits our analysis in terms of firm-year observations and the timespan from 2002 to 2014. Table 4.1 shows descriptive statistics for the full sample of corporate bonds.

For our sample of corporate bonds issued around the world, we find a mean yield spread of 2.15%, the median is 1.47%. Insider ownership is in our sample on average 3.46%, and in certain companies it reaches considerable magnitudes. The sample has a tilt towards financially healthy companies: the mean Moody's bond rating is 6.30, equivalent to a BBB rating, and the lowest observed rating is CCC. S&P ratings are less frequently acquired by issuing firms, and only 44.5% of the issuers in our sample obtain both ratings.

Table 4.2 presents mean values of firm and issue characteristics for, respectively, the subset of firms that experiences less than 10% insider ownership and the firms that have at least 10% insider ownership. Firms with at least 10% insider ownership have on average a smaller equity-market capitalization, a higher leverage ratio, a higher stock price volatility, and a lower dividend yield. Bond issues of firms with substantial insider ownership not only have, on average, a higher yield spread but also a lower Moody's rating, a somewhat shorter maturity, and slightly more often seniority and put features. It is also interesting to see that these firms score somewhat higher on the shareholder rights index. Given these differences, we carefully account for firm and bond covariates in our regressions.

Empirical Analysis

4.3 Insider Ownership and Corporate Bond Spreads

We start with the relation between insider ownership and corporate bond yield spreads based on the entire sample. We estimate this relation by means of pooled ordinary least squares regressions with random effects:

$$\begin{aligned} Yield\ Spread_{ijt} = \alpha_0 + \beta_1 Insider\ Ownership_{jt} + \gamma_h Issue\ Controls_{ij(t)} + \\ \delta_k Firm\ Controls_{jt} + \theta_l Country_l + \upsilon_m Industry_m \\ + \omega_p Currency_p + \varphi_t Year_t + \rho_i + \epsilon_{ijt} \end{aligned} \tag{4.1}$$

where i denotes an individual bond and j stands for the issuing firm. *Insider Ownership* is the percentage of shares owned by directors, managers and other insiders directly or through private firms. *Issue Controls* is a set of $h = 1, ..., H$ time-varying issue-specific control variables and time-invariant bond features, and *Firm Controls* denotes $k = 1, ..., K$ issuer-level control variables. *Country*, *Industry*, *Currency*, and *Year* each represent a matrix of country, industry, currency, and year dummy indicators, where the index l=1,...,L and m=1,...,M (p=1,...,P) are for notational convenience only as they are determined by j (i). ρ_i stands for the bond-specific random error term, $\epsilon_i jt$ is the residual.

The firm-level control variables include firm size (*ln Market Value Equity*), *Leverage*, *ReturnonAssets*, stock return volatility (*Volatility*), and *DividendYield*. As for issue level controls, we include the *Moodys Rating* and the *Investment Grade Rating* dummy, which should both be negatively related to the spread. Because rating agencies are likely to assess firms using a variety of variables that also appear as separate controls in equation 1, the model alternatively includes an *OrthogonalRating*. In addition, we include the *SplitRating* dummy because split ratings indicate rating uncertainty (Elton, 2004), and the *SecondRating* dummy as additional credit analyst coverage reduces information asymmetry (Hsueh and Kidwell, 1988). Other issue specific controls are the logarithm of the amount issued (*ln Amount Issued*), *Time to Maturity*, and the dummy *Globally Issued Bond*. We exclude convertible, inflation-, and index-linked bonds, and include dummies for *Senior* and *Secured* bonds as well as *Put Option* and *Call Option* features. In Table 4.3, the coefficient estimates on the controls largely match those of earlier studies: yield spreads are lower for firms that are larger, more profitable, have bonds traded globally and have larger issue sizes, but higher for bonds issued by firms that have greater financial leverage, a higher cash flow volatility, and a higher dividend yield. The observation that a longer time to maturity positively relates to the yield spread is also in line with prior studies (Borisova et al., 2015).

We now turn to the coefficient estimates for Insider ownership. Table 4.3 shows that across all variants of regression specification 4.1, larger insider ownership is associated with a higher yield spread. Column 1 of Table 4.3 shows that *Insider Ownership* has a coefficient that is economically largest in models that include as controls year, country, industry, and currency fixed effects ($\beta_1 = 0.038$, $p < 0.01$). Columns 2 and 3 indicate that the coefficient becomes economically smaller but continues to be statistically significant at the 1% level once we add firm-specific financials ($\beta_1 = 0.013$, $p < 0.01$) and issue-specific control variables ($\beta_1 = 0.014$, $p < 0.01$). Columns 4 and 5 point out that the positive relation between insider ownership and the yield spread remains similar in magnitude under the most conservative specifications we estimate.

A potential concern with the sample composition is the large representation of U.S. firms in the sample. Given that Ortiz-Molina (2006) documents a positive relation between top management ownership and issue yields on U.S. corporate bonds, the estimates in Table 4.3 could be driven by the relatively large subsample of U.S. issuers. However, Table 4.4 indicates that the coefficients on *Insider Ownership* remain qualitatively similar when we exclude bonds issued by firms headquartered in the United States.

In Table 4.5 we break down the sample even further, by regions, markets, and type of governance structure. Specifically, Panel A of Table 4.5 shows that the positive and significant relation between insider ownership and the yield spread does not only hold for the full and the non-U.S. sample (columns 1 and 2), but also holds for subsamples North America (β_1= 0.011, $p < 0.05$) and Europe (β_1= 0.012, $p < 0.05$). The relation is positive but not statistically significant based on samples from Asia and

Oceania, and positive and significant based on a sample that includes all remaining countries (β_1= 0.021, p $<$ 0.05) 5%-level). In another sample decomposition, shown in columns 8 and 9, we find that insider ownership is positively related to the spread in both developed markets (β_1= 0.011, p $<$ 0.01) and emerging markets (β_1= 0.024, p $<$ 0.05), although the effects differ across the samples in magnitude. In addition, columns 11 and 12 point to a larger coefficient estimate regarding *Insider Ownership* for bonds issued by firms in civil law countries (β_1= 0.015, p $<$ 0.01) compared to those of firms in common law countries (β_1= 0.011, p $<$ 0.01). As literature finds that creditor rights are weaker in civil law countries, this also suggests that insider ownership is more heavily reflected in spreads when firms reside in countries with weaker creditor protection (Djankov, La Porta, Lopez-di Silanes, and Shleifer, 2008).

The positive relation between insider ownership and yield spreads that we observe contrasts with the idea that bondholders associate greater ownership with stronger management commitment and incentive alignment. Instead, the evidence suggests that bondholders associate greater insider ownership either with an increased likelihood that insiders extract private benefits or with increased risk taking. We further explore these alternative economic mechanisms in the next section.

4.4 Insider Ownership and Risk Taking

One interpretation of the observed positive relation between insider ownership and yield spreads is theoretically rooted in differences in risk appetite between holders of a firm's equity and holders of debt. Ortiz-Molina (2006) suggests that spreads reflect an expression of bondholders' concerns about the risk-shifting potential that comes with management incentives to behave in the interest of shareholders. Using 1360 issue yield spreads of U.S. bonds issued between 1993 and 2000, he documents an average yield spread increase of 1.8 basis points per additional percentage of managerial ownership. While our global results are qualitatively similar to Ortiz-Molina's (2006) study of issue yields in the U.S., we note two observations suggesting that insiders' risk-taking incentive is not the only driver of the observed effect.
First, Tables 4.3 and 4.4 show that insider ownership continues to be positively associated with the yield spread after controlling for the level of stock price volatility, which prior studies have used to link insiders' shareholdings and equity incentives to risk taking (e.g. Wright et al., 1996), and proxies for future values of volatility such as leverage.

Second, we have so far estimated linear relations between insider ownership and corporate bond spreads, whereas a risk-taking story could imply a nonlinear relationship. Wright et al. (1996); Wright, Kroll, Krug, and Pettus (2007) and Ortiz-Molina (2006) hypothesize that managers with high levels of ownership are relatively more concerned about non-systematic risk, which would reduce incentives to take risk. We explore this possibility in Table 4.6, which shows regression results that we obtain after replacing insider ownership by dummy variables that mark specific threshold levels of ownership. That is, we assign firms to a hypothetical control group if the insider ownership percentage is smaller than 5%, and compare bonds of this control group to firms that exceed higher thresholds of insider ownership. To make a clear distinction between the levels of insider ownership in the control and treated group, we drop firms with insider ownership levels between 5% and the higher thresholds. Firms that exceed the higher threshold are allocated to a dummy variable that replaces *Insider Ownership* in our regressions. Panel A shows the estimations based on the full sample, Panel B shows the results after excluding bonds issued by U.S. based corporations.

The coefficients on the different threshold levels of insider ownership indicate that higher threshold levels for insider ownership are associated with higher spreads. Regressions based on our global sample indicate that bonds issued by companies with at least 10% insider ownership trade at an additional spread of approximately 27 basis points compared to bonds of companies with less than 5% insider ownership (equivalent to an increase of 12.6% at the average spread of 215 basis points in our sample), whereas bonds issued by firms with at least 20% insider ownership trade at an additional 51 basis points. Only beyond the 50% threshold, the impact seems to decline again. However, this result should be interpreted with caution, because few firms exhibit such high levels of insider ownership, and because the declining effect disappears once we exclude U.S. bonds from our sample (See Panel B). In fact, in our non-U.S. sample spreads are significantly higher for firms with at least 50% insider ownership.

Taken together, we interpret these results as evidence that the yield spread increase associated with greater insider ownership occurs for reasons beyond just risk shifting, which motivates our exploration into an alternative channel from insider ownership to bond spreads.

4.5 Insider Ownership and Shareholder Rights

As an alternative to a risk-taking view, in line with the private-benefits view, our results could suggest that bondholders anticipate more consumption of private benefits when insiders have greater levels of share ownership in the spirit of Morck et al. (1988). In this section, we aim to distinguish between bondholders' concerns about consumption of private benefits and risk-taking caused by insider ownership.

To accomplish that objective, we introduce a unique global index of firm-level shareholder-rights provisions as a moderator variable in the relation between insider ownership and the spread. Essentially, when insiders have sufficient power to consume corporate resources, not only bondholders but also shareholders face a threat of expropriation by insiders. It stands to reason that in such cases bondholders and shareholders have a common interest in shareholder-rights mechanisms that weaken the ability of insiders with greater ownership to extract private benefits at the expense of outsiders. For example, shareholder rights can directly help to control tunnelling (Atanasov et al., 2011; Jung and Chung, 2016) and corporate governance might simultaneously moderate tunnelling harmfulness (Wahab, Haron, Lok, and Yahya, 2011). However, shareholder rights provisions may also align the risk preferences of insiders and outside shareholders to the detriment of bondholder wealth (Klock et al., 2005; Ashbaugh-Skaife et al., 2006; Cremers et al., 2007). Therefore, if bondholders value insider ownership due to concerns about risk taking, we expect that shareholder-rights provisions do not weaken (if not strengthen) the positive relation between insider ownership and the spread[4.3].

[4.3] Potentially further supporting this line of reasoning is our earlier result in Table 4.5 that insider ownership more positively relates to spreads in civil law countries. According to Johnson et al. (2000), courts in civil-law countries are compared to common-law countries effectively more lenient towards insiders engaging in tunneling, which in turn could facilitate consumption of private benefits.

We test these alternative predictions by running regressions in which regression specification 4.1 is augmented with an interactive effect between insider ownership and a firm level shareholder rights measure. Models that are estimated take the form:

$$
\begin{aligned}
Yield\ Spread_{ijt} &= \alpha_0 + \beta_1 Insider\ Ownership_{jt} + \\
\beta_2 Insider\ Ownership * Shareholder - Rights\ Index_{jt} &+ \\
\beta_3 Shareholder - Rights\ Index_{jt} + \gamma_h Issue\ Controls_{ij(t)} &+ \delta_k Firm\ Controls_{jt} + \\
\theta_l Country_l + \upsilon_m Industry_m + \omega_p Currency_p &+ \varphi_t Year_t + \rho_i + \epsilon_{ijt}
\end{aligned}
\tag{4.2}
$$

where i denotes an individual bond and j stands for the issuing firm. *Shareholder-Rights Index* represents an time-variant index at the firm-level j and is determined by the existence or absence of five governance and anti-takeover provisions: the presence of (i) classified boards, (ii) poison pills, and (iii) golden parachutes, (iv) the limitation of the shareholder right to approve bylaw amendments, and (v) the limitation of the right to approve charter amendments. Since fewer provisions imply more shareholder rights, we subtract one point for every mechanism in place from the maximum of five points. The components of the index are similar to those that jointly comprise the "Entrenchment Index" for U.S. firms developed by Bebchuk et al. (2008), but our global index is converted to an index that can be thought of as a shareholder-rights measure; more points on the index indicates fewer restrictions on shareholder rights, and thus comparably weaker management power.

The results in Table 4.7 point to a negative coefficient on the interaction between insider ownership and shareholder rights and a positive coefficient on insider ownership: the positive relation between insider ownership and the yield spread *decreases* with higher values of the shareholder-rights index[4.4]. In Panel A, one percent additional insider ownership is associated with a spread increase of 3.2 basis points if shareholder rights are relatively weak ($Shareholder\text{-}Rights\ Index = 0$). In contrast,

[4.4] In non-reported regressions, we estimate separately models that include the Shareholder-Rights index without its interaction with insider ownership. The full-sample coefficient on the index is positive and marginally significant. However, our international sample yields smaller effects than these U.S. studies, and the coefficients are statistically insignificant in region-specific subsamples.

the yield spread increase diminishes to 0.7 basis points if shareholder rights stay unrestricted. One additional point on the shareholder-rights index reduces the insider ownership effect by 15.6%.

Table 4.8 presents an alternative way to study the effect of insider ownership on the spread conditional on shareholder rights. Reported are coefficients on insider ownership variables *(Insider Ownership* $>$ 10%*, Insider Ownership* $>$ 20% *Insider Ownership)* that were estimated independently after breaking down the sample based on the average level of the shareholder-rights index. According to Panel A of Table 4.8, the relation between insider ownership and the yield spread is in magnitude weaker among firms with above-average shareholder rights (columns 1 to 3) than among firms with weaker shareholder rights (column 4 to 6). Panel B shows that the coefficients on the insider ownership variables are no longer significant for firms with more shareholder rights once U.S. firms drop out of the subsamples.

Hence, the shareholder-rights index negatively moderates the positive relation between insider ownership and corporate spreads, which we interpret as evidence consistent with the private-benefits view.

4.6 Insider Ownership and Tunnelling

Finding that more shareholder rights negatively moderate the positive effect of insider ownership on bond spreads can be thought of as indirect evidence that consumption of private benefits is an underlying channel of transmission from insider ownership to bond spreads. To provide more direct evidence on this economic channel, we turn to a corporate practice that the literature deems symptomatic of private consumption: tunnelling. Tunneling can manifest itself in illegal activities such as “outright theft or fraud” (Johnson et al., 2000), but is not limited to this spectrum. One measurable way in which tunneling manifests itself are related-party transactions (RPTs) (Enriques and Volpin, 2007). IAS24 defines a related party transaction as “a transfer of resources, services, or obligations between related parties, regardless of whether a price is charged”[4.5]. There is a widespread concern that insiders abuse RPTs even though, in theory, certain cases of such transactions can be economically beneficial (OECD, 2012).

[4.5] E.g., see Deloitte (2017).

GMI records whether there have been related party transactions “involving the CEO, company Chairman or other senior executive, a controlling shareholder, non-executive director or a relative of any of these individuals”. We use these data points to estimate firm-level probit models with the indicator that a RPT by firm i took place in year t as dependent variable and where our $Insider\ Ownership$ variable is expected to positively influence the probability of RPTs. Leverage and firm size are proxies for firms’ tunneling capacity and visibility. Since RPTs are controversial and related studies suggests that they are detrimental to firm value, we expect firm size to negatively influence the probability of a RPT. We also control for firm opacity, by means of analyst coverage and the number of stock indexes that the firm is part of. We use the World Bank enforcing contracts score to control for differences in legal environments, which might influence the probability of whether RPTs have to be consistently reported which in turn can also have a disciplining effect on tunneling.

Table 4.9 shows the marginal effects that arise from the estimation of probit models with RPT as the dependent variable. The estimated marginal effects in Panel A point out that the percentage of insider ownership is positively related to the occurrence of an RPT, even after controlling for other plausible determinants of tunneling likelihood. A one-percent increase in insider ownership is associated with a 0.6 percent increase in the probability that an RPT is recorded by GMI ($p < 0.01$). This positive effect is largely consistent across different levels of insider ownership, as illustrated by the similarity of the marginal effects estimated at the sample means and the average marginal effect across the sample. In addition, the marginal effect associated with $Insider\ Ownership$ remains positive when firms located outside the U.S. are excluded from the sample, as shown in Panel B.

These effects support the idea that the consumption of private benefits is more likely to occur in firms with more insider ownership. Since legal liability associated with abusive RPTs is either weak or difficult to enforce (OECD, 2012), investors may weigh the effects of connected-party transactions in the pricing of corporate bonds. If the bond market values consumption of private benefits ex ante, then we could expect that our RPT variable positively influences the yield spread (to the extent an observed RPT influences bond investors’ ex ante expectation of consumption of private benefits). In Table 4.10, we formally introduce RPTs as determinant of the spread in variants of model regression specification 4.1, where we replace insider ownership by RPT. Column (1) in Panel A reports the full-sample regression result, columns (2) and (3) pertain to samples of BBB- and BB-rated bonds, respectively.

The RPT variable is significantly positively associated with the yield spread, and the coefficients increase as the sample is reduced to bonds with relatively greater credit risk. When GMI records that a company has engaged in an RPT in the past two years, the spread is estimated to rise by 10.3 bp. The spread is estimated to rise by 15.8 bp (30.5 bp) based on a sample of below BBB (BB) bonds. We further explore the effect of RPT on the spread in Panel B of Table 4.8, which excludes non-U.S. firms. The coefficient on RPT is statistically significant for non-U.S. bonds rated below BB, and according to its magnitude the spread is over 50 bp higher when a related-party transaction is recorded.

In Table 4.11, we include RPT alongside insider ownership in models of the yield spread. As in Table 4.10, full-sample estimates for the coefficient on RPT are positive and significant. The coefficients on insider ownership variables that were explored in Section remain positive in the presence of RPT, suggesting that bondholders may consider insider ownership in the pricing of debt also for reasons beyond the threat of related-party transactions. Since RPTs represent just one of several alternative practices that can help insiders' extract private benefits, an interesting avenue for future research would be to study bondholders' response to a wider range of practices that are symptomatic of tunneling.

4.7 Endogeneity of Insider Ownership

We acknowledge the endogeneity of insider ownership (e.g., Demsetz and Villalonga, 2001) and the possibility that insiders change their ownership in response to financial performance, instead of financial performance being exogenously affected by insider ownership. To date, no valid instrument to cleanly identify causal effects from block-ownership has been put forward (Edmans and Holderness, 2016). However, we provide several considerations of these concerns.

One alternative story could be that insiders buy shares of their companies in order to strengthen the financial position of the firm once these experience weaker financial conditions (and higher yield spreads). Even though this alternative explanation is theoretically counterintuitive because our sample is tilted towards financially healthy issuers, we investigate whether the positive association between insider ownership and the spread disappears once firms with ownership changes are dropped from the sample. Panel A of Table 4.11 reports the effect of insider ownership on yield spreads using the global sample as well different regional samples after dropping all bonds from firms with changes of more than 1% in insider ownership. The positive coefficient on *Insider Ownership* continues to be significantly different from zero and robust in magnitude.

To further test whether the observed effect could be driven by insider repurchases in response to financial performance deterioration, we exclude from the sample firms that experienced a bond rating downgrade between 2003 and 2014 before re-estimating regression specification 4.1. This exclusion largely reduces the sample, since downgrades often occur during the financial crisis. Panel B of Table 4.12 shows that the coefficient on *Insider Ownership* remains positive and significant under this sample restriction.

Another alternative interpretation of our results could be that insiders enjoy superior information and buy shares as the firm financing conditions deteriorate, in anticipation of a subsequent recovery. However, also when we use 1-year and 2-year lagged values of *Insider Ownership* as the independent variable in regression specification 4.1, insider ownership relates positively to the yield spread; see Table 4.13.

4.8 Additional Robustness Tests

In addition to ruling out alternative interpretations of the relation between insider ownership and corporate bond spreads, we conduct several additional robustness tests. To begin with, we verify that our results are not affected by other ownership characteristics. First, some studies suggest that the wedge between ownership and control (voting rights) drives related-party transactions and self-dealing (Enriques and Volpin, 2007), while other studies such as Aslan and Kumar (2012) and Lin, Ma, Malatesta, and Xuan (2011) find that a greater wedge is positively associated with bank loan rates. Since consumption of private benefits may harm firm value, insiders with fewer cash flow-rights (ownership) relative to voting rights (control) theoretically have more incentives to expropriate wealth. Given that ownership and voting rights tend to be highly correlated, the question arises whether the percentage of shares held by insiders is associated positively with spreads only because it is a proxy for the control-ownership wedge[4.6]. Since studies on U.S. firms such as Gompers, Ishii, and Metrick (2011) suggests that insider ownership in terms of cash flow rights could

[4.6] We acknowledge however that mechanisms other than deviation from one share-one-vote could elevate the percentage of votes that insiders enjoy, which could be positively correlated with the percentage of shares held. For example, using Swedish data, Cronqvist and M (2003) report regressions that yield a negative relation between controlling owner vote ownership and Tobin's q, but no relation between firm value and deviation from one-share-one-vote. They refer to potential multicollinearity problems regarding their vote ownership and equity ownership variables.

lead to higher firm value after controlling for voting rights, it is possible that for firms with no control-ownership wedge more insider ownership provides relatively greater incentive-alignment rather than incentives to consume private benefits. If so, we could expect the coefficient on *Insider Ownership* to decrease or become negative in samples composed of these firms. Although we do not measure cash flow rights and voting rights directly, we do present evidence along two lines suggesting that our main results are not driven by the wedge. Specifically, we have access to information about deviations from a one-share-one vote policy, which is also known to exacerbate the control-ownership wedge. The GMI database contains information about whether common or ordinary equity shares have "one-share, one-vote, with no restrictions". In Table 4.14, we see that insider ownership positively relates to the spread also after excluding firms without a one-share-one-vote policy as identified by GMI. Next, in tests we do not report for the sake of brevity, we identify using Datastream firms with cross-ownership, which is known to cause the wedge between ownership and control. Excluding firms with cross-ownership reduces the sample by 1608 bonds from 260 firms. The coefficients stay similar in magnitude and significance, even though the significance is sometimes affected by this exclusion. Taken together, the additional results up to this point suggest that insider ownership positively relates to bonds spreads even after excluding firms in which consumption of private benefits is theoretically more likely to occur because of disproportionate voting rights in the hands of certain owners.[4.7]

Second, apart from considering the control-ownership wedge, we also consider potentially confounding roles of other types of ownership. We exclude 77 firms with government ownership stakes, because government ownership matters for bond pricing according to earlier empirical evidence on yields of publicly traded debt. (Borisova et al., 2015). Reducing the sample by 852 corporate bonds from these 77 firms causes the insider ownership coefficients to slightly increase in magnitude. Third, our results are similar after adding control variables such as the percentage of shares owned by institutions and dummy variables that indicate institutional blocks to our regression specification (see, e.g, Bhojraj and Sengupta, 2003; Cremers et al., 2007)[4.8]

[4.7] While these results are different from studies that link the control-ownership wedge to bank loan spreads, we note that Cheung, Rau, and Stouraitis (2006) find no relation between the likelihood of related-party transactions and the ownership-control wedge in their Hong Kong sample.
[4.8] Results not reported, but available upon request.

Finally, we make use of alternative estimators and collapse the data to firm-level observations in order to address two potential concerns. First, throughout the paper, regression specification 4.1 is estimated using random effects, although unobservable firm or bond characteristics might be correlated with the error terms. The other potential concern is that bond observations from the same issuer are inherently correlated. Four additional tests are reported in Table 4.15 to mitigate these concerns. We first convert yearly spread observations at the bond level to observations at the firm level, by taking a weighted average of bond spreads that a firm has outstanding. In separate random-effects regressions, a firm-level spread-year is computed as either an equal-weighted average across outstanding bonds (Panel A) or a weighted average based on bond issue size (Panel B). The effect of insider ownership on yield spreads is equal in magnitude and significant for the full sample as well as various subsamples broken down by region. Finally, we further reduce these annual equal- and value-weighted yield spread observations to one observation per firm, i.e., the firm-level annual yields are averaged across time, because spreads may exhibit limited time variation. The results in Panels C and D are qualitatively similar.

4.9 Conclusion

Based on 10,470 corporate bonds publicly issued by 1,222 firms in 48 countries over the period from 2003 to 2014, we study the impact of insider ownership and governance mechanisms on bonds' yield spreads. First, we find that insider ownership is positively related to bond spreads. While this finding is consistent with the conventional hypothesis that bondholders anticipate a higher risk emerging from higher levels of insider ownership, this effect exists after controlling for measures of current and future levels of risk. We therefore suggest that the positive relation is not solely driven by an impact of insider ownership on managerial risk taking, and consider consumption of private benefits as another economic channel through which insider ownership hurts bondholders.

In line with our expectations, the positive association between insider ownership and the yield spread is weaker in firms where consumption of private benefits is less likely to occur due to stronger rights of shareholders. Related party transactions, which are known to provide private benefits, are more likely to occur in firms with more insider ownership and positively influence bond spreads. We conclude that bondholders expect that greater insider ownership facilitates consumption of private benefits next to risk-taking incentives.

The bond markets' pricing of insider ownership has implications for disclosure practice and corporate governance policy. Mechanisms to tackle expropriation by insiders have been a long-standing concern among policymakers (OECD, 2012), and have developed further in recent years. However, consumption of private benefits would not necessarily constitute an expropriation problem if bondholders anticipate the amount consumed and adjust their willingness to pay for corporate bonds accordingly. On the other hand, it might be questionable whether the penalties paid by insider owners through their cash flow rights for engaging in RPTs is tightly enough connected to their true value (Atanasov et al., 2011). More regulatory efforts to improve regulation, disclosure quality, board effectiveness and shareholder rights might be needed to effectively control self-dealing of powerful insiders, which in turn raises the empirical question how these efforts affect bondholders' valuation of insider ownership.

Table 4.1: Descriptive Statistics of the Full Sample

Table 4.1 shows descriptive statistics for our sample covering 10,470 corporate bonds issued by 1,221 non-financial firms in 48 countries from 2003 to 2014. The number of observations in this table refers to bond-years. We present complete variable descriptions in Appendix C.1, the distribution of observations across countries in Appendix C.2, and the scheme for transforming Moody's and S&P ratings to numerical ratings in Appendix 4.9.

	N	**Mean**	**St. Dev.**	**P25**	**P75**
Panel A: Firm Characteristics					
% Insider Ownership	50,143	3.426	8.452	0.155	2.823
Shareholder-Rights Index	50,143	3.162	1.333	2	4
Market Capitalization	50,143	33.17	47.26	5.819	37.92
Leverage	50,143	0.345	0.157	0.238	0.425
Return on Assets	50,143	5.894	5.782	3.460	8.290
Volatility	50,143	23.29	8.721	16.84	27.58
Dividend Yield	50,143	2.897	2.246	1.410	4.140
Panel B: Bond Characteristics					
Spread	50,143	2.147	2.166	0.865	2.612
Moody's Rating	50,143	6.297	1.044	6	7
S&P Rating (9)	22,328	6.065	1.132	6	7
Split Rating	50,143	0.319	0.466	0	1
Second Rating	50,143	0.445	0.497	0	1
Globally Issued Bond	50,143	0.303	0.460	0	1
Maturity (Years)	50,143	15.04	11.49	8	20
Amount Issued (Million U.S. Dollar)	50,143	470.5	525.3	150	600
Senior Bond	50,143	0.700	0.458	0	1
Secured Bond	50,143	0.0593	0.236	0	0
Put Option	50,143	0.0203	0.141	0	0
Call Option	50,143	0.623	0.485	0	1

Table 4.2: Descriptive Statistics for Insider and Non-Insider Owned Firms

Table 4.2 shows descriptive statistics for our sample split into insider-owned and non-insider-owned issuing companies. The number of observations in this table refers to the number of firms (Panel A, firm characteristics) and number of bonds (Panel B, bond characteristics). We present complete variable descriptions in Appendix C.1, the distribution of observations across countries in Appendix C.2, and the scheme for transforming Moody's and S&P ratings to numerical ratings in Appendix 4.9.

	N	**<10%**	**N**	**>10%**	**Difference**	**P-Value**
Panel A: Firm Characteristics						
% Insider Ownership	1,002	1.86	220	32.49	-30.62	0.00
Shareholder-Rights Index	1,002	3.28	220	3.78	-0.50	0.00
Market Capitalization	1,002	17.16	220	8.25	8.92	0.00
Leverage	1,002	0.33	220	0.38	-0.05	0.00
Return on Assets	1,002	6.20	220	5.33	0.88	0.11
Volatility	1,002	28.02	220	33.14	-5.11	0.00
Dividend Yield	1,002	2.12	220	1.75	0.36	0.03
Panel B: Bond Characteristics						
Spread	9,445	2.03	1,026	3.12	-1.09	0.00
Moody's Rating	9,445	6.29	1,026	5.71	0.59	0.00
S&P Rating (9)	4,636	6.07	521	6.12	-0.05	0.38
Split Rating	9,445	0.36	1,026	0.39	-0.03	0.05
Second Rating	9,445	0.49	1,026	0.51	-0.02	0.30
Globally Issued Bond	9,445	0.31	1,026	0.33	-0.02	0.28
Maturity (Years)	9,445	12.91	1,026	10.21	2.70	0.00
Amount Issued (Mio. USD)	9,445	490.37	1,026	521.08	-30.71	0.08
Senior Bond	9,445	0.71	1,026	0.75	-0.03	0.03
Secured Bond	9,445	0.06	1,026	0.06	-0.00	0.69
Put Option	9,445	0.01	1,026	0.00	0.01	0.06
Call Option	9,445	0.64	1,026	0.64	-0.00	0.98

Table 4.3: Insider Ownership and Bond Spreads – Global Estimates

See table description below.

	(1)	(2)	(3)	(4)	(5)
% Insider Ownership	0.038***	0.013***	0.014***	0.011***	0.014***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
Moody's Rating (9)				-0.461***	
				(0.051)	
Orthogonal Rating					-0.523***
					(0.052)
Investment Grade Rating				-1.439***	
				(0.260)	
Split Rating				0.154***	
				(0.026)	
Second Rating				-0.157***	
				(0.024)	
Ln Market Value		-0.545***	-0.549***	-0.368***	-0.496***
		(0.041)	(0.041)	(0.028)	(0.030)
Leverage		0.926***	0.948***	0.520***	1.047***
		(0.210)	(0.204)	(0.160)	(0.170)
Return on Assets		-0.048***	-0.048***	-0.045***	-0.050***
		(0.007)	(0.007)	(0.006)	(0.007)
Volatility		0.078***	0.079***	0.057***	0.086***
		(0.005)	(0.005)	(0.007)	(0.005)
Dividend Yield		0.061***	0.061***	0.077***	0.067***
		(0.021)	(0.021)	(0.020)	(0.020)
Globally Issued Bond			-0.014	-0.009	-0.011
			(0.031)	(0.027)	(0.028)
Time to Maturity			0.016***	0.018***	0.016***
			(0.002)	(0.002)	(0.002)
Ln Amount Issued			-0.003	-0.004	-0.003
			(0.010)	(0.008)	(0.009)
Senior Bond			0.006	0.024	0.001
			(0.027)	(0.024)	(0.025)
Secured Bond			-0.052	-0.046	-0.063
			(0.058)	(0.046)	(0.047)
Put Option				0.138	0.184
				(0.114)	(0.116)
Call Option				-0.033	0.052
				(0.055)	(0.056)
# Bond Years	50,143	50,143	50,143	50,143	50,143
# Bonds	10,471	10,471	10,471	10,471	10,471
Countr/Curr/Ind/Year FE & Bond Features	Yes	Yes	Yes	Yes	Yes
Overall R2	0.353	0.613	0.619	0.669	0.661

In Table 4.3, we estimate models with the bond yield spread as dependent variable, and as independent variables insider ownership and control variables. The first model includes insider ownership while controlling for country, industry, currency, and year fixed effects. We then sequentially augment the model by including issuer controls in column (2), bond-specific controls in column (3), ratings in column (4) and orthogonal ratings in column (5). The bond spread is measured over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. *Insider Ownership* is the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. The number of observations in this table refers to bond-years. Robust standard errors clustered at the firm level are shown in parentheses. Complete variable descriptions can be found in Appendix C.1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.4: Insider Ownership and Bonds Spreads – Excluding U.S. Firms

See table description below.

	(1)	(2)	(3)	(4)	(5)
% Insider Ownership	0.027***	0.011***	0.011***	0.011***	0.013***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Moody's Rating (9)				-0.528***	
				(0.117)	
Orthogonal Rating					-0.541***
					(0.114)
Investment Grade Rating				-1.007**	
				(0.507)	
Split Rating				0.141***	
				(0.035)	
Second Rating				-0.147***	
				(0.034)	
Ln Market Value		-0.664***	-0.666***	-0.434***	-0.574***
		(0.101)	(0.100)	(0.054)	(0.066)
Leverage		0.619**	0.600**	0.365	0.825***
		(0.277)	(0.276)	(0.239)	(0.258)
Return on Assets		-0.028**	-0.028**	-0.028***	-0.033***
		(0.011)	(0.011)	(0.010)	(0.011)
Volatility		0.056***	0.057***	0.036**	0.066***
		(0.010)	(0.010)	(0.015)	(0.010)
Dividend Yield		0.033	0.033	0.049**	0.038
		(0.026)	(0.026)	(0.024)	(0.025)
Globally Issued Bond			-0.078**	-0.065*	-0.067*
			(0.040)	(0.036)	(0.036)
Time to Maturity			0.017***	0.019***	0.017***
			(0.003)	(0.002)	(0.002)
Ln Amount Issued			-0.018	-0.018	-0.020
			(0.016)	(0.014)	(0.014)
Senior Bond			0.015	0.023	0.002
			(0.038)	(0.034)	(0.035)
Secured Bond			0.088	0.064	0.047
			(0.086)	(0.072)	(0.073)
Put Option				0.127	0.181
				(0.353)	(0.357)
Call Option				0.030	0.139
				(0.103)	(0.093)
Bond Years	17,973	17,973	17,973	17,973	17,973
Number of Bonds	4,289	4,289	4,289	4,289	4,289
Countr/Curr/Ind/Year FE & Bond Features	Yes	Yes	Yes	Yes	Yes
Overall R-sq	0.401	0.580	0.586	0.637	0.632

In Table 4.4, we regress the bond yield spread on insider ownership and control variables using a sample that is limited to bonds issued by firms with headquarters outside of the United States. The first model includes insider ownership while controlling for country, industry, currency, and year effects. We then sequentially augment the model by including issuer controls in column (2), bond-specific controls in column (3), ratings in column (4) and orthogonal ratings in column (5). The spread is measured over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. Robust standard errors clustered at the firm level are shown in parentheses, complete variable descriptions can be found in Appendix C.1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.5: Insider Ownership and Bond Spreads – Regional Sub-samples

In Panel A of Table 4.5, we breakdown the global bond sample into regional subsamples based on location of firm headquarters and estimate models with the yield spread as dependent variable, and as independent variables insider ownership along with firm-specific control variables, bond characteristics, credit ratings, country fixed effects, industry fixed effects, currency fixed effects and year fixed effects. The bond spread is measured over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. The number of observations in this table refers to bond-years. Robust standard errors clustered at the firm level are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging	Common	Civil
% Insider Ownership	0.011***	0.011***	0.011**	0.012**	0.007	0.011	0.021**	0.011***	0.024**	0.010***	0.015***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.003)	(0.010)	(0.004)	(0.004)
Observations	50,143	17,973	33,611	5,903	5,786	2,330	2,513	45,706	3,965	40,912	9,231
Number of Bonds	10,471	4,289	6,528	1,437	1,488	433	585	9,413	964	8,137	2,334
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.595	0.496	0.637	0.573	0.421	0.679	0.487	0.605	0.606	0.619	0.504
Between R2	0.727	0.719	0.732	0.716	0.733	0.768	0.780	0.728	0.787	0.726	0.729
Overall R2	0.669	0.637	0.688	0.649	0.627	0.709	0.705	0.673	0.709	0.677	0.646

Table 4.6: Insider Ownership Thresholds and Bond Spreads

See table description below.

	Panel A: Full Sample					*Panel B: Sample Excluding USA*				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
>10% Insider Ownership	0.273***					0.260**				
	(0.086)					(0.118)				
>15% Insider Ownership		0.333***					0.322**			
		(0.112)					(0.142)			
>20% Insider Ownership			0.512***					0.387**		
			(0.157)					(0.160)		
>25% Insider Ownership				0.957***					0.437**	
				(0.361)					(0.176)	
>50% Insider Ownership					0.484					0.799***
					(0.438)					(0.294)
Observations	45,749	43,941	43,333	27,781	27,434	16,278	15,493	15,368	15,246	14,514
Number of Bonds	10,012	9,644	9,498	5,603	5,514	4,071	3,888	3,857	3,835	3,647
Number of Firms	1,222	1,222	1,222	1,222	1,222	522	522	522	522	522
Number of Insider-Owned Firms	114	90	82	75	36	95	62	43	34	14
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R2	0.663	0.659	0.656	0.671	0.667	0.630	0.626	0.627	0.626	0.624

Table 4.6 shows the impact of insider ownership on bond spreads when separating the sample into treatment (bonds issued by firms with insider ownership) and control (bonds issued by firms without insider ownership). The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. All regressions include the complete set of control variables as outlined in Table 3, column 4. Observations are considered as part of the treated if the respective issuers passed a certain threshold of insider ownership as indicated on the left. Panel A refers to the whole sample, Panel B is limited to issues by firms with headquarters outside of the United States. The number of observations refers to bond years. Robust standard errors clustered at firm level are depicted in parentheses, complete variable descriptions can be found in Appendix C.1. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.7: Shareholder Rights, Insider Ownership and Bond Spreads

	Panel A: Full Sample			*Panel B: Sample Excluding USA*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Shareholder-Rights Index	0.050***	0.044**	0.041**	0.053*	0.054*	0.059**
	(0.018)	(0.019)	(0.019)	(0.028)	(0.029)	(0.029)
% Insider Ownership	0.032***			0.037***		
	(0.007)			(0.010)		
% Insider Ownership x	-0.005***			-0.006***		
Shareholder Rights	(0.002)			(0.002)		
>10% Insider Ownership		0.698***			0.949***	
		(0.179)			(0.262)	
>10% Insider Ownership x		-0.125***			-0.182***	
Shareholder Rights		(0.045)			(0.059)	
>20% Insider Ownership			1.119***			1.398***
			(0.303)			(0.437)
>20% Insider Ownership x			-0.160**			-0.244**
Shareholder Rights			(0.067)			(0.096)
Observations	50,143	45,749	43,333	17,973	16,278	15,368
Number of Bonds	10,471	10,012	9,498	4,289	4,071	3,857
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.596	0.601	0.599	0.499	0.495	0.494
Between R2	0.728	0.712	0.707	0.719	0.714	0.711
Overall R2	0.670	0.664	0.657	0.637	0.630	0.627

Table 4.7 shows the interaction of insider ownership, shareholder rights, and their individual and mutual impact on bond spreads. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. In column 2 and 3, insider ownership is measured through a dummy indicating whether the percentage of insider ownership crosses the 10% and the 20% ownership threshold, respectively. Governance is measured by means of the Shareholder-Rights Index, constructed similar to Bebchuk et al. (2008) and based on data from GMI Ratings. A higher index indicates that a company has adopted fewer shareholder rights limitations. The index comprises six dimensions and thus varies from 0 to 5, with a high index hence indicating more shareholder-friendly governance. All regressions include the complete set of control variables as outlined in Table 3, column 4. Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to bond years. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.8: Shareholder Rights, Insider Ownership and Bond Spreads

Table 4.8 shows the impact of insider ownership on bond spreads depending on the shareholder rights associated with the issuing firm. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. The shareholder-rights index is constructed similar to Bebchuk et al. (2008) and Cremers et al (2007), and based on global data from GMI Ratings. A higher index indicates that a company has adopted fewer shareholder-rights limitations. The index comprises six dimensions and thus varies from 0 to 5, with a high index hence indicating more shareholder-friendly governance. In columns 1 to 3, issuers with an Shareholder-Rights Index above the year-country mean are included in the regressions, in columns 4-6 results pertain to issuers with an index value below the year-country mean. All regressions include the complete set of control variables as outlined in Table 3, column 4. Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to bond years. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Sample Excluding USA

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Unrestricted Shareholder Rights			*Restricted Shareholder Rights*		
% Insider Ownership	0.009**			0.017***		
	(0.004)			(0.004)		
>10% Insider Ownership		0.191*			0.366***	
		(0.107)			(0.125)	
>20% Insider Ownership			0.444**			0.593***
			(0.204)			(0.163)
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,015	23,812	22,369	24,128	21,937	20,964
Number of Bonds	7,696	7,322	6,940	6,661	6,282	6,007
Overall R2	0.688	0.679	0.670	0.664	0.660	0.656

Panel B: Sample Excluding USA

	(1)	(2)	(3)	(4)	(5)	(6)
	Unrestricted Shareholder Rights			*Restricted Shareholder Rights*		
% Insider Ownership	0.006			0.023***		
	(0.004)			(0.005)		
>10% Insider Ownership		0.014			0.530***	
		(0.134)			(0.160)	
>20% Insider Ownership			0.164			0.805***
			(0.196)			(0.187)
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,104	8,897	8,348	7,869	7,381	7,020
Number of Bonds	3,131	2,946	2,785	2,604	2,423	2,310
Overall R2	0.670	0.659	0.654	0.637	0.627	0.627

Table 4.9: Insider Ownership and Related-Party Transactions

Table 4.9 shows the impact of insider ownership on the probability of predicted party transactions (RPTs) involving directors, managers, major shareholders or family members. The dependent variable is an indicator whether related party transactions that have happened in the past two years have become public and reported by GMI Ratings. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. Column 1 and 2 show the marginal effect at the sample means as estimated by probit regressions, columns 3 and 4 show the average marginal effects. Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to firm years. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Full Sample

	Marginal Effect (Mean)		*Average Marginal Effect*	
	(1)	**(2)**	**(3)**	**(4)**
% Insider Ownership	0.006***	0.006***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln Market Value		0.002		0.002
		(0.009)		(0.010)
Leverage		0.000		0.000
		(0.001)		(0.001)
# Analysts		-0.002		-0.002
		(0.002)		(0.002)
# Local Index Inclusions		-0.028**		-0.031**
		(0.013)		(0.014)
WB Enforcing Contracts		-0.012*		-0.013*
		(0.006)		(0.007)
Observations	8,797	8,260	8,797	8,260
Countr/Ind/Year FE	Yes	Yes	Yes	Yes

Panel B: Sample Excluding USA

	Marginal Effect (Mean)		*Average Marginal Effect*	
	(1)	**(2)**	**(3)**	**(4)**
% Insider Ownership	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln Market Value		0.003		0.003
		(0.013)		(0.015)
Leverage		0.001		0.001
		(0.001)		(0.001)
# Analysts		-0.000		-0.000
		(0.002)		(0.002)
# Local Index Inclusions		-0.042***		-0.046***
		(0.013)		(0.015)
WB Enforcing Contracts		-0.015*		-0.017*
		(0.008)		(0.009)
Observations	3,188	2,831	3,188	2,831
Countr/Ind/Year FE	Yes	Yes	Yes	Yes

Table 4.10: Related-Party Transactions and Bond Spreads

In Table 4.10, the dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. Column 1 shows the impact of related party transactions for the full sample, columns 2 and 3 show the coefficients estimated based on a sample including bonds with, respectively, a BBB rating and lower and BB rating and lower. Panel A includes all issuers, Panel B only issuers with headquarters outside of the United States. Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to bond years. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Panel A: Full Sample

	(1)	**(2)**	**(3)**
Realized Related Party Transaction	0.103***	0.158***	0.305**
	(0.039)	(0.055)	(0.121)
Observations	42,610	23,115	6,231
Number of Bonds	9,812	6,012	2,053
Issuer/Bond/Rating Controls	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes
Overall R2	0.666	0.688	0.628

Panel B: Sample Excluding USA

	(1)	**(2)**	**(3)**
Realized Related Party Transaction	0.001	0.164	0.515***
	(0.069)	(0.116)	(0.180)
Observations	15,464	7,493	1,802
Number of Bonds	3,879	2,236	672
Issuer/Bond/Rating Controls	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes
Overall R2	0.638	0.631	0.686

Table 4.11: Insider Ownership, Related-Party Transactions and Bond Spreads

Table 4.11 shows the impact of related-party transactions and the percentage of insider ownership on yield spreads. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. Column 1 and 3 show the impact of insider ownership separately, columns 4-6 include the indicator on realized related party transactions, Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to bond years. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
% Insider Ownership	0.011***			0.011***		
	(0.003)			(0.003)		
>10% Insider Ownership		0.245***			0.226***	
		(0.086)			(0.086)	
>20% Insider Ownership			0.474***			0.451***
			(0.149)			(0.150)
Related Party-Transaction				0.088**	0.084**	0.083**
				(0.039)	(0.039)	(0.040)
Observations	42,610	39,009	37,002	42,610	39,009	37,002
Number of Bonds	9,812	9,358	8,874	9,812	9,358	8,874
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Overall R2	0.668	0.663	0.655	0.668	0.663	0.655

Table 4.12: Insider Ownership and Bond Spreads: Additional Tests

Table 4.12 shows the impact of insider ownership on bond spreads for different regional or country groups as indicated by the column headers. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. All regressions include the complete set of control variables as outlined in Table 2/3, column 4. Robust standard errors clustered at firm level are depicted in parentheses, the number of observations in this table refers to bond years. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Panel A: Sample excl. Bonds from Issuers with Changes in Insider Ownership > 1%

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
% Insider Ownership	0.017***	0.013**	0.018***	0.033**	-0.003	0.004	0.025	0.016***	0.045*
	(0.004)	(0.005)	(0.005)	(0.013)	(0.006)	(0.015)	(0.022)	(0.004)	(0.024)
Observations	37,733	12,777	25,590	4,321	3,979	2,044	1,799	34,539	3,034
Number of Bonds	7,816	3,056	4,920	1,047	1,078	372	399	7,075	708
Countr/Curr/Ind/Year FE & Bond Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.618	0.522	0.666	0.600	0.405	0.692	0.538	0.632	0.660
Between R2	0.695	0.701	0.681	0.687	0.733	0.732	0.838	0.694	0.746
Overall R2	0.656	0.633	0.670	0.645	0.632	0.687	0.742	0.660	0.696

Panel B:

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
% Insider Ownership	0.012***	0.012***	0.014***	0.010	0.009*	0.006	0.036**	0.011***	0.027**
	(0.003)	(0.004)	(0.004)	(0.007)	(0.005)	(0.006)	(0.017)	(0.003)	(0.011)
Observations	27,418	9,682	18,260	2,802	3,606	1,402	1,348	25,160	2,126
Number of Bonds	6,100	2,522	3,729	769	990	275	337	5,504	564
Countr/Curr/Ind/Year FE & Bond Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.617	0.513	0.654	0.528	0.417	0.767	0.527	0.625	0.517
Between R2	0.750	0.753	0.756	0.784	0.783	0.794	0.801	0.747	0.857
Overall R2	0.688	0.682	0.698	0.715	0.677	0.762	0.727	0.686	0.763

Table 4.13: Insider Ownership and Bond Spreads – Lagged Ownership

Table 4.13 shows the impact of insider ownership on bond spreads for different regional or country groups as indicated by the column headers. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is defined as the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. All regressions include the complete set of control variables as outlined in Table 3, column 4. Robust standard errors clustered at firm level are shown in parentheses; the number of observations in this table refers to bond-years. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: 1-year Lag

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
% Insider Ownership	0.010***	0.011***	0.009*	0.019***	0.007	0.013	0.022**	0.010***	0.024**
(1 Year Lag)	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.010)	(0.010)	(0.004)	(0.010)
Observations	39,672	13,684	27,083	4,466	4,298	1,897	1,928	36,293	3,001
Number of Bonds	9,287	3,749	5,832	1,249	1,312	392	502	8,361	840
Bond Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.599	0.487	0.642	0.565	0.410	0.686	0.495	0.612	0.581
Between R2	0.710	0.698	0.716	0.704	0.721	0.728	0.799	0.710	0.791
Overall R2	0.666	0.625	0.687	0.643	0.617	0.694	0.714	0.671	0.711

Panel B: 2-year Lag

	(1) All	**(2)** Ex US	**(3)** NA	**(4)** Europe	**(5)** Asia	**(6)** Oceania	**(7)** RoW	**(8)** Developed	**(9)** Emerging
% Insider Ownership	0.008**	0.012***	0.005	0.016*	0.014**	0.014	0.009	0.007*	0.029***
(2 Year Lag)	(0.004)	(0.004)	(0.006)	(0.009)	(0.006)	(0.011)	(0.009)	(0.004)	(0.011)
Observations	30,385	9,935	21,251	3,217	2,986	1,505	1,426	27,932	2,161
Number of Bonds	7,869	3,064	5,048	1,010	1,048	349	414	7,114	679
Bond Features	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.601	0.482	0.644	0.544	0.447	0.677	0.512	0.618	0.553
Between R2	0.680	0.667	0.691	0.674	0.635	0.718	0.807	0.676	0.759
Overall R2	0.660	0.617	0.681	0.634	0.594	0.681	0.726	0.665	0.698

Table 4.14: Insider Ownership and the Yield Spread: One-Share-One-Vote Policy

After removing firms without a one-share-one vote policy according to GMI, we estimate models with the yield spread as dependent variable, and as independent variables insider ownership along with firm-specific control variables, bond characteristics, credit ratings, country fixed effects, industry fixed effects, currency fixed effects and year fixed effects in Table 4.14 (see equation 4.1). The bond spread is measured over the yield of a government benchmark with the same currency and the closest maturity available, retrieved from Datastream. Insider ownership is the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. All regressions include the complete set of control variables as outlined in Table 3, column 4. The number of observations in this table refers to bond-years. Robust standard errors clustered at the firm level are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
% Insider Ownership	0.010***	0.009***	0.009**	0.008*	0.004	0.010	0.023**	0.009***	0.022***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)	(0.010)	(0.003)	(0.008)
Observations	43,596	14,038	30,020	4,666	4,573	2,186	2,151	40,269	2,874
Number of Bonds	9,125	3,363	5,870	1,141	1,207	404	503	8,317	715
Issuer/Bond/Rating Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R2	0.603	0.495	0.642	0.516	0.439	0.692	0.498	0.612	0.504
Between R2	0.755	0.747	0.758	0.787	0.751	0.799	0.787	0.752	0.867
Overall R2	0.686	0.652	0.702	0.701	0.639	0.729	0.688	0.688	0.743

Table 4.15: Insider Ownership and Firm-Level Bond Spreads

Table 4.15 shows the impact of insider ownership on bond spreads for different regional or country groups as indicated by the column headers. The dependent variable is the spread of corporate bonds over the yield of a government benchmark with the same currency and the closest maturity available. Insider ownership is the percentage of shares held by individual insiders such as directors, managers and family members directly, obtained through employee stock options or held through private companies based on information provided by FactSet. All regressions include the complete set of control variables as outlined in Table /3, column 4. Panel A and B show the coefficients, estimated using random effects with robust standard errors, when bond observations for each firm are equal-weighted and issue size-weighted, respectively. Panel C and D show OLS estimations, with standard errors clustered at firm level, when yearly firm-level observations are further averaged over time to obtain one observation per firm. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
Panel A: Random effects, using firm-level yield spreads based on equal-weighting of bond yields									
% Insider Ownership	0.013***	0.010***	0.015***	0.009	0.002	0.020**	0.032***	0.012***	0.016
	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.011)	(0.003)	(0.012)
# Firm-year obs.	8,829	3,220	5,836	960	1,141	369	523	7,990	739
Number of Firms	1,222	522	742	164	183	52	81	1,087	121
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R2	0.722	0.679	0.744	0.717	0.681	0.807	0.673	0.728	0.730

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	All	Ex US	NA	Europe	Asia	Oceania	RoW	Developed	Emerging
Panel B: Random effects, using firm-level yield spreads based on issue size-weighted bond yields									
% Insider Ownership	0.012***	0.010**	0.013***	0.008	0.001	0.021**	0.033***	0.011***	0.016
	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.009)	(0.003)	(0.011)
# Firm-year obs.	8,829	3,220	5,836	960	1,141	369	523	7,990	739
Number of Firms	1,222	522	742	164	183	52	81	1,087	121
Countr/Curr/Ind/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R2	0.731	0.690	0.752	0.721	0.702	0.800	0.691	0.736	0.744
Panel C: Firm-level spread; yields are equal-weighted average across bond and time; OLS estimator									
% Insider Ownership	0.016***	0.015***	0.020***	0.014*	0.008	0.024	0.039	0.015***	0.031
	(0.004)	(0.006)	(0.006)	(0.008)	(0.011)	(0.020)	(0.027)	(0.004)	(0.020)
# Firm observations	1,222	522	742	164	183	52	81	1,087	121
Countr/Curr/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.762	0.764	0.783	0.852	0.813	0.982	0.849	0.771	0.833
Panel D: Firm-level spread; yearly average yields are issue size-weighted across bonds; OLS estimator									
% Insider Ownership	0.011***	0.009**	0.012**	0.019**	0.005	0.050***	0.041*	0.010***	0.017
	(0.003)	(0.005)	(0.005)	(0.008)	(0.007)	(0.012)	(0.023)	(0.003)	(0.015)
# Firm observations	1,222	522	742	164	183	52	81	1,087	121
Countr/Curr/Ind/ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.796	0.804	0.806	0.866	0.865	0.967	0.881	0.799	0.916

Table C.1: Variable Descriptions

Name	**Description**	**Source**
Dependent Variable		
Spread	Yield spread in percent as provided by Datastream. Defined as the annualized yield to maturity of the corporate bond over the yield to maturity of a government security of the respective currency and closest time to maturity available.	Datastream
Ownership		
% Insider Ownership	Sum of the percentage of shares obtained through employee stock options, shares held by individual corporate insiders and private companies.	FactSet
% Ins. Own. (Alternative)	Sum of the percentage of shares obtained through employee stock options and shares held by individual corporate insiders.	FactSet
>x % Insider Ownership	Dummy indicating whether the percentage of insider ownership calculates as indicated above exceeds x %. In order to cleanly separate firms with and without insider ownership, observations of bonds issued by firms with less than five percent are labeled 0, others are excluded in this definition.	FactSet
% Institutional Ownership	Percentage of shares held by institutional owners and investment banks.	Datastream
% Government Ownership	Percentage of shares held by the government or a government institution.	Datastream
% Cross Ownership	Percentage of shares held by one company in another.	Datastream
Corporate Governance		
Shareholder-Rights Index	Governance Index constructed largely in line with Bebchuk et al. (2008). GMI provides information on five out of the six original dimensions, comprising the existence of a poison pill, golden parachutes, limitation of the shareholder right to prevent charter amendments, limitation of the shareholder right to prevent bylaw amendments and the existence of a classified board. For the existence of every provision one point is deducted from six, the maximum of the governance index.	GMI

Name	**Description**	**Source**
Related Party Transaction	Dummy indicating whether there have been related party transactions ”involving the CEO, company Chairman or other senior executive, a controlling shareholder, non-executive director or a relative of any of these individuals”.	GMI
One-Share One-Vote	Dummy indicating whether the firm deviated from a one-share one-vote policy.	GMI
Multiple Share Classes	Dummy indicating whether the firm currently has multiple share classes outstanding.	Datastream
Legal Environment		
Enforcing Contracts Score	The enforcing contracts indicator measures the time and cost for resolving a commercial dispute through a local first-instance court, and the quality of judicial processes index, evaluating whether each economy has adopted a series of good practices that promote quality and efficiency in the court system (World Bank, 2016) The score thereby ranging from 0 (weak contract enforcement) to 100 (strong contract enforcement).	World Bank
Strength of Legal Rights Index	The strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending (World Bank, 2016). The index ranges from 0 to 12.	World Bank
Rating Variables		
Moody's Rating	Moody's security level rating, converted into nine rating categories.	FactSet
Moody's Rating (Orthogonal)	Residuals from a regression of Moody's security level ratings on the remaining control variables including market value, leverage, return on assets, stock volatility, dividend yield, zero coupon dummy, maturity, amount issued, seniority, securitization, bond features, year, industry, country and bond currency dummies.	FactSet
Moody's Investment Grade	Dummy indicating whether a bond is considered to possess investment grade quality. The threshold for investment grade bonds is set at B. Corporate bonds rated triple CCC or worse are considered below investment grade.	FactSet
S&P Rating	S&P security level rating, converted into nine rating categories.	Datastream
Split Rating	Dummy indicating whether Moody's and S&P ratings are known not to be in accordance.	DS&FactSet
Second Rating	Dummy indicating whether the firm acquired ratings from both Moody's and S&P.	DS&FactSet
Issue Controls		

Name	**Description**	**Source**
Globally Issued Bond	Dummy indicating whether a bond is issued globally, meaning that is traded both on the local and on an international trading platform.	Datastream
Zero Coupon Bond	Dummy indicating whether bonds are not paying coupons.	Datastream
Senior	Dummy indicating whether a bond is considered senior.	Datastream
Secured	Dummy indicating whether a bond is secured.	Datastream
Ln(Amount Issued)	Natural logarithm of the amount of the bond issue in million U.S. dollar.	Datastream
Time to Maturity	Remaining time to maturity calculated from the year end of the observation year to the redemption date.	Datastream
Put	Dummy indicating whether a bond can be put early by the holder. Information obtained from Datastream is supplemented by FactSet. Comprised in the control for bond features.	DS&FactSet
Call	Dummy indicating whether a bond can be called early by the issuer. Information obtained from Datastream is supplemented by FactSet. Comprised in the control for bond features.	DS&FactSet
Issuer Controls		
Ln Market Cap	Natural logarithm of the market capitalization, expressed in million U.S. dollar.	Datastream
Leverage	Total debt divided by total assets (%).	Datastream
Return on Assets	Return on assets (%).	Datastream
Dividend Yield	Dividend yield (%).	Datastream
Volatility	Stock's average annual price movement (%) to a high and low from a mean price for each year. Defined in the Datastream Worldscope module as follow: "A stock's price volatility of 20% indicates that the stock's annual high and low price has shown a historical variation of +20% to -20% from its annual average price."	Worldscope
Analysts	Number of analysts following the firm.	Datastream
Index Coverage	Number of stock indexes covering the firm.	Datastream
Fixed Effects		
Currency FE	Dummies generated according to 3-digit currency codes as defined by the International Standards Organization.	Datastream
Country FE	Dummies generated according to 3-digit country codes as defined by the International Standards Organization.	Datastream
Industry FE	Dummies generated using the first digit of the Standard Industry Classification codes.	Datastream
Year FE	Dummies indicating the observation year.	Datastream

Name	Description	Source
Regional Classifications		
Europe	Includes issuers with headquarters in Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Italy, Luxemburg, the Netherlands, Norway, Portugal, Spain, Sweden and Switzerland.	FactSet
Asia	Includes issuers with headquarters in Hong Kong, Indonesia, India, Japan, Malaysia, the Philippines, Singapore, South Korea, Taiwan and Thailand.	FactSet
Oceania	Australia and New Zealand.	FactSet
Rest of the World	Includes issuers with headquarters in/on the Bahamas, Bermuda, Brazil, Chile, Cyprus, Egypt, Israel, Mexico, Pakistan, Puerto Rico, Qatar, South Africa and the United Arab Emirates.	FactSet
Developed Markets	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Luxemburg, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, United Kingdom and the United States of America.	FTSE Classification
Emerging Markets	Includes issuers with headquarters in Brazil, Chile, China, Egypt, India, Indonesia, Hungary, Malaysia, Mexico, Pakistan, the Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Turkey and the United Arab Emirates.	FTSE Classification
Civil Law Counties	As classified in Djankov, La Porta, Lopez-di-Silanes and Shleifer (2006), this subset includes issuers with headquarters in civil law countries.	Djankov et al. (2006)
Common Law Countries	As classified in Djankov, La Porta, Lopez-di-Silanes and Shleifer (2006), this subset includes issuers with headquarters in common law countries.	Djankov et al. (2006)

Table C.2: Geographical Distribution

ISO Country Code	Country Name	Firms	Bonds	Bond-Years
ARE	United Arab Emirates	1	1	3
AUS	Australia	50	431	2327
AUT	Austria	9	226	781
BEL	Belgium	8	96	429
BHS	Bahamas	1	41	223
BMU	Bermuda	9	37	179
BRA	Brazil	12	176	859
CAN	Canada	42	346	1441
CHE	Switzerland	1	17	60
CHL	Chile	1	1	2
CHN	China	25	127	550
CYP	Cyprus	1	1	2
DEU	Germany	17	43	101
DNK	Denmark	1	50	232
EGY	Egypt	2	12	58
ESP	Spain	8	100	464
FIN	Finland	2	6	22
FRA	France	17	99	344
GBR	Great Britain	57	368	1707
HKG	Hong Kong	36	351	1425
HUN	Hungary	1	1	1
IDN	Indonesia	4	45	173
IND	India	26	242	997
IRL	Ireland	5	22	81
ISR	Israel	5	23	82
ITA	Italy	10	88	361
JPN	Japan	70	604	2189
KOR	South Korea	14	61	273
LUX	Luxemburg	3	55	330
MCO	Monaco	1	4	10
MEX	Mexico	2	30	64
MYS	Malaysia	4	15	52
NLD	Netherlands	11	73	231
NOR	Norway	1	9	19
NZL	New Zealand	2	2	3
PAK	Pakistan	2	30	154
PHL	Philippines	3	7	12
POL	Poland	4	112	529
PRI	Puerto Rico	1	10	53
PRT	Portugal	3	52	187
QAT	Qatar	1	6	6
RUS	Russia	6	37	89
SGP	Singapore	10	104	431

ISO Country Code	**Country Name**	**Firms**	**Bonds**	**Bond-Years**
SWE	Sweden	5	5	16
TUR	Turkey	7	43	145
TWN	Taiwan	16	59	234
USA	United States of America	700	6182	32170
ZAF	South Africa	4	20	37
Total		1,221	10,470	50,138

Table C.4: Rating Conversion Scheme

Rating Conversion from Text to Numerical

Conversion	**S&P Debt Rating**	**Grade**
9	AAA	Investment
8	AA+	Investment
8	AA	Investment
8	AA-	Investment
7	A+	Investment
7	A	Investment
7	A-	Investment
6	BBB+	Investment
6	BBB	Investment
6	BBB-	Investment
5	BB+	Speculative
5	BB	Speculative
5	BB-	Speculative
4	B+	Speculative
4	B	Speculative
4	B-	Speculative
3	CCC+	Speculative
3	CCC	Speculative
3	CCC-	Speculative
2	CC	Speculative
1	C	Speculative
1	D	Speculative

5
Summary of the Findings

The chapters of this dissertation investigate the firm-level cost of climate change, the awareness of investors of the financial repercussions of climate change, the adaptation of supply-chains to climate shocks, as well as the implications of insider ownership and governance mechanisms for the pricing of corporate debt. The three studies are connected through their objective to better understand the interrelation between finance, firm behaviour, and socio-economic issues and generate new insights for corporate finance and investments by viewing societal challenges through a financial lens.

Chapter 2 addresses one of the biggest societal challenges of our time - climate change. The focus of this chapters lies on the firm-level impact of extremely high temperatures as the most pervasive, projected trend of climate change. Despite the projected global warming, it is not entirely clear whether extremely high temperatures affect the performance of listed firms, and in spite of the increased pressure on investors to disclose their exposure to climate-related risk, the question of whether investors anticipate that there is a link between heat exposure and financial returns remains open. To study both questions, I link firm performance records, analyst forecasts, and earnings announcement returns with four temporally and spatially high-resoluted, firm-specific measures of heat exposure. For the resulting international sample of 4,400 local firms, I subsequently estimate the financial effect of an increase in the number of days when firms are exposed to heat. The results show that an increase in firms' exposure to heat reduces revenues and operating income. Moreover, the results show that more days with extremely high temperatures cause more negative earnings surprises, which can be measured by errors in analyst forecasts and the returns after public earnings announcements. Altogether, the findings of the chapter indicate that extreme temperatures cause firm-level repercussions for performance, and that investors do not anticipate the economic implications of heat as a physical climate risk.

Chapter 3 investigates how firms share the cost of climate-related shocks through supply-chains, and adjust their production networks in response to adverse climate trends. For this purpose, I combine a large sample of global supplier-customer relationships with granular data on local temperatures and flooding incidents. The analyses based on this dataset show that the occurrence of climate shocks has both a large direct and indirect negative effect on earnings and revenues of suppliers and their customers. In addition, the analyses show that customers are 10% to 20% more likely to terminate existing supplier-relationships when realized climate shocks at the supplier firms exceed ex-ante expected climate shocks. Further, customers subsequently switch to suppliers with lower heatwave and flooding exposure. In sum, the results of the chapter indicate that climate change affects the formation of global production networks. With this result, the chapter is connected to the global goal to achieve sustainable economic development, as the responses of firms to climate change could reshape economic dynamics around the world.

In contrast to Chapter 2 and 3, Chapter 4 focuses on shareholder rights and the risk of expropriation, and closely connects to issues addressed in the new Shareholder Rights Directive II of the EU. In the chapter, I study the effect of insider ownership on corporate bond yield spreads from 2003 to 2014 using a sample of 10,470 bonds issued by 1,222 non-financial firms from 48 countries. The results indicate that greater insider ownership is associated with higher yield spreads. The positive relationship holds after controlling for measures of risk-taking, which shows that bondholders price-protect against greater insider ownership for reasons beyond insiders' heightened incentives to take risks. As another economic channel through which insider ownership hurts bondholders, I consider consumption of private benefits. The results in the chapter show that the positive association between insider ownership and the spread decreases for firms with relatively stronger shareholder rights, in which consumption of private benefits is less likely to occur. Furthermore, the chapter presents evidence that the probability of tunnelling through related-party transactions is larger in firms with more insider ownership. Therefore, the results support the conclusion that bondholders anticipate that greater insider ownership facilitates consumption of private benefits, with implications for the valuation of corporate debt around the world.

Taken together this dissertation investigates three different links between corporate finance and global challenges, and illustrates that this interrelation is a two-way street: First, Chapter 2 and 3 illustrate *how firms are affected* by a major societal challenge. Second, Chapter 3 focuses on *how firms respond* to climate change as a global challenge, and how this response could in turn affect sustainable economic development. In addition, investors can only help to bridge the gap between traditional corporate goals and societal goals in the face of global challenges if they anticipate how firms are affected by societal challenges, and incentivize firms to adjust their behaviour. Chapter 2 and 4 study these aspects, and investigate to what extent investors are aware of and responsive to firm behaviour that will affect the societal progress towards the sustainable development goals.

6
Research Impact

The global challenges which we face today call policy makers and regulators to attention. At the same time, their scope and urgency highlight that public institutions alone might not always be able to effectively manage them. In response to these issues, policy makers and international institutions call for support from the private sector. These demands create a close link between policy debates and business matters, and this dissertation ties into the resulting discussions at the interface of public policy and (corporate) finance. Thereby, the thesis generates insights for a variety of the actors and decision makers in the face of global challenges – including firms, investors, data providers, policy makers and regulators.

First, the dissertation emphasizes that climate change-related physical risks are financially material. However, firms cannot be expected to mitigate adverse effects if they are unaware of how their operations are financially affected. Despite the fact that firms are legally obliged to inform investors about any type of risk exposure that matters for the bottom line, the disclosure on the financial consequences of climate risks to date has been scarce. In a survey of S&P Global 100 companies, only 28 percent had undertaken some form of climate assessments (McKinsey, 2015). Therefore, a lack of awareness is a plausible hypothesis for the lack of reporting. As Chapters 2 and 3 indicate that heat exposure and floods negatively affect firms' financial performance directly and indirectly through supply-chain links, they underline the demand for enhanced corporate reporting.

Moreover, the thesis indicates that investors do not fully anticipate the financial repercussions caused by the physical effects of climate change. Again, a plausible hypothesis for this observation is that the disclosure of firms on these effects has been limited. Hence, the results in this thesis lend support to the initiatives of the TCFD, and directly connect to the suggestions of the EBRD, which aim to establish common reporting standards. According to the EBRD, "corporations should consider all first-order impacts when undertaking a physical climate risk assessment: heat stress, extreme rainfall, drought, cyclones, sea-level rise and wildfires", and Chapter 2 particularly supports the case of heat stress. Moreover, through the use of highly granular data on firms' exposure to heat in combination with financial performance records, Chapter 2 can be seen as an illustration of how investors can quantitatively assess their exposure to climate hazards.

Further, the research design of Chapter 2 and 3 illustrates the need for new research and data collaborations across two otherwise hardly related disciplines: climate science and (corporate) finance. The need consolidated climate and financial data extends beyond the world of research to investment practice. Until now, investors who are concerned with sustainability issues largely rely on so-called ESG ratings. However, as the findings in the chapters highlight that climate risks are financially material and that firms adapt to climate shocks, ESG ratings might insufficiently cover some of the most evident societal challenges that companies are facing today.

In addition, the results highlight that firms' management of climate change is directly related to firms' management of supply-chains. However, in times of global production networks, there is often a lack of supply-chain visibility. This low visibility means that firms are often not even aware of their geographical footprint, let alone their risk exposure to climate change along the supply-chain. Furthermore, the results indicate that supply-chain adaptation could become a concern to policy makers. While it is evident that particularly the societies and economies in developing countries will suffer disproportionately from climate-change impacts (e.g. Burke et al. (2015b); Carleton and Hsiang (2016)), the magnitude of the adverse effects in developing countries will still largely depend on the economic dynamics that climate change induces. If climate change reduces economic activities disproportionately in areas that are particularly exposed to climate change – for example, as firms in these regions become less attractive as supply-chain partners as indicated in Chapter 3 – firms' adaptation strategies could run counter to the sustainable development goals.

The same feedback loop is also important for another group of actors in the face of global challenges: Investors committed to so-called ESG engagement. If firms are financially harmed by the climate vulnerability of their suppliers, firms can decide to abandon these suppliers – and as Chapter 3 shows, they might often face financial incentives to do so. However, an alternative opportunity could lie in engaging with these suppliers, and to reduce their risk exposure to the minimum possible level so that the relationships can be maintained. If the more natural alternative to abandon heavily exposed suppliers has adverse consequences for sustainable development, it is important that investors encourage target firms to investigate if this alternative approach is feasible. In general, supply-chains have recently received more attention (Principles for Responsible Investment, 2017) in the broader context of ESG issues, and hence, the dissertation points to climate adaptation as an important future topic on the agenda for shareholder engagement.

On a different note, Chapter 4 backs a well-known policy issue in improving corporate governance: There is no one-size-fits-all approach. The chapter shows that equity ownership of corporate insiders such as managers and board members is positively related to bond spreads. Further, this finding indicates that bondholders associate insider ownership with heightened levels of risk. However, the observed link is weaker if firms have adopted stronger shareholder rights provisions – despite the fact that such provisions are known to concern bondholders when ownership structures are not taken into account. Hence, effective policy initiatives have to consider different dimensions of corporate governance in conjunction. Moreover, the bond markets' pricing of insider ownership has implications for the disclosure practices of related-party transactions and mechanisms to tackle expropriation by insiders. Chapter 4 argues that bondholders expect the consumption of private benefits to increase with insider ownership. Also, it shows that this expectation can be fuelled by related party transactions, which are more likely to occur in firms with more insider ownership. These aspects have been a long-standing concern among policymakers (OECD, 2012), and have also been taken up again in the recent SRD II.

Altogether, the enclosed studies on the financial economics of climate change and the agency cost of debt help to meet a new demand for research at the interface of (corporate) finance and global sustainability challenges. This demand has recently been expressed as the Dutch Central Bank has brought a Climate Risks Working Group to life (De Nederlandsche Bank, 2018), with the establishment of the Technical Expert Group on Sustainable Finance (TEG) of the European Commission (European Commission, 2018), and as central banks and supervisors have founded the Network for Greening the Financial System (NGFS) (Banque de France, 2019). The topics of this dissertation speak to both policy makers and central banks, and parts of the thesis have been presented both to the TEG at the European Commission in Brussels and the NGFS at the Bundesbank in Berlin.

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Curriculum Vitae

Nora Miriam Careen Pankratz was born on 24 April 1992 in Heuchelheim, Germany. She attended high school at the Herderschule in Giessen, obtained a B.Sc. in Business Administration from the University of Mannheim in 2013, and an M.Sc. in International Business, Sustainable Finance from Maastricht University in 2015.

In 2015, Nora joined the Finance Department and the European Center for Sustainable Finance at Maastricht University as a Ph.D. candidate under the supervision of Rob Bauer and Jeroen Derwall. She presented her work at international conferences and seminars at London Business School, the University of Toronto, Miami, Geneva, Reading, Zurich, Victoria, Goethe Universitaet Frankfurt, HEC Paris, HEC Liege, KU Leuven, the Bundesbank, and the European Commission. Furthermore, Nora has taught graduate and undergraduate finance and business ethics courses and has received the Finance Department Education Award in 2017.

In 2017, Nora attended Toulouse School of Economics as a visiting scholar hosted by Sebastien Pouget. In 2018 and 2019, she visited Rotman School of Management at the University of Toronto hosted by Mike Simutin. Moreover, she has been guest researcher at 427 Climate Solutions in Berkeley, California in 2018. A research grant from the French Social Investment Forum (FIR) and the Principles for Responsible Investment (PRI) awarded in 2017 facilitated the funding of these visits.

Since September 2019, Nora is a postdoctoral researcher at the Luskin School of Public Affairs, Department of Public Policy, and the Luskin Center for Innovation at the University of California, Los Angeles.