RUHR
ECONOMIC PAPERS

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At Boiling Point: Temperature Shocks in Global Business Groups

#905

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
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Editors

Editorial Office

Ruhr Economic Papers #905

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-96973-046-1

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Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973046
ISSN 1864-4872 (online)
ISBN 978-3-96973-046-1

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At Boiling Point: Temperature Shocks in Global Business Groups

Abstract

This paper investigates the impact of temperature on operating revenue as a measure of economic output for more than a quarter of a million business group firms operating in 32 countries. For this purpose, we construct a novel global dataset that combines information on firm financials, ownership and location with global data on heat and precipitation from 2002 to 2012. The temperature-output-relationship takes a non-linear shape, with particularly strong negative effects at high temperatures. On average, an additional day with temperature above 32°C decreases annual operating revenue by 1.3%. This effect is driven by firms that operate in countries with relatively hot climates, i.e. average yearly temperature above 13°C. We then assess if shocks propagate within firm networks with exposure to these countries. We find that the weighted local shocks from subsidiaries translate into an on average drop in annual headquarter operating revenue by 4.2% per additional heat day. The estimates suggest that, under future warming, specific business group production networks might be severely impacted by heat-induced output losses.

JEL-Code: D22, F23, Q54

Keywords: Climate change; temperature extremes; multinational corporation

April 2021

1 Michael Themann, RWI. - I am grateful to Nicolas Koch, Leonie Wenz, Manuel Frondel, Christoph M. Schmidt and Nils aus dem Moore for helpful comments and suggestions. Claudia Günther provided excellent research assistance. – All correspondence to: Michael Themann, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: michael.themann@rwi-essen.de

1 Introduction

The scientific evidence for anthropogenic climate change is overwhelming. The global mean temperature is projected to increase by 2.6 - 4.8°C by the end of this century which would entail major consequences for ecosystems, economies and societies (Field et al. 2014; Pachauri et al. 2015). Although the economic costs associated with these impacts are generally expected to decrease average global incomes by 2100 (Burke et al. 2015), fundamental questions on the eventual size, distribution and functional form of the social cost of carbon and its underlying drivers still persist. In a warming world, addressing these questions is crucial to properly design effective policy responses both in terms of mitigation and adaptation. Recent empirical studies have thus sought to provide an empirical basis for the so-called damage function, the central component of Integrated Assessment Models (IAMs) that are commonly used to estimate the economic costs of climate change. Until recently IAMs have been widely challenged as lacking a sufficient theoretical and empirical foundation in this important aspect (Pindyck 2013; Stern 2016).

Extreme weather and high temperatures in particular have been identified as one of the main drivers that strongly lower local economic output in many world regions (Dell et al. 2014; Carleton and Hsiang 2016). At the same time, the world economy has grown increasingly integrated. This poses the question if local shocks can be transmitted between firms, sectors and countries. Business groups are an important pillar of the global economy. For instance, multinational companies account for around a third of total global output and half of global exports (OECD 2018). These companies integrate supply, production and sales within their firm networks that can span different economic sectors, world regions and climatic zones (Altomonte and Rungi 2013). Despite this economic importance, the potential impacts of climate change on global business groups and the potential transmission of shocks within their networks has received relatively little attention by policymakers.

This study aims to contribute to this discussion by estimating the impact of temperature on economic output for more than a quarter of a million business group firms operating in 32 countries. In a second step, we identify the sources of temperature shocks by assessing different responses across climatic regions. In a third step, we aggregate local weather variation at the subsidiary level and estimate its impact at the level of the business group headquarter to investigate whether temperature shocks propagate within business group networks.

For this purpose, we construct a novel dataset that combines information on firm financials, ownership and location with global data on temperature and precipitation from 2002 to 2012. We focus on the climate impact channel with the most direct first-order effects, i.e. the impact of temperature on output and economic performance (Carleton and Hsiang 2016). The empirical framework draws from the advances of recent empirical studies in terms of data and methodology (Dell et al. 2014). It utilizes yearly exogenous variation in local weather to identify the effect of temperature on operating revenue as a measure of a firm's economic output. We employ a semi-parametric approach that allows for non-linear temperature effects. The annual temperature distribution is divided into bins and the effect of each bin is estimated all while maintaining the daily variation in temperature to accurately depict the impact of heat days.

The key assumption to identify the effects is that weather is random conditional on a set of time-invariant and time-varying factors. In this vein, we utilize the panel structure of our data to isolate the effect of weather on firm operating revenue from any confounding factors. Given the overlap in current and future weather distributions, the approach can provide us with a useful estimate of potential medium-run impacts of climate change induced heat stress. It also enables us to learn about adaptation by analyzing different responses in different world regions and climatic zones.

The results show that the temperature-output-relationship takes a non-linear shape, with particularly strong negative effects at high temperatures. On average, an additional day with temperature above 32°C decreases annual operating revenue by 1.3%. This effect is driven by firms that operate in countries with hot climates, i.e. average yearly temperature above 13°C. We then assess if shocks propagate within firm networks with exposure to these countries. We find that the weighted local shocks from subsidiaries translate into an on average drop in annual headquarter operating revenue by 4.2% per additional heat day. This is in line with previous empirical findings which have indicated that economic impacts can be greatly aggravated if important firm relationships (e.g. supplier-customer) are affected by the shock, especially if it results in important inputs shortages (Wenz and Levermann 2016; Giroud and Mueller 2019). Since our data consists of stable, long-term owner-subsidiary relationships, it appears plausible that the estimates we obtain capture losses incurred by the specific structure of economic dependencies within the firm network. The estimates would then suggest that, under future warming, specific business group production networks might be severely impacted by heat-induced output losses.

Related studies The contributions of this study relate to two fields of research. First, the new field of climate econometrics has shown that non-linearities in responses to temperature exposure are a key factor that can drive costs to levels many times above previous estimates (Heal and Park 2016; Burke and Tanutama 2019). Studies have demonstrated that temperature increases can substantially reduce average global incomes (Burke et al. 2015), increase global inequalities in economic output (Kalkuhl and Wenz 2018) and can be particularly important for economies that are well integrated in the world economy (Zhang et al. 2018).

Analyzing the impacts of temperature on output in a global context remains challenging due to limitations with respect to econometric identification and data availability. Cross-country studies use data at the sector, county or country level and thus cannot adequately control for heterogeneous firm responses. Studies that do use firm data are often constrained to analyzing a single sector in a specific country. This paper attempts to resolve these issues by delivering a cross-country analysis based on global firm data that accounts for firm, sector and country heterogeneity. The results confirm previous findings of a non-linear temperature-output-relationship with strong responses at high temperatures for a cross-country sample of business group firms that comprises different world regions and climatic zones. We also find that responses to heat are particularly robust and driven by companies that operate in countries with average yearly temperature above 13°C.

Second, this study provides new evidence on the transmission of shocks in business groups. The economic response in production networks to external shocks is a long-standing issue in theoretical and empirical studies (Bena and Erel 2017). Most empirical studies lack data that consistently combines information on firm ownership with financial data. Hence, they do not identify global firm networks across time and space. The difficulty of finding the exogenous variation that is needed to properly identify shocks in these networks further contributes to the scarcity in empirical studies.

In this field, the contributions of this paper are manifold. First, our dataset allows us to identify and track firm networks consistently across time, space and different climate areas. Second, utilizing exogenous variation in weather jointly with panel data the research design aims to identify shock transmission isolated from other factors that may impact the economic output of business groups. Third, this paper delivers a first attempt at providing evidence on vertical spillovers that occur upstream, i.e. from a subsidiary to the headquarter. It also sheds light on a key factor in shock transmission by focusing on long term headquarter-affiliate-relationships that are potentially of strategic importance to the network. Fourth, empirical results indicate that shock transmission occurs by exposure to countries with hot climates via long-standing network relationships. At the same time, transmitted shocks are more sizeable than the initial local shocks. This suggests that local shocks may be absorbed to some degree by the network. In this sense, this paper complements recent empirical research on the propagation of natural disasters in production networks (Barrot and Sauvagnat 2016), that sales growth between subsidiaries and headquarters co-move and that source-country shocks are transmitted to foreign affiliates (Cravino and Levchenko 2017) and that network structures can provide additional resilience to their subsidiaries (Giroud and Mueller 2019). In the context of the economy-climate literature, these cross-border and transmission effects, although potentially critical for damage functions, remain largely under-investigated (Dell et al. 2014). The findings contribute to recent sector-level studies that show that local temperature induced losses can cascade through value chains (Wenz and Levermann 2016).

The remainder of this paper is structured as follows: Section 2 details the identification strategy. Section 3 describes the data. Section 4 presents the empirical results. Section 5 concludes with a discussion of the results.

2 Empirical framework

To design our empirical strategy, we bring together the insights from the literature on climate econometrics and global business group production.

First, we follow the semi-parametric approach by Deschênes and Greenstone (2011) that allows temperature to affect economic output in a non-linear shape. Measuring the potential non-linear impact of temperature on different economic and non-economic outcomes in such a way is well established (e.g. Deryugina and Hsiang (2014) and Auffhammer (2018)).

For this purpose, we divide the annual temperature distribution into $m = 1 \ldots 10$ bins and estimate the effect of these bins on economic output. Each temperature bin m corresponds to the number of days per year that fall into the given category. Utilizing the data in such a way preserves the daily variation in temperature which is important to accurately depict the impact of a certain heat day on economic output (Dell et al. 2014). For instance, $m = 3$, counts the number of days at a certain location that fall into this bin (]-7°C,-1°C]) in a given year. The bins are constructed at a 6-7°C width with temperatures below minus 12°C at the lower end and temperatures above 32°C at the upper end. The full list of 10 bins is thus the following in °C:]-12; [-12,-7];]-7,-1];]-1,4];]4,10];]10,16];]16,21];]21,27];]27,32];]32. We apply the standard practice to omit the middle temperature bin bin (in our case:]16,21]) to avoid multicollinearity (Zhang et al. 2018). Results are robust to omitting alternative bins.

The main identifying assumption is that variation in weather is random conditional on a set of fixed effects (Deschênes and Greenstone 2007; Deschênes and Greenstone 2011; Auffhammer 2018). Conditional on these controls, the coefficient β_1^m is a semi-elasticity that measures the marginal effect of an additional day in temperature bin m relative to a day in the 16-20°C bin (Zhang et al. 2018). This approach has strong identification properties as, under these conditions, it appears very plausible that weather variation is exogenous (Blanc and Schlenker 2017; Dell et al. 2014). These considerations result in the following baseline specification. For firm i in year t, we model a log-linear regression specification:

$$\ln y_{it} = \sum_m \beta_1^m T_{it}^m + \delta W_{it} + D_{it} + X_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} is the operating revenue and T_{it}^m is the number of days in year t experienced by firm i with daily temperature that falls in bin m. In addition, we include both linear and quadratic effects of precipitation in vector W_{it} which is a standard practice to account for general weather conditions (e.g. Blanc and Schlenker (2017), Burke and Emerick (2016), and Kalkuhl and Wenz (2018)).

We exploit the panel structure of our data to isolate the effect of weather on economic output from any time-invariant and time-varying factors that could be associated with temperature and economic output. Accounting for these sources of omitted variable bias has been a major contribution in the recent literature (Hsiang 2016). We therefore include vectors of fixed effects D to account for observed and unobserved heterogeneity.

Included are firm fixed effects, country-industry-specific characteristics (such as technology), sector-year fixed effects (such as overall technological progress, changes in input or output prices), and country-year fixed effects (country-specific annual shocks such as economic progress). We also include a set of control variables X_{it} to account for important time-variant developments at the firm level, such as firm growth. However, these variables can be affected by weather and are potentially endogenous. We thus follow Barrot and Sauvagnat (2016) and instead include dummies for each tercile of the yearly distribution of each control variable (total assets, return on assets and firm age) interacted with year-dummies.

Second, we adapt the approach by Barrot and Sauvagnat (2016) and conduct a two-step analysis to estimate the impact of external shocks on global business groups. In a first stage, we estimate specification 1 for a global sample that contains all companies that are part of a business group at some point in time. This provides us with a comprehensive picture of this fundamental part of the global economy. These results are then tested in terms of robustness. In a second step, we analyze how temperature shocks at the subsidiary level affect economic outcomes at the level of headquarters.

Short-term weather data provides a great deal of variation to properly identify the causal effects of temperature on economic performance, especially in a global sample with a great variety of locations. In addition, it can help to provide an intuition on medium-term impacts of climate change since, for most locations, there is a substantial overlap between the distributions of current weather and future weather (Hsiang 2016; Dell et al. 2014). Hence, while climate change will shift its distribution, temperature will largely remain within the historical support. This enables us to learn to some degree about the propensity of adaptation under future warming (Dell et al. 2014). For instance, if hot regions already suffer from negative impacts of high temperatures, these effects may continue and the potential for adaptation may be limited. For this purpose, we conduct a heterogeneity analysis to identify differences in responses in different world regions and climate zones. In addition, we assess if firms operating under moderate to hot climates have already adapted to extreme heat days and thereby give an indication of the potential for future adaptation.

Some limitations to the econometric approach remain (Hsiang 2016; Dell et al. 2014). Our estimates may underestimate actual outcomes if the current distribution does not contain observations on important future events. For instance, the surpassing of tipping points in the earth system may lead to non-linearities that can increase costs beyond current estimates (Steffen et al. 2018; Lemoine and Traeger 2014). Also, our approach may overestimate future impacts if adaptation becomes more viable, e.g. via innovation or economic growth. However, persistent impacts in developed and developing economies suggest until now that economic convergence may not necessarily offset the problem (Burke and Tanutama 2019).

3 Data

We construct a novel database that is suitable for assessing the impacts of weather variation on business groups in a global cross-country setting. For the period of 2002-2012, we bring together three sources of raw data: Firm financial data and information on firm ownership from ORBIS and weather data from the WATCH-Forcing-Data-ERA-Interim meteorological data set (WFDEI).

3.1 Firm financial and location data

Our main source of data is the ORBIS database as provided by Bureau van Dijk (BvD). ORBIS compiles firm data from administrative sources, such as detailed balance sheets, income statements, and profit and loss accounts. The database is constantly being updated and particularly suitable for cross-country comparisons: Information on firm financials and ownership is harmonized across countries and delivered in a global standard format. The financial data we use was retrieved by BvD in the last week of November 2015. The data comprises all firms above total assets of 2 million Euro, a turnover of one million Euro, or a total number of 15 employees in 2015. This corresponds to a sample of around 12.5 million firms. Our financial accounting data is reported in thousands of Euros for the years 2002-2012. We employ unconsolidated financial data from local registry filings to ensure a high quality of the raw information. Industries are classified according to their four-digit industry NACE Rev. 2 codes.

We then follow a thorough four-step procedure of data cleaning that is based on Gopinath et al. (2017). First, we account for reporting mistakes and drop observations with missing information or implausible values. Second, we assess the internal consistency of the balance sheet data. For example, we calculate the sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of their respective aggregate, i.e. total fixed assets. [1] We then estimate the distribution of this ratio and remove extreme values (below the 0.1 percentile and above the 99.9 percentile. Third, we control the quality of all variables that are part of our analysis more specifically. Fourth, we winsorize these variables at the 1 and 99 percentiles. In addition, we account for missing values by interpolating data for one period, i.e. if data is missing for one year between two periods with reported values for the respective variable.

In order to properly identify shocks in business groups, we then account for firm-year observations that exhibit a lot of noise or can be related to shell firms. For this purpose, we drop any firms that are part of the financial services industries and government-related sectors (Bena and Erel 2017).

[1] This process is also applied to the following aggregates: total assets, total current assets, total shareholder funds and liabilities.

All nominal variables used in our analysis are deflated with a yearly GDP price deflator as retrieved from the Worldbank.[2] This procedure ensures that the growth rates of the variables are not driven by price changes (Gal 2013). After deflating all financial covariates over time, we account for price differences across countries. We then convert them into a common currency (USD). In order to mitigate the influence of fluctuating exchange rates, we fix the exchange rate at the middle of the sample period, in 2007 (Gal 2013).

We then identify latitudes and longitudes for each firm location. For this step, we apply algorithms provided by OpenCage and Google[3] to the address data contained in ORBIS (street, postal code, city, region and country) to obtain each geographic location. For each country, we conduct a thorough testing process and assess (i) general quality of the match and (ii) precision based on the respective indicators provided by each algorithm. We also compare geo-coded output on location and addresses with the address data in ORBIS and own identification done via Google Maps and Open Street Maps. We then account for systematic matching errors and adjust the matching algorithms accordingly. For 94% of the matched sample, the precision is very high, i.e. within a grid cell radius of less than 2 km. For 4%, the grid cell radius is less than 15 km. We remove any firms with a grid cell radius above 15 km (2%). Given that the spatial correlation of weather is very high, especially in small geographical grid cells, measurement error should be minimal (Auffhammer et al. 2013). In sum, this indicates a very high matching quality.

3.2 Weather data

Weather data is obtained for the period of 2002-2012 from the WATCH-Forcing-Data-ERA-Interim meteorological data set (WFDEI, Weedon et al. (2018) and Dee et al. (2011)). This dataset provides extensive coverage on a complete global grid all while providing the variation of high frequency daily average weather data.[4] In contrast, many other datasets either suffer from incomplete coverage in certain world regions and/or deliver only monthly weather averages. We refer to Dell et al. (2014) and Auffhammer et al. (2013) for an overview and discussion of different weather data types in the context of econometric analyses. Subsequently, temperature data is converted into Celsius and sorted into bins. Annual precipita-

[2] As retrieved from https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS

[3] Available on https://opencagedata.com/ and https://developers.google.com/maps/documentation/geocoding/

[4] ERA-interim reanalysis data combines information from ground stations, satellites and other sources with a climate model to create gridded weather data and extend global coverage. This data is then bias corrected such that the monthly temperature means correspond to observational data.

tion is obtained by adding snowfall to rainfall data, converted into mm/day and aggregated to a full year.[5]

We then match the geographic location of each firm in ORBIS with the corresponding 0.5x.0.5 grid cell in the WFDEI data. We also match each firm location with its respective administrative area as contained in the GADM database of Global Administrative Areas.[6] Matching and mapping exercises are conducted via shape files and algorithms in GNU R. Hence, we obtain for each firm-year-combination in ORBIS the average weather in the respective cell. For the matched ORBIS dataset, Figure 1 plots the distribution of unique firm observations along with the temperature data on a world map (Figure 2: Europe). Administrative areas are presented according to the GADM classification system. For each area, we calculate (i) the average daily temperature based on the corresponding grid cells and (ii) the total number of firms. Black dots constitute administrative areas with less than 10,000 firms (Figure 2: 200 firms). Bubbles represent areas with up to more than 70,000 firms (Figure 2: 1,000 firms). Regions are ranked with respect to their heat exposure using the average number of days with average temperature above 27°C in 2002-2012. The dataset covers a wide range of climatic zones. As it is common in ORBIS, data availability differs substantially across world regions. While most firms are concentrated in European countries, the sample still covers firms from non-European countries. We then apply the three country-based criteria established by Cravino and Levchenko (2017) to construct data that is suitable for a global analysis of firm networks in ORBIS: (i) countries need to have at least 750 firms on average in 2002-2012, (ii) aggregate revenues in ORBIS need to cover at least 40% of aggregate economic output and (iii) the correlation between the growth rates in GDP as measured by the Worldbank and in aggregate revenues in ORBIS needs to be above 0.50. We then limit our sample to the 32 countries that jointly meet these criteria.[7] We consider such an approach crucial for obtaining empirically meaningful results both in terms of a consistent global analysis of business groups and the analysis of shock transmissions within them.

For the heterogeneity analysis, we divide our sample broadly along the lines of the standard Koeppen-Geiger climate classification system (Beck et al. 2018) and define countries with average yearly temperature above 13°C as having a moderate to hot climate. For the

[5] The data was provided by the Inter-Sectoral Impact Model Intercomparison Project (https://www.isimip.org/). We thank Leonie Wenz and Stefan Lange for their continued guidance on this data and the necessary processing steps. The steps were conducted via Python.

[6] The data can be retrieved from https://gadm.org/

[7] The selected countries are Austria, Australia, Belgium, Bulgaria, the Czech Republic, Germany, Estonia, Spain, Finland, France, Great Britain, Greece, Croatia, Hungary, Ireland, Italy, Japan, South Korea, Lithuania, Latvia, the Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Singapore, Slovenia, Slovak Republic, Turkey and Ukraine.

period of our analysis, this definition applies to 10 out of 32 countries in our sample.[8] In practice, we utilize the WFDEI data and calculate yearly temperature in the sample period of 2002-2012. We then split our sample accordingly in two subsamples: one with moderate to hot climates (subsequently "Southern sample") and one with moderate to cold climates ("Northern sample").

[8]The selected countries for the Southern sample are Australia, Bulgaria, Croatia, Greece, Italy, Portugal, Romania, Singapore, Spain and Turkey. This corresponds for instance to countries with mostly dry or hot summer climates under the Koeppen-Geiger classification (Beck et al. 2018).

Figure 1: Firm coverage and temperature distribution: World

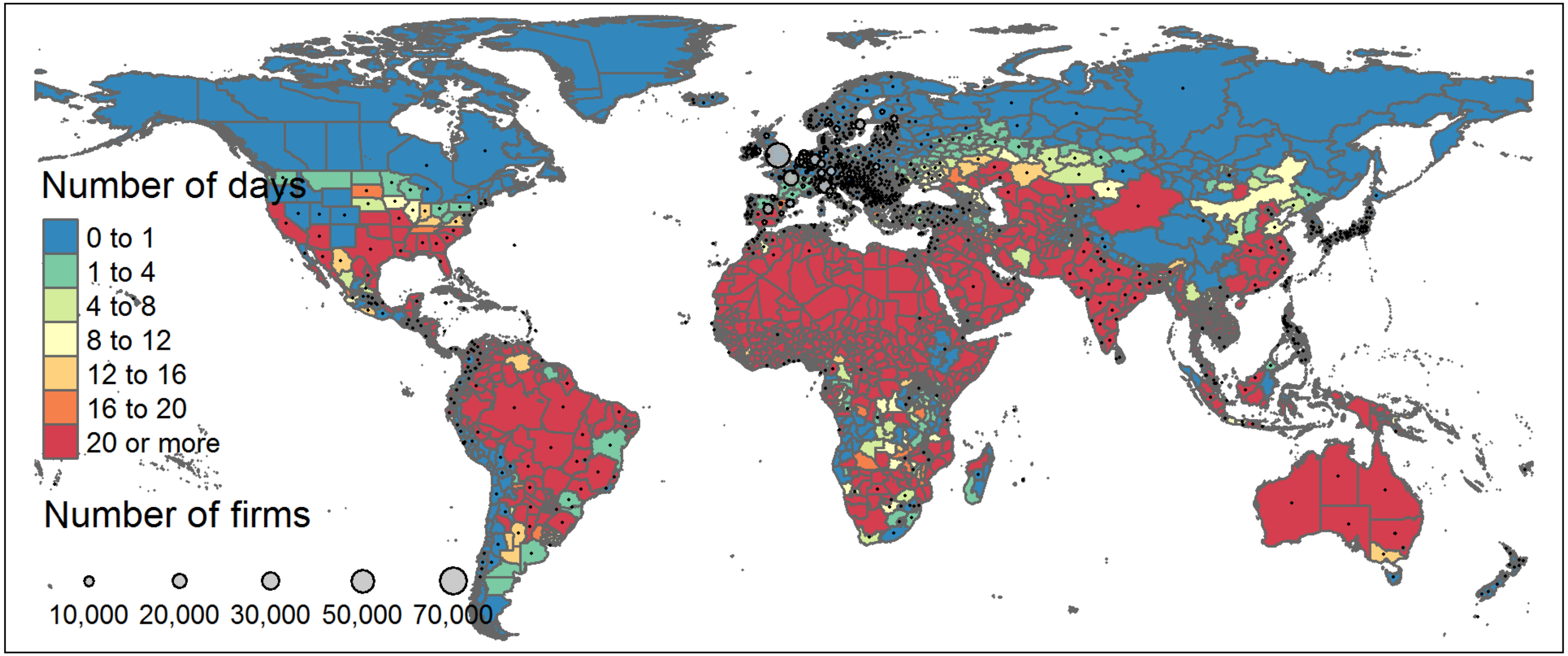
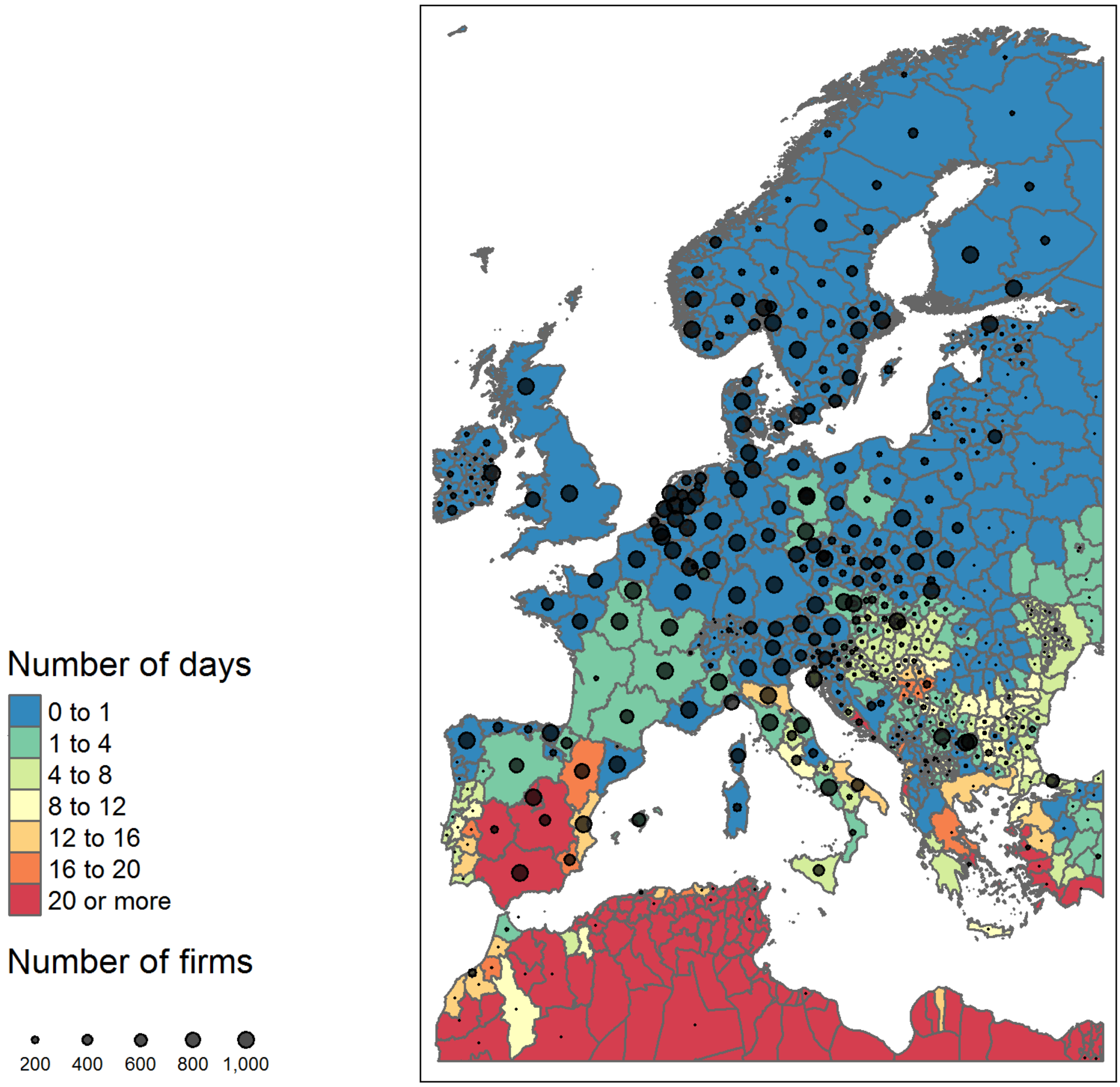


Figure 2: Firm coverage and temperature distribution: Europe



3.3 Ownership data

We utilize a novel dataset on firm ownership as prepared in aus dem Moore et al. (2019). This dataset identifies business groups based on the raw information on firm ownership in ORBIS. In principle, firms with more than 50.01% ownership shares are linked until the top of the command chain is reached. This allows the identification of each firm belonging to a certain network along with the network's global ultimate owner (GUO). For a detailed description of the methodology we refer to aus dem Moore et al. (2019). The novelty of this approach is that, unlike the static approaches employed in the vast majority of empirical studies, the data allows to track ownership relations across time, i.e. for each firm and each year in 2002-2012. Many empirical studies have used time-invariant information based on the last year of the panel thus introducing a potentially strong measurement error.

However, the yearly ownership data contains substantial amounts of noise as the data in ORBIS is constantly updated and extended (aus dem Moore et al. 2019). Missing information over longer periods of time can impede the proper tracking of network structures and severely hamper the identification of shock transmission (Cravino and Levchenko 2017), e.g. through unobserved changes in ownership.

We therefore clean the data in various steps. First, we fill in ownership gaps if the information before and after the gap is identical.[9] Second, we require firms to report at least ownership information for one year meaning that they are either a subsidiary and/or a GUO at some point in time and thus discard any firms with continuously missing information.

Table 1: Summary statistics: Firm financials (in logs)

	Mean	Std. Dev.
Operating revenue	4.92	2.58
Total assets	4.97	2.55
Return on assets	-2.76	1.35
Firm age	2.61	0.91

Summary statistics are reported in Tables 1 and 2. Table 2 shows that the final sample contains around a quarter of a million firms (Column 2) that at some point between 2002 and 2012 are either a subsidiary (Column 4) and/or a GUO (Column 6). The sample is comprehensive in size for both firm types (subsidiaries: 213,931, GUOs: 67,474). It is also dominated by firms operating in European countries (around 240,000) but still retains around 10,000 firms from the rest of the world and covers a range of climatic zones.

Table 2: Summary statistics: Firm observations

	# Obs	# Firms
Total	1,971,108	250,767
Subsidiaries	1,184,481	213,931
GUOs	253,839	67,474
Indep/Miss	532,788	172,030

Note: Number of subsidiary firms plus number of GUO firms exceeds number of total firms as firms can be subsidiaries and GUOs at different points in time.

Note that there is still a substantial amount of observations with missing ownership information (Column 7, "Independent/missing") as the availability of ownership data in OR-

[9]For instance, if a subsidiary is owned by the same firm in the years 2002 and 2004, but the information in the year 2003 is missing, we take this firm as the respective GUO in year 2003. This is done for up to four consecutive years. The vast majority of observations recuperated from this step stems from one-year gaps.

BIS gradually increases over time. Two thirds of firms are affected by missing data at least to some degree (Column 8). Third, for the spillover analysis, we thus focus on relationships where in the period of 2002-2012 a subsidiary has (i) full ownership information and (ii) is owned by the same GUO. While this step does substantially reduce sample size, it allows us to focus on high quality, stable business group firm data that is suitable to properly identify the transmission of spillovers in a panel data context. The "spillover" sample still contains more than 5,100 GUOs that own a total of around 105,000 subsidiaries.

4 Empirical results

4.1 Main results

Table 3 presents the results for our baseline and preferred specification.

For the baseline specification (Column 1), effects for the hot section of the temperature spectrum are highly significant at the 1% level for temperatures between 27 and 32°C and above 32°C. In economic terms, the magnitude of the effect of extreme temperature days are important. Relative to a day in the 16-20°C bin, an extra day with temperature above 32°C decreases annual output by 1.3% (0.1% for temperature between 27-32°C). Some coefficients for the cold section are significant at the 5% level. However, these effects are minor in terms of magnitude. Relative to a day in the 16-20°C bin, an extra day with temperature in the minus 12°C-minus 7°C bin decreases annual output by 0.1% (0.07% for temperature between minus 7°C and minus 1°C).

Figure 3 illustrates the non-linear shape of the temperature-output relationship. For this purpose, we plot the point estimates and the corresponding 95% confidence intervals for each ${\beta_1}^m$ as in our baseline specification.

4.2 Robustness

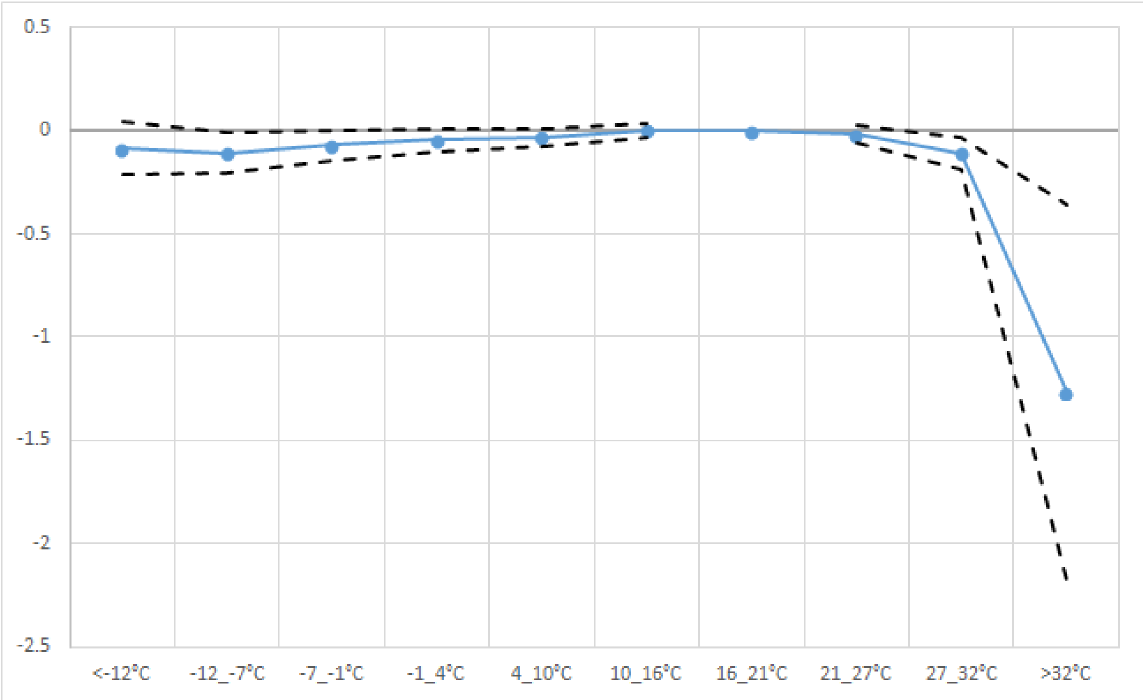
A source of potential bias may arise if past temperatures affect both contemporaneous economic outcomes and temperature (Deschênes and Greenstone 2011). We account for this and augment the baseline specification by controlling for weather with a one-year lag. Column 2 in Table 3 shows the coefficients when jointly estimating current and lagged temperature bins. The shape of the relationship between output and current temperature remains very similar to the original findings. Our main results in terms of heat appear to be robust to

Table 3: Temperature effects on firm output

	Baseline	Baseline + Wit-1
	(1)	(2)
]- 12°C	-0.0009	0.0001
	(0.0007)	(0.0006)
[- 12°C, - 7°C]	-0.0011**	-0.0007
	(0.0005)	(0.0005)
]-7°C,- 1°C]	-0.0007**	-0.0003
	(0.0004)	(0.0003)
]- 1°C, 4°C]	-0.0005	-0.0002
	(0.0002)	(0.0003)
]4°C, 10°C]	-0.0003	-0.0001
	(0.0002)	(0.0002)
]10°C, 16°C]	0.0000	0.0000
	(0.0002)	(0.0002)
]21°C, 27°C]	-0.0002	-0.0002
	(0.0002)	(0.0002)
]27°C, 32°C]	-0.0011***	-0.0010**
	(0.0004)	(0.0004)
]32°C	-0.0127***	-0.0128**
	(0.0046)	(0.0050)
precipitation	1.31	1.59
	(1.577)	(1.567)
precipitation^2	-26.43	-21.64
	(39.020)	(38.872)
Firm FE	Yes	Yes
Year x country FE	Yes	Yes
Country x industry FE	Yes	Yes
Year x industry FE	Yes	Yes
Control variables	Yes	Yes
Temperature, precipitation t-1	-	Yes
Observations	1,511,588	1,287,622

Note: Standard errors (in parentheses) are clustered at the firm level.* p<0.10, ** p<0.05, *** p<0.01.

Figure 3: Non-linear temperature effect on firm output



this potential bias. In contrast, bins at the cold part of the temperature spectrum are now insignificant.

In addition, the impact of lagged temperature on output is highly insignificant. These results are consistent with the tests conducted in previous studies on the shape of the output-temperature relationship (e.g. Deschênes and Greenstone (2011), Burke and Tanutama (2019), and Zhang et al. (2018)). We include lagged temperature for the subsequent analysis for additional robustness as our preferred specification.

4.3 Heterogeneous treatment effects

A heterogeneity analysis provides a number of insights. First, we identify differences in responses in different world regions and climate zones. Second, we can assess if firms operating under moderate to hot climates have adapted to extreme heat days and thereby provide some insights of the potential for adaptation under future warming.

Table 4 presents the results for our preferred specification in the hot and cold countries. For the sample of comparatively hot countries, effects for three temperature bins of the hot part of the spectrum are highly significant at the 1% level (21-27°C bin, 27-32°C bin, and >32°C bin). Again, the magnitude for the coefficient of extreme heat days is economically important. Relative to a day in the 16-20°C bin, an extra day with temperature above 32°C

Table 4: Temperature effects on firm output: Heterogeneity

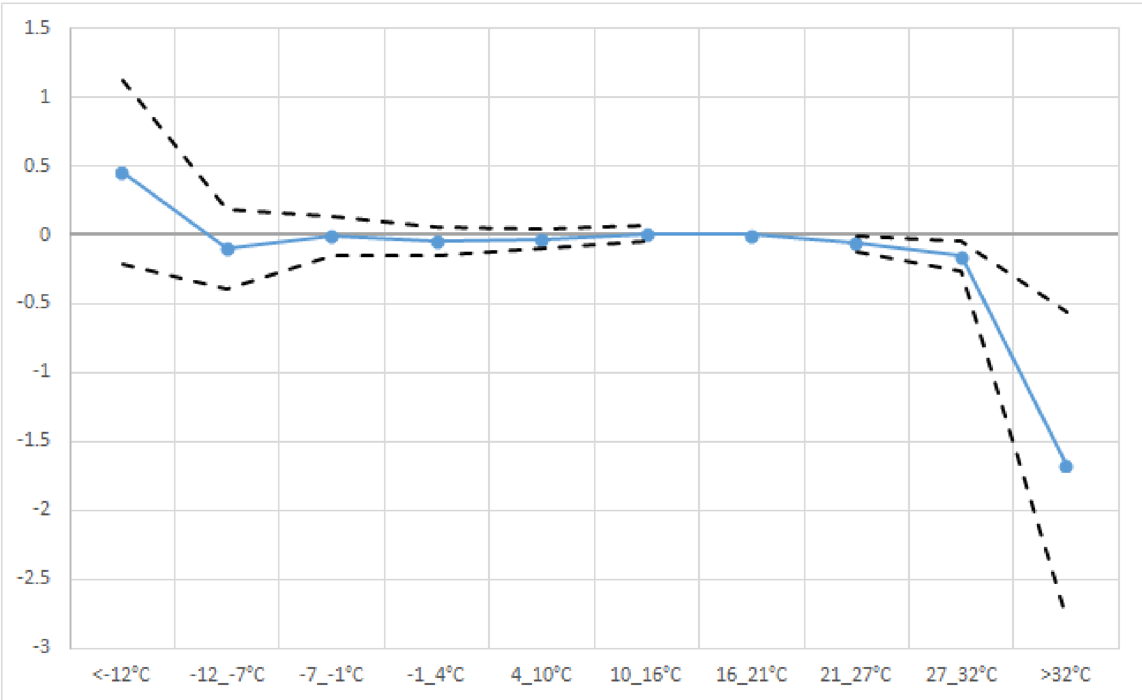
	Baseline	Southern Countries	Northern Countries
	(1)	(2)	(3)
]- 12°C	0.0001	0.0052	0.0001
	(0.0006)	(0.0034)	(0.0007)
[- 12°C, - 7°C]	-0.0007	-0.0019	-0.0006
	(0.0005)	(0.0015)	(0.0006)
]-7°C,- 1°C]	-0.0003	-0.0001	-0.0002
	(0.0003)	(0.0007)	(0.0004)
]- 1°C, 4°C]	-0.0002	-0.0005	0.0001
	(0.0003)	(0.0005)	(0.0003)
]4°C, 10°C]	-0.0001	0.0000	0.0001
	(0.0002)	(0.0004)	(0.0003)
]10°C, 16°C]	0.0000	0.0004	0.0000
	(0.0002)	(0.0003)	(0.0002)
]21°C, 27°C]	-0.0002	-0.0006**	-0.0001
	(0.0002)	(0.0003)	(0.0003)
]27°C, 32°C]	-0.0010**	-0.0014**	-0.0004
	(0.0004)	(0.0006)	(0.0006)
]32°C	-0.0128**	-0.0158***	-0.0064
	(0.0050)	(0.0057)	(0.0098)
precipitation	1.59	1.77	.23
	(1.567)	(3.609)	(1.749)
precipitation^2	-21.64	29.67	-3.42
	(38.872)	(137.131)	(40.038)
Firm FE	Yes	Yes	Yes
Year x country FE	Yes	Yes	Yes
Country x industry FE	Yes	Yes	Yes
Year x industry FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Temperature, precipitation t-1	Yes	Yes	Yes
Observations	1,287,622	398,034	889,588

Note: Standard errors in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

decreases annual output by 1.6% (0.14% for the 27-32°C bin and 0.06% for the 21-27°C bin). Compared to the results for our full sample (1.3%), the effect is notably more pronounced in magnitude.

We can also identify small but highly significant effects of lesser temperature bins (21-27°C bin). Like the results in the preferred specification of the full sample, we cannot identify effects for colder temperatures. All bins in this part of the temperature spectrum are clearly insignificant.

Figure 4: Non-linear temperature effect on firm output: Southern Countries



In Figure 4, we plot the point estimates for the Southern sample and the corresponding 95% confidence intervals for each ${\beta_1}^m$ (as in Column 2). The non-linearity of the effect of temperature on output is again evident. Effects are zero in the cold and moderate parts but highly significant in the hot parts of the temperature spectrum. For the Northern sample, we do not find any evidence for temperature effects neither at the hot nor the cold spectrum.[10]

In sum, we find that temperature responses at the global level appear to be driven by differences in long-term climate exposure. Strong negative effects from hot temperatures are driven by firms operating in countries with relatively hot climates. In contrast, we do not find any effects in cooler regions which may be a result of the notably lower variation

[10]When using the baseline specification we do find effects for five bins of the cold spectrum that are significant but small in magnitude. However, they are not robust to using the preferred specification.

in extreme heat days. Both findings are consistent with results obtained by other studies (Zhang et al. 2018) showing that effects stem from regions with long-term exposure to high temperatures.

Since only shocks from extreme heat, i.e. temperatures above 32°C, appear to be economically meaningful, we focus our subsequent analysis on the question if heat shocks to subsidiary firms operating in hot climates induce a shock transmission to the subsidiary's global ultimate owner, i.e. translate into output losses at the headquarter level.

4.4 Temperature shock transmission

The analysis on temperature shock transmission is conducted at the level of the headquarter, i.e. for firm i that in year t is the global ultimate owner of subsidiary firm j. Hence, we aggregate local weather shocks at the subsidiary level to the level of the respective global ultimate owner in each year. Each local weather shock at the subsidiary level is weighted by the affiliate's respective annual shares in total operating revenue of the entire business group to which it belongs.

We exploit the exogeneous variation in weather at the subsidiary level to identify its causal effect on economic output at the headquarter level. We also control for network specific characteristics such as the size of the network and include dummies for each tercile of the number of companies in the network in a given year (Barrot and Sauvagnat 2016). In addition, we account for the potential bias arising from past weather shocks and control for lagged weather at the local subsidiary level (Zhang et al. 2018; Burke and Tanutama 2019). This results in the following specification:

$$\ln y_{it} = \sum_m \beta_1^m T_{it}^m + \sum_m \beta_2^m TS_{it}^m + \sum_m \beta_3^m TS_{it-1}^m + \delta W_{it} + D_{it} + X_{it} + \epsilon_{it}, \tag{2}$$

where TS_{it}^m is the sum of weighted temperature bins. We define it as $TS_{it}^m = \sum_{mit} w_{ijt} T_{ijt}^m$, where w_{ijt} is the weight for each subsidiary j of firm i in year t and T_{ijt}^m is the respective temperature in each bin m.

The results presented in Table 5 show that extreme temperature shocks propagate within exposed firm networks.

Relative to a day in the 16-20°C bin, an additional day with temperature above 32°C at the subsidiary level decreases annual output at the headquarter level by 4.2% and the effect is significant at the 5% percent level. At the same time, exposures to more moderate

Table 5: Temperature transmission effects on firm output at the GUO level

	(1)
]- 12°C	0.0122
	(0.0124)
[- 12°C, - 7°C]	-0.0008
	(0.0045)
]-7°C,- 1°C]	0.0017
	(0.0014)
]- 1°C, 4°C]	0.0007
	(0.0009)
]4°C, 10°C]	0.0012
	(0.0007)
]10°C, 16°C]	0.0008
	(0.0006)
]21°C, 27°C]	0.0009
	(0.0008)
]27°C, 32°C]	0.0010
	(0.0009)
]32°C	-0.0421**
	(0.0213)
precipitation	-6.87
	(8.223)
precipitation^2	54.52
	(212.729)
Firm FE	Yes
Year x country FE	Yes
Country x industry FE	Yes
Year x industry FE	Yes
Control variables	Yes
Temperature, precipitation (headquarter)	Yes
Temperature, precipitation t-1 (subsidiary)	Yes
Observations	36,302

Note: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

and colder temperatures are apparently not transmitted with the respective temperate bins clearly insignificant.

Compared to the local effect on business group firms in the Southern sample (1.6%) reported in Table 4, the transmission effect of extreme heat days at the headquarter level is clearly more pronounced in magnitude. Local effects for the corresponding sample of subsidiary firms are of similar magnitude as the coefficients for the Southern Sample (1.9%).[11] Thus, the high coefficient for the transmission shock suggests that output losses due to extreme temperatures can be amplified within certain firm networks, i.e. a local shock to a subsidiary can affect headquarter revenues disproportionately.

5 Discussion

Recent studies on climate econometrics have aimed to substantially improve damage estimates of climate change. This paper contributes to this discussion and assesses the impact of temperature on economic output using a cross-country sample of business group firms that comprises different world regions and climatic zones.

In a first step, the results show a non-linear temperature-output-relationship with strong responses at high temperatures. An additional day with temperature above 32°C decreases annual output by 1.3%. In the second analytical step, negative effects from hot temperatures appear to arise from firms operating in countries with relatively hot climates and vice versa, but to a far lesser extent, for cold temperatures. Results for hot temperatures are robust to different sets of fixed effects, the inclusion of lagged weather data and time-variant firm behavior. This evidence for a comprehensive sample of 32 countries is in line with previous firm level studies that focus on specific countries and sectors. For instance, Zhang et al. (2018) detect for the Chinese manufacturing sector an inverted-U-shape relation, strong negative effects of extreme heat and differences among comparatively hot and cold sub-national regions. Similar effects have been found among world regions by studies using comprehensive county- and country-level data (Burke et al. 2015; Burke and Tanutama 2019).

In a third step, this study sheds light on a potentially important cost driver: The transmission of temperature shocks within global business groups. An additional local day with temperature above 32°C incurs annual output losses of 4.2%. Importantly, losses incurred at the headquarter level are notably higher than the corresponding first order effect at the local

[11] Results are available upon request.

subsidiary level. This means that, under future warming, temperature shocks could become amplified within certain types of firm networks.

Given the nature of our data, it appears plausible that the estimates we obtain are driven by higher order effects, i.e. losses incurred by the specific structure of economic dependencies within the network (Wenz and Levermann 2016). Stable, long-term ownership can possibly capture relationships that are of important value to the network. For instance, Barrot and Sauvagnat (2016) show that shock propagation between supplier and customer firms is substantially stronger and more significant if the supplier produces specific inputs that are hard to replace. The divergence between first and higher order effect sizes might also be related with subsidiary firms being more resilient to shocks as the bulk of the impact is absorbed by the network. Giroud and Mueller (2019) demonstrate that subsidiaries have smaller employment elasticities with respect to local shocks than independent companies. However, one has to consider that our study aims to deliver a first analysis of a specific type of ownership relation. More research on the interplay between shock exposure and structural business group features is needed.

The strong impacts of extreme heat on and within business groups are in line with recent findings on economic outcomes. For instance, studies demonstrated that average global incomes could decrease by up to 23% by 2100 (Burke et al. 2015) or that losses in Chinese manufacturing could incur yearly GDP losses of around 5% by 2050 (Zhang et al. 2018). Wenz and Levermann (2016) find that inter-sectoral trade can greatly amplify heat-induced losses. While we cannot provide representative aggregate estimates with our dataset, the firm-based estimates suggest that the effects are economically important. Given the overlap in current and future weather distributions, the results can provide us with a useful estimate of potential medium-run impacts of climate change induced heat stress.

An important empirical question is to what degree the effects we obtain for the medium-run persist into the long-run. Although firms that operate in relatively hot climates had sufficient time to adapt, the magnitude of the coefficients is sizeable which suggests that effects may continue into the future. However, no clear consensus has emerged so far on adaptation with some studies detecting limited potentials and other studies indicating the opposite (Behrer and Park 2018). More research on how to alleviate the impacts of extreme temperature, particularly using longer time horizons, is needed (Kalkuhl and Wenz 2018).

From a policy perspective, it is important to understand if local shocks can be contained and prevented from spreading to the regional and global level. In terms of adaptation, one would expect business groups to move their subsidiary locations or to integrate new, less exposed firms into their networks. However, the empirical literature on network production demonstrates that switching costs can be substantial and thus impede adaptation to economic shocks at least in the short run (Antràs and Yeaple 2013; Bernard and Moxnes 2018). In line with recent evidence (Barrot and Sauvagnat 2016), results suggest that the importance of switching costs may be high when it comes to specific long-standing relationships. More research on the persistence of effects and the importance of switching costs in the long run as well on how to alleviate these impacts is needed.

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