The sensitivity of UK manufacturing firms to extreme weather events.*

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Abstract

Climate models predict that the increase in greenhouse gas concentrations is likely to lead to climate change and increased temperatures. The likelihood of extreme weather events will also increase as a consequence. Whilst predictions on the costs of climate change can be made through economic modelling, this study seeks to measure precisely one component of these costs, namely the impact of extreme weather events on economic activity. To the extent that future extreme weather events will be more frequent but not necessarily stronger than in the past we can use historic data to get an idea of their impact. This is the first study to examine such effects using firm level production data for the UK. By exploiting firm level variation in the exposure to both domestic and foreign weather events we can derive more reliable estimates of their impact.We can also make progress in distinguishing

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channels and mechanisms through which weather events affect the performance of businesses. We differentiate between three channels through which weather can impact firms: upstream, production and downstream disturbances. We find statistically significant results showing that summer heat waves in the UK affect negatively labour productivity. Similarly, importing from countries experiencing exceptional heat reduces productivity while exporting to "hot" countries increases productivity. This is consistent with the fact that other countries' producers will also be affected by heat waves and the idea that difficulties abroad might also be beneficial for domestic firms, if for example, foreign consumers shift to domestic suppliers as a consequence of a weather event. These effects are also shown to be economically significant.

1 Introduction

It is now well established that some form of climate change will result as a consequence of the increased release of greenhouse gases. Current projections suggest that an increase of global mean temperature of at least 2°C is very likely (IPCC, 2007). This could lead to sea level rise, changed weather patterns, including more violent storms, as well as an increase in the incidence of heat waves (Barriopedro et al., 2011).What is less clear is the economic impact of this. Bottom-up calculations of the costs typically involve strong assumptions about assets lost due to sea level rise and storms as well as some form of modelling of the impacts on agricultural output of increased temperatures.[1] However, little systematic evidence is available about the direct impact on economic activity of extreme weather such has summer heat waves, storms or winter cold spells.

Climate models suggest that one consequence of higher concentrations of greenhouse gases could be more frequent occurrences of such extreme weather events (IPCC, 2007). One aspect of the costs of climate change is consequently the economic impact of these events. While there are other likely economic impacts and costs - e.g. damage from sea level rise or ocean acidification - we should be able to assess the impact from extreme weather events more precisely. This is because extreme weather events have happened in the past on a scale that is comparable to what is expected for the future although at lower frequency. We can consequently use historic data to estimate the cost impact. Clearly, more frequent occurrences of extreme weather might trigger adaptation behaviour - e.g. installation of air conditioning etc. - which could mitigate the cost impact of such events. However, historic cost impacts can provide guidance on the amount of investment in such adaptation measures is warranted. Also, understanding how extreme weather events in other, in particular developing, countries impact the rest of the world through their exports, can help target the funding of adaptation measures in such countries in a more efficient way.

This is the first study exploring the impact of extreme weather event on UK businesses using a

[1] This could include also increases in agricultural output.

large sample of firm level data for the UK between 1993 and 2003. We use advanced econometric techniques to isolate the effect of weather events both in the UK and abroad on manufacturing firms' productivity. The next section will present existing literature on this topic. Section 3 presents our empirical approach, Section 4 presents the data and its construction from the raw data, while Section 5 provides results from the econometric analysis. It is then shown that the figures found are not only statistically significant but also economically meaningful in Section6, by computing potential aggregate effects on GDP implied by our results. Section 7 concludes.

2 Literature review

The impact of major weather events on the UK's economy have been the focus of a number of recent studies. The 2007 central England summer floods cost the economy over £3 billion (ASC, 2010); the harsh winter of 2009 cost £1 billion and prompted a Government review into the resilience of England's transport system (DfT, 2010), the lack of which was highlighted further in 2010; the disruption to Britain's airports costing BAA alone £24 million (BAA, 2011). The weather also impacts positively on an economy; Subak et al (2000) showed that the hot summer of 1995 increased expenditure in tourism by around £239 million.

There is also a wealth of econometric studies that have gone beyond estimating the impacts of one-off events in individual countries. They adopt different approaches to examine the relationship between weather, extreme events and the economic performance of countries. Studies have looked at temperature and precipitation at the national level, focused on extreme events, and estimated the impact of fluctuations in weather on sectors within a country. An in-depth assessment of the literature and the different approaches adopted is presented by Fankhauser et al. (2009). One approach (e.g. Sachs and Warner, 1997;Gallup et al., 1999) has been to examine the impact of the climate on a range of aggregate economic variables in a cross-section of countries. These analyses have shown a strong relationship between climate and economic performance; however they have come into criticism from other authors as to their robustness, with institutional quality being a key omitted variable (e.g.Acemoglu et al., 2002).Dell et al. (2008) avoid making assumptions as to which mechanisms to include by examining aggregate outcomes directly. They combine global data on temperature and precipitation from 1950 to 2003 with aggregate output data. The study finds that higher temperatures impact negatively on growth, but only in low income countries. The temperature has both an impact on the level of output as well as on an economy's ability to grow. Jones and Olken (2010) use data on exports to show large negative impacts of temperature on poor countries: 1 °C warmer in a given year reduces the growth of that country's exports by between 2% and 5.7% in that year. At the level of employee data, it has been shown that US labour productivity declines in hotter weather (Zivin and Neidell, 2010), especially in the absence of air conditioning.

The economic literature is divided as to the impacts of extreme events on an economy. Noy and Nualsri (2007) claim this can be explained by the underlying economic growth model used in a given analysis. Using a neoclassical growth model would ascribe to extreme events having a positive impact on economic growth due to the increase in capital required to rebuild and repair as well as the chance to adopt new technologies. This “creative destruction” hypothesis is supported by Skidmore and Toya (2002)’s finding that a higher frequency of natural disasters is associated with a higher growth rate in the long run.On the other hand endogenous growth theory indicates that there would be a negative impact on a country’s economy due to the destruction in human capital and technology. Gassebner et al. (2010) present statistically significant results that natural disasters impact negatively on trade; an additional disaster reduces imports on average by 0.2% and exports by 0.1%. Furthermore Noy and Nualsri (2007) find a statistically significant negative impact of natural disasters on growth when human capital is destroyed but insignificant results with respect to a reduction of physical capital. Lis and Nickel (2009) estimate the impact of large scale extreme weather events on the budget balances of 138 countries from 1985 until 2007. The results suggest that the budgetary impact of extreme weather events ranges from 0.23% to 1.1% in less developed countries whilst no impact is found for OECD and EU countries, due to their high GDP per capita, sound public finance position and resilient economies. Noy (2009) also finds much larger output declines following a disaster in developing and smaller countries than in developed and larger economies. Lazo et al. (2010) uses a transcendental logarithmic production function which incorporates weather variables to estimate the weather sensitivity of eleven non-governmental sectors. The study models the relationship between gross state product and inputs such as energy, capital, labour and weather variables such as temperature and precipitation. It concludes that U.S economic output varies by up to 3.6% due to weather variability. This can not be interpreted as a loss but as variability around the historical average weather conditions that could be reduced with better weather forecasting for example.

Subak et al. (2000) assessed selected impacts on tertiary activities of the anomalous hot summer of 1995 in the UK, where the central temperature was 1.6 ^{0}C above the 1961-1990 average. Regressing temperature and precipitation against activity time series data from the sectors, they show large gains for beer and wine production, valued at around £134 million as well as a gain for the tourism sector of around £239 million. Losses for the clothing and footwear series are estimated at £383 million over the 12-month period.

3 Empirical approach

Most existing studies on the impact of weather on economic activity rely on country or at best industry level data. In this study on the other hand we rely on a large longitudinal sample of firm level data for the UK. This has two advantages. Firstly, we can greatly increase the sample size;

e.g. in our analysis below we rely on samples of almost 40,000 data points. Studying the same time period for the UK with aggregate yearly data would have to rely on only 11 data points. Secondly, using firm level data offers various avenues for examining the mechanisms and channels through which weather events impact on economic activity. In this study we distinguish 3 channels:

1. Upstream disturbances: losses dues to weather disturbances for suppliers of business i
2. Production disturbances: losses dues to weather disturbances at the production locations of business i
3. Downstream disturbances: losses dues to weather disturbances at the locations of customers of business i.

The structure of our regression model is as follows:

$$y_{it} = W_{it}\beta_W + \alpha_t + \alpha_i + \epsilon_{it} \tag{1}$$

where i indexes firms, t time, W_{it} is a vector of variables capturing weather events α_t and α_i are a time and firm fixed effect. y_{it} represents different firm level outcomes; e.g. labour productivity.

3.1 Construction of weather indices

The central element of our strategy are construction of weather variables that vary at the firm level. Corresponding to our three disturbance channels we construct 3 types weather indices: firstly, to capture upstream disturbances we construct import weighted averages of global weather events; i.e. suppose W_{ct} captures a weather outcome in country c at time t and suppose that firm i imports the amount IM_{ict} from country c. We consequently construct the upstream weather index - in principle - as

$$W_{i,t}^{IMPORTS} = \frac{\sum_c W_{c,t} IM_{ict}}{\sum_c IM_{ict}}$$

In practice we do not access firm level data on imports[2]. As we explain in more detail in the data section, we consequently replace firm level imports with 4 digit sectoral level inputs. This might imply that some of the effects we pick up might be due to demand variations rather than only supply disruptions; e.g. suppose that as a consequence of a weather event abroad domestic consumers - rather than firms - reduce their imports and shift their demand to domestic producers instead. Another limitation is that such an import based upstream measure would not pick up

[2]In future work we might be able to overcome this limitation using newly available data from HMRC.

within country upstream linkages.[3] Secondly, to capture production disturbances we construct weighted averages of weather variables at all production locations within the UK of firm i. As weights, we use the average employment at different locations, which is the only performance variable available at this level of dis-aggregation:

$$W_{it}^{HOME} = \frac{\sum_{j \in J(i)} \bar{L}_{ji} W_{jt}}{\sum_{j \in J(i)} \bar{L}_{ji}}$$

where j indexes different locations, $J(i)$ is the set of production locations of firm i in the UK and $\bar{L_{ji}}$ the employment of firm i in location j averaged over time.

Finally, to capture downstream disturbances we construct an export weighted index of global weather variables:

$$W_{i,t}^{EXPORTS} = \frac{\sum_c W_{c,t} EX_{ict}}{\sum_c EX_{ict}}$$

The same limitations as for the import weighted index apply: currently we only have exports at the sectoral level and as a downstream measure it cannot pick up downstream effects occurring within the UK.

A couple of remarks are useful at this point: Firstly, while our import and export based measures cannot capture domestic upstream and downstream disturbances, this does not necessarily imply that we fail to pick up such effects. To the extent that upstream and downstream weather events are correlated with weather events at the production locations of firms - $W_{it}^{HOME}-$ these would be picked up by the production location effects - W_{it}^{HOME}. Secondly, because we only use sectoral information for import and export weights and also because we use country level weather information, the import and export based measures are bound to be less precise than the UK based measure for which we exploit more finely grained weather information as well as firm level weights. Thirdly, we have no reason to believe that any of these issues should lead to systematic errors of type I, rather they might lead to errors of type II; i.e. we have no reason to expect that our approach would identify weather events spuriously. On the other hand we might not be fully capturing some effects that are nevertheless present.

3.2 Estimation

We use two estimation approaches to identify equation 1: estimation in differences from means (i.e. Fixed Effects or "Within" regression) and regression in first differences. Both approaches address

[3]It might be possible to capture such linkages using input output tables in conjunction with information on the distribution of production locations across the UK, using weather variables at these locations.

the issue of fixed un-observed heterogeneity captured by the firm fixed effects in equation 1; i.e. we run least squares regressions on the following transformations

$$y_{it} - y_{it-1} = (W_{it} - W_{it-1})\,\beta_W + \alpha_t + \epsilon_{it} - \epsilon_{it-1}$$

$$y_{it} - \bar{y}_i = \left(W_{it} - \bar{W}_i\right)\beta_W + \alpha_t + \epsilon_{it} - \bar{\epsilon}_i$$

where a bar indicates the mean value of the same variable for all years where we observe firm i. Note that all regressions also include year fixed effects. Asymptotically - i.e. if we had infinitely many observations - both approaches should lead to the same value for the parameters β. In practice - i.e. in finite samples - estimates can differ. However, as a sign of robustness we would expect that the results are quantitatively and qualitatively similar. Below we will give more credence to results where this is the case. Note that our prime objective in this exercise is not to "explain" outcome variables such as productivity (or have a high R2) but to establish the causal effect of weather on them. For that we need to be reasonably confident that our error terms are independent of the weather variables. Hence we only include time dummies to account for the fact that in our relatively short sample period average weather and general business cycle shocks may have been correlated. It might also be the case that more productive businesses locate systematically in areas with certain weather; e.g. warmer weather in the south. We account for that by allowing for fixed effects and only exploiting deviations. On the other hand, our identification rests on the fact that any factors that are driving location specific deviations in productivity are not correlated with weather variables.

4 Data

4.1 Annual Respondents Database

The Annual Respondents Database (ARD) is the most comprehensive and detailed business level dataset for the UK, maintained by the Office of National Statistics. It is an annual production survey that covers about 10,000 plants in the manufacturing sector. Larger plants are sampled every year whereas smaller plants are included on a random basis. Here and in the remainder of the paper a "firm" corresponds to a so-called ARD reporting unit. This is the lowest aggregation level for which production data is available in the ARD. Most (about 80%) firms defined in that way consist of only 1 business location (local unit) (For more details seeCriscuolo et al., 2003). The ARD comprises a wide range of economic characteristics of the plant, including turnover, value added, total purchases of goods and materials, employment number and costs, inventories, and

Table 1: ARD variables descriptive statistics

	mean	sd	count	p50	p10	p90
Value Added/Employment	34.4	37.2	36,735	27.9	14.6	56.6
Labour expenditure	6,878.3	21,254.3	36,735	2,570.0	384.0	14,102.0
Employment	299.0	762.3	36,735	137.0	23.0	637.0
Capital stock	31,166.5	150,936.2	36,734	7,228.3	747.0	53,624.7

Source: Annual Respondant's database. Notes: Statistics of each variable for manufacturing firms (reporting units) in UK SIC92 sectors 15 to 39 between 1992 and 2003.

net capital expenditure. We restrict our analysis to observations between 1992 and 2003 and to manufacturing firms due to data restrictions. The summary statistics of the variables from ARD used in our analysis are presented in Table 1 for our sample.

4.2 Weather data

4.2.1 UK Met Office historical data

The Met Office holds a historical database of weather observations that come from an irregular spaced and gradually evolving network of meteorological stations across the UK. From this database it has been possible to construct 36 weather variables for 5 km x 5 km gridded datasets for the UK, by using normalisation, regression and interpolation for many of the climate variables, with the regression modelling general circulation patterns and trends particular to each month, and the interpolation accounting for local variations (see Perry and Hollis, 2005). To approximate six main weather event types, we use the following statistics derived by the Met Office from temperature or rainfall data:

- **Heat**: Summer heat wave duration. The summer heat wave is the number of days with daily maximum temperature more than 3 °C above the 1961–90 daily normal for more than 5 consecutive days between May and October.

- **Cold**: Winter cold wave duration. The winter cold wave is the number of days with daily minimum temperature more than 3 °C below the 1961–90 daily normal for more than 5 consecutive days between November and April.

- **Rain**: Days of Rain. Number of days during the year with more than 10 mm precipitation between 9A.M. and 9 P.M.

- **Storm**: Maximum average wind speed. Highest hourly mean wind speed (knots) at a height of 10 m above ground level averaged over the month
- **Snow**: Snow lying. Number of days with greater than 50% of the ground covered by snow at 9 A.M.
- **Drought**: Consecutive Dry Days. Maximum number of consecutive days with rainfall below 0.2 millimeters.

We matched the UK weather data to the ARD on the basis of each production facility's[4] latitude and longitude. The weather variables were then aggregated to the firm (or Reporting Unit (RU)) level by using employment shares. For example take a given RU comprising two LUs, A and B, with 70% of its employment in A and 30% in B. In the location of A, the summer heatwave in 2001 was 6 days long, while in B's location it was 15 days long. The summer heatwave associated to this RU for 2001 will then be $70\% \times 6 + 30\% \times 15 = 8.7$ days.

A central requirement of our identification strategy is that weather variables vary sufficiently across different firms. Table 2 reports descriptive statistics for a selection of our weather variables in the matched sample of manufacturing firms included in the regression analysis[5]. We see that weather variables vary greatly both over time and between firms. For example in 2003 the mean number of summer heat days is 5 times higher than in 2002. In most years the standard deviation of heat days is as high as the mean number of heat days.

Figure 1 shows this variation graphically in density plots; e.g. notice that in 2003 a number of firms experienced heat waves with 40 or more days of above average temperatures, whereas in 2000 no firm experienced such a weather event. The dip between 0 and 5 days is due to the definition of the variable as being the number of heat days with a minimum of six days needed to be considered as a heat wave.

4.2.2 HadEX world extreme weather indices

HadEX is a global climate extremes dataset available from the Met Office Hadley Centre (Caesar and Alexander, 2006) that includes 27 indices of temperature and precipitation on a 2.5° x 3.75° grid from 1951 to 2003. The indices are derived from daily data from about 2500 temperature stations and 6000 precipitation stations worldwide. Angular-distance weighting is used to interpolate the station data onto the grid which was then matched to a country level dataset. [6]

[4] Or local unit (LU) in ONS speak.

[5] Given outliers to the sample whose labour productivity growth is greater than 200% on a year to year basis are dropped from the sample, the starting year is effectively 1993.

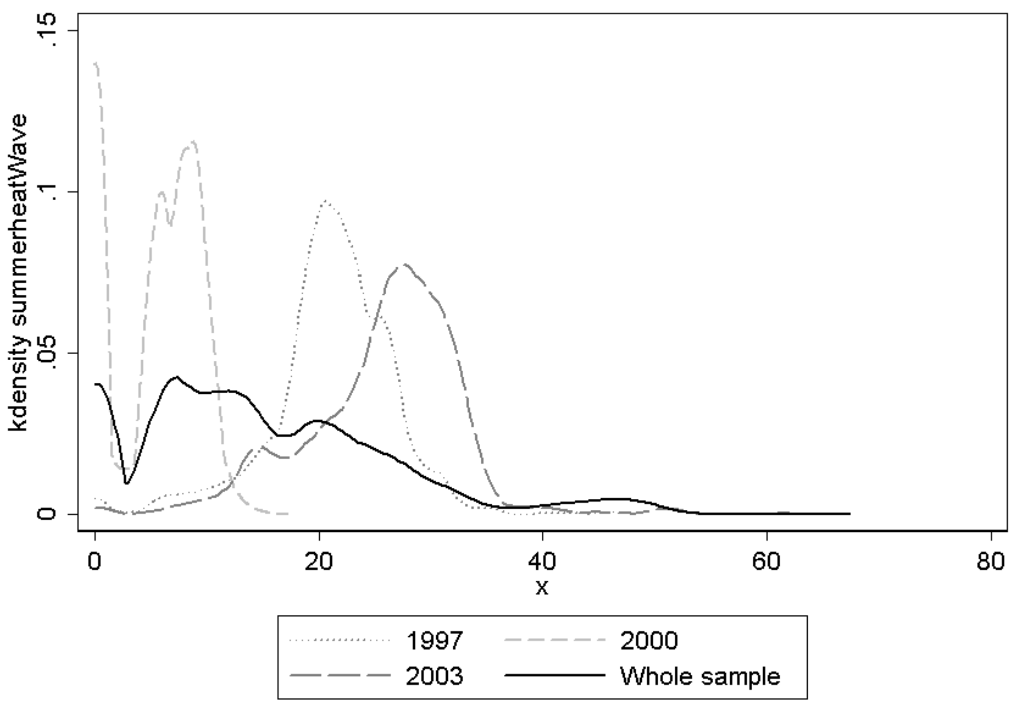
[6] For a more detailed description of the dataset and its production process, see Alexander et al. (2006)

Table 2: UK Weather variables descriptive statistics

	year	mean	sd	count	p50	min	max
Heat: Summer Heat Wave	1993	4.52	3.03	3207	5.65	0	16.37
	1994	7.38	5.17	3188	8.26	0	19.6
	1995	42.52	7.48	2254	44.34	6.46	60.03
	1996	10.6	4.48	3239	11.87	0	32.6
	1997	21.15	5.74	3585	21.42	0	46.29
	1998	12.36	5.32	2981	13.46	0	22.48
	1999	17.7	4.75	3084	18.1	0	35.47
	2000	5.32	3.89	3280	6.08	0	17.24
	2001	18.77	6.85	3559	20.22	0	40.61
	2002	4.51	4.92	4041	2.37	0	19.04
	2003	25.76	7.18	4129	26.85	0	67.41
Rain: Days of Rain (>10mm)	1993	24.64	8.7	3207	22.26	11.57	90.27
	1994	23.58	12.11	3188	19.25	6.88	99.13
	1995	19.62	8.98	2254	16.56	7.44	75.34
	1996	17.15	8.81	3239	14.1	4.92	70.49
	1997	20.18	9.03	3585	18.15	6.43	84.43
	1998	26.27	12.14	2981	22.04	9.37	95.82
	1999	24.67	11.04	3084	22.04	8.64	86.84
	2000	30.92	11.05	3280	28.11	14.22	99.45
	2001	22.18	8.33	3559	20.44	7.08	62.99
	2002	29.01	13.13	4041	26.02	9.17	87.49
	2003	17.29	8.37	4129	14	4.59	69.97
Snow: Snow Lying	1993	5.77	4.88	3207	4.77	0	30.64
	1994	6.08	3.6	3188	5.37	0	31.02
	1995	9.02	5.62	2254	8.24	0	50.84
	1996	13.14	8.06	3239	11.54	0	70.79
	1997	6.62	3.7	3585	6.44	0	31.41
	1998	2.36	3.38	2981	1.25	0	45.19
	1999	5.37	4.81	3084	4.35	0	62.7
	2000	5.14	2.85	3280	4.42	0	43.97
	2001	7.27	6.46	3559	5.57	0	73.41
	2002	2.69	2.5	4041	2.28	0	30.21
	2003	5	3.75	4129	4.43	0	38.89

Source: UKCP09 MetOffice. Notes: Reporting Unit level weather data weighted by employment of Local Units in corresponding weather grid points for the sample of firms included in the regression analysis.

Figure 1: Distribution of summer heat waves



The indices that were used in this analysis to measure identical weather categories[7] as above are the following:

- **Heat**: Proportion of days with very hot maximum temperature (TX90p). The temperature threshold for a 'hot day' in any grid point is defined by the daily maximum temperature (TX) which is exceeded on the 10% warmest of days in the standard climate period (1970-99). The TX90p index is then defined as the frequency with which daily maximum temperature exceeds this threshold in any year.
- **Cold**: Proportion of days with very cold minimum temperatures (TX10p). The temperature threshold for a 'cold day' in any grid point is defined by the daily maximum temperature (TX) below which the 10% coldest days in the standard climate period (1970-99) fall. The TX10p index is defined as the frequency with which daily maximum temperature falls below this threshold in any year.
- **Rain**: Days of rain. Number of days with more than 20mm rain within the year

The grid points were matched to countries and the data then aggregated by country by taking the average value of each weather variable across the grid points covering that country. For example , the USA includes 114 grid points.

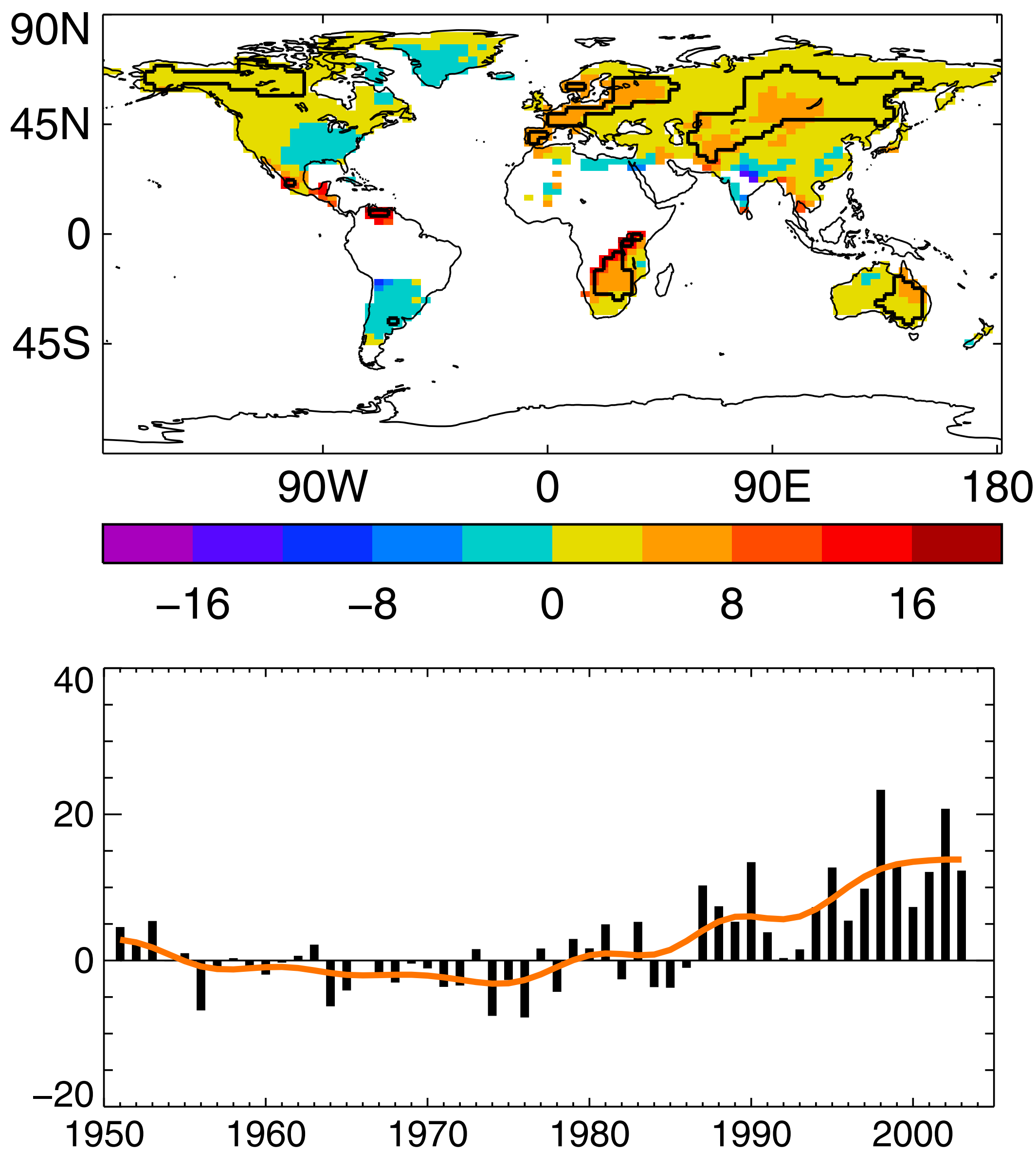
4.2.3 EM-DAT world disasters database

The EM-DAT international disaster database (see CRED) is compiled by the Centre for Research on the Epidemiology of Disasters School of Public Health of the Université Catholique de Louvain (UCL) in Brussels. It provides information on the number of people killed, injured or affected and lists the disasters by country, region, start and end-date. Disasters are classified in different categories. For a disaster to be entered into the database at least one of the following criteria must be fulfilled: ten or more people are reported killed, 100 or more people are reported affected, a state of emergency is declared, there is a call for international assistance. We select the following three disaster types to measure three weather categories internationally.

- **Storm**: Includes tropical storms, extra-tropical cyclones or winter storms, and local or severe storms. Local windstorm refers to strong winds caused by regional atmospheric phenomena such as foehn winds, Mistral, Bora etc. A severe storm is the result of convection and condensation in the lower atmosphere and the accompanying formation of a cumulonimbus cloud that comes along with high winds, heavy precipitation (rain, sleet, hail), thunder and lightning.

[7] While a flood measure could not be derived from the UK MetOffice data, an indicator of snow was not available internationally.

Figure 2: HadEX heat index TX90p



Source: Hadley centre HadEX

- **Snow:** Extreme winter conditions. Refers to damage to buildings, infrastructure, traffic - especially navigation - inflicted by snow and ice in form of snow pressure, freezing rain, frozen waterways etc.

- **Drought**: Extended period of time characterised by a deficiency in a region's water supply that is the result of constantly below average precipitation. It's consequences can be losses to agriculture, inland navigation and hydropower plants affected, lack of drinking water and famine.

- **Flood**: Significant rise of water level in a stream, lake, reservoir or coastal region. Also includes rapid inland floods due to intense rainfall.

4.3 COMEXT Trade data

In order to measure each sector's exposure to foreign weather through trade, we use Eurostat's COMEXT database. It contains the official European Union Foreign Trade Statistics by including detailed statistics on trade (imports and exports) in goods of all EU member states, including the UK, both within and outside of Europe. Trade goods are classified by the 8-digit European Harmonized System (Combined Nomenclature) which is then aggregated to the UK SIC92 sectoral classification using a look-up table provided by EUROSTAT. The data is available for the UK since 1988, but we only use information from 1992 onwards.

The ARD includes information on which primary industry a firm belongs to, using the UK SIC92 classification. For each of the five HadEX and EM-DAT variables $W_{i,c,t}$ (in year t and country c) described above, two sector (s) level weather variables are then computed as:

$$W_{i,s,t}^{EXPORTS} = \sum_c \eta_{c,s,t}^{EX} W_{c,i,t}$$

and

$$W_{i,s,t}^{IMPORTS} = \sum_c \eta_{c,s,t}^{IM} W_{c,i,t}$$

where $\eta_{c,s,t}$ is the share of sector s's exports or imports from the UK to country c in year t, such that:

$$\eta_{c,s,t}^{EX} = \frac{Exports_{UK,c,s,t}}{\sum_c Exports_{UK,c,s,t}}$$

and similarly for imports.

$$\eta^{IM}_{c,s,t} = \frac{Imports_{UK,c,s,t}}{\sum_c Imports_{UK,c,s,t}}$$

The resulting 4-digit SIC92 level trade-weighted international weather variables are described for the sample of firms used in the regression analysis in 3.

5 Regression Results

5.1 Baseline regressions

Using the data constructed as described in Section 4, the empirical approach described in Section 3 is implemented. Figure 3gives an overview of the results. The coefficients of the univariate and multivariate regressions for each weather variable as well as each econometric specification (fixed-effects and first differences) are represented by a bar. The stars show the statistical significance of this coefficient.

For each of the seven categories of weather extremes, we include each of the three types of weights discussed above; i.e. a home measure aiming to capture production disruptions, an export weighted measure to capture upstream disturbances and an import weighted measure for downstream disturbances[8].

We run a total of 2 different estimation routines: Fixed effects and first differences. For every weather variable we run a uni-variate specification; i.e. including only one variable in the regression and a multivariate specification where we include all available weather variables simultaneously. This leads to a total of 4 specifications for each variable which are reported in different colours in Figure 3.

One main result comes out as strongly significant across the different specifications: there is a strong and significant negative effect of summer heat waves in the UK on labour productivity. It also appears that exporting to countries experiencing exceptional heat positively affects productivity while importing from such countries negatively impacts productivity, which is consistent with the fact that other countries' producers will also be affected by heat waves. This is consistent with the idea that difficulties abroad might also be beneficial for domestic firms if for example foreign consumers shift to domestic suppliers as a consequence of a weather event.

The results for other weather measures are less or not significant, and are not consistent across different specifications. Another significant positive impact is that of importing from countries experiencing storms. This is somewhat counterintuitive, but might have to do with the current

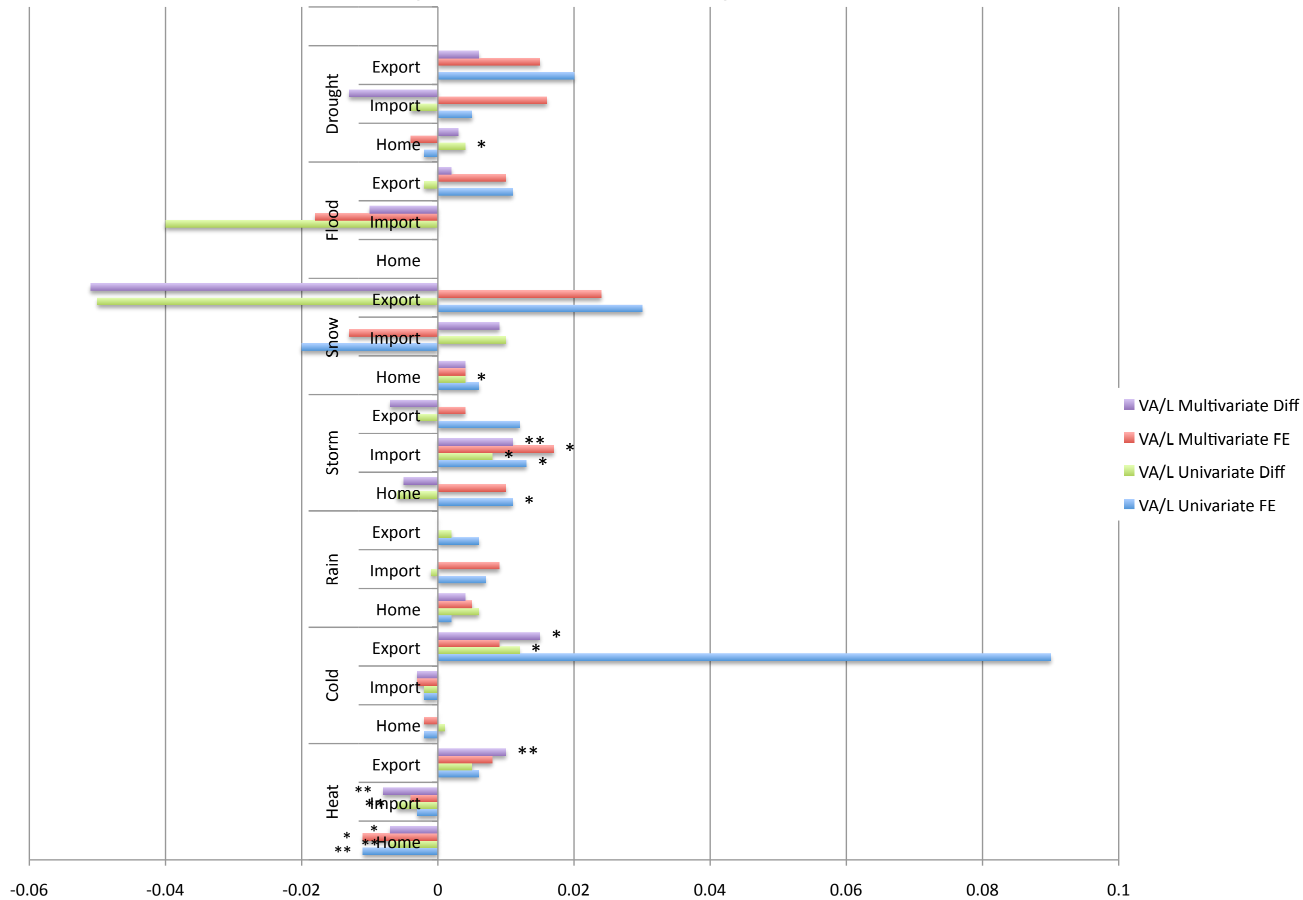
[8]No flood measure is available at a fine geographical definition for the UK at present.

Table 3: World Weather variables descriptive statistics

	year	mean	sd	count	p50	min	max
	1993	9.36	0.82	3220	9.36	2.98	13.61
	1994	11.38	1.06	3203	11.44	4.29	15.34
	1995	12.94	1.6	2263	12.73	5.07	19.77
	1996	8.35	0.7	3256	8.39	3.26	10.66
Heat - Exports:	1997	12.41	1.4	3600	12.2	5.15	17.67
TX90p,	1998	13.25	1.06	2991	13.36	7.29	20.31
exports weighted	1999	12.11	0.82	3102	12.24	5.97	14.29
	2000	12.41	0.98	3296	12.47	5.12	15.81
	2001	11.48	0.92	3578	11.63	6.5	14.57
	2002	13.23	0.99	4066	13.29	6.07	15.51
	2003	14.56	1.58	4160	14.64	5.08	18.66
	1993	9.92	3.4	3220	9.37	1.71	30.69
	1994	9	2.53	3203	8.9	1.01	20.82
	1995	9.41	2.81	2263	9.19	2.12	23.5
	1996	8.75	2.56	3256	8.81	2.26	21.12
Rain - Imports:	1997	8.11	2.03	3600	8.05	0.31	20.74
Days of Rain	1998	9.59	2.74	2991	9.21	1.99	29.23
(>20mm), imports	1999	9.09	2.44	3102	8.98	1.95	21.37
weighted	2000	8.71	2.43	3296	8.37	2.33	20.46
	2001	8.5	2.52	3578	8.09	1.38	20.28
	2002	9.53	2.36	4066	9.28	2.42	20.66
	2003	8.04	2.69	4160	8.03	1.15	22.05
	1993	2.8	1.48	3220	2.58	0	9.03
	1994	1.37	0.68	3203	1.34	0.05	8.52
	1995	1.4	0.67	2263	1.27	0.1	3.71
	1996	1.31	0.63	3256	1.17	0.09	4.35
Storm - Exports:	1997	2.51	1.54	3600	2.26	0	8.52
Storm disaster,	1998	2.77	1.51	2991	2.53	0.22	8.36
exports weighted	1999	2.88	1.33	3102	2.63	0.44	7.95
	2000	2.31	0.95	3296	2.14	0.45	6.65
	2001	2.86	1.66	3578	2.63	0.07	8.75
	2002	2.54	1.28	4066	2.38	0.01	6.58
	2003	2.03	1.02	4160	1.88	0	6.43

Source: HadEX Hadley Centre, EM Dat UCL and COMEXT- Eurostat. Notes: Each country level weather event is weighted for each firm by the share of the firm's 4-digit sector corresponding trade share to or from that country.

Figure 3: Overview of regression results



Notes: Each bar represents the size of the coefficient of each weather variable for the different specifications described in the legend. Year fixed effects are included. The stars show the significance of this coefficient: *** p<0.01, ** p<0.05, * p<0.1

limitations of our measure for upstream disturbances. Remember that it is the sectoral import weights. Hence, if as a consequence of storms abroad domestic consumers reduce their imports from foreign suppliers and shift to domestic ones we would see a positive productivity effect. We will examine this in future work where we aim to use firm level import information.

Tables 4and 5 respectively report in more detail the univariate and multivariate regressions of firm level labour productivity on each weather indicator that were used to construct Figure 3.

5.2 Robustness checks on summer heat waves

The clearest and most robust result we obtained in the previous section is a negative and significant impact of summer heat waves. In this section we subject this result to further robust tests.First, we examine if it is correlated with other variables capturing hot summers. Table 6shows that it is highly correlated with other measures such as "Sunshine days" or "Maximum Temperature" etc.

We also check that the results are not driven by outliers. Figure 4 plots for each firm and year the deviation of their labour productivity and summer heat wave from the mean for that firm. The light grey fitted line of negative slope corresponds to the -0.011 coefficient of the regression, with the black fine line being the horizontal axis. It appears that no firm in any year appears to be an outlier that would be driving the result. This figure also illustrates the need to resort to econometric analysis to precisely identify the results. The lack of outliers is also confirmed in Table 7's columns (2) and (3) which show that the coefficient on summer heat waves remains significant even when observations for 2003, a very hot year, are dropped (Column 2) or when the top decile of summer heat wave durations are not included in the sample (Column 3).

Our results also show that there is some non-linearity involved in the relation between productivity and summer heat waves. First, the variable is measured as either 0 or above 5, given that any exceptional temperatures for less than five days will not be counted as a heat wave. Second, when including in the regression a dummy of whether the firm experienced or not a heat wave at all, we find that this dummy is not significant while the actual length of the heat wave remains strongly significant, as shown in Table 7's columns (4) to (6). However, if including the length of the heat wave squared, it does not appear to be significant[9].

Besides, in order to understand which sectors are most affected by summer heat waves, we run separate regressions for each 2-digit UK SIC92 sector. The results of the first difference multivariate regressions are plotted in Figure 5 with the different specifications reported in Table 8. It appears that the chemicals industry is most strongly negatively affected. Apparel firms are positively affected, with statistical significance at the 5% in various specifications. Further research will be needed to understand whether these results are demand or process driven.

[9] results available from the authors on request.

Table 4: Univariate weather regressions

		Labour productivity		
		Fixed-effects	First difference	n. obs./n. Firms
HEAT	Summer heat wave	-0.011**	-0.007**	40348
		(0.006)	(0.003)	13895
	TX90p – exports	0.006	0.005	36735
		(0.007)	(0.004)	12341
	TX90p – imports	-0.003	-0.006*	36735
		(0.006)	(0.004)	12341
COLD	Winter cold wave	-0.002	-0.001	40348
		(0.003)	(0.002)	13895
	TX10p – exports	0.009	0.012**	36735
		(0.009)	(0.006)	12341
	TX10p – imports	-0.002	-0.002	36735
		(0.007)	(0.004)	12341
RAIN	Days of rain (>10mm)	0.002	0.006	53986
		(0.006)	(0.004)	17424
	Days of rain (>20mm) – Exports	0.006	0.002	36735
		(0.007)	(0.004)	12341
	Days of rain (>20mm) – Imports	0.007	-0.001	36735
		(0.008)	(0.005)	12341
STORM	Maximum average wind speed	0.011*	-0.006	53986
		(0.007)	(0.004)	17424
	Storm – exports	0.012	-0.003	36735
		(0.010)	(0.007)	12341
	Storm – imports	0.013*	0.008*	36735
		(0.007)	(0.004)	12341
SNOW	Snow lying	0.006	0.004*	53986
		(0.004)	(0.002)	17424
	Extreme winter – exports	0.03	-0.05	36735
		(0.073)	(0.050)	12341
	Extreme winter – imports	-0.02	0.01	36729
		(0.050)	(0.032)	12341
FLOOD	Flood – exports	0.011	-0.002	36735
		(0.012)	(0.007)	12341
	Flood – imports	0.000	-0.004	36735
		(0.009)	(0.006)	12341
DROUGHT	Consecutive dry days	-0.002	0.004*	45237
		(0.004)	(0.002)	15259
	Drought – exports	0.002	0.000	36735
		(0.007)	(0.005)	12341
	Drought – imports	0.005	-0.004	36735
		(0.006)	(0.004)	12341
	R- squared	0.080	0.020	

Notes: Each line represents one univariate regression of labour productivity on the listed dependant weather variables. The first column reports fixed-effects regressions results and the second first differences. Year dummies are included in each regression. The last line reports R-squared which is identical for all regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Multivariate UK and Trade weather regressions

		Labour productivity	
		Fixed-effects	First difference
HEAT	Summer heat wave	-0.011*	-0.007*
		(0.006)	(0.004)
	TX90p – exports	0.008	0.010**
		(0.008)	(0.005)
	TX90p – imports	-0.004	-0.008**
		(0.006)	(0.004)
COLD	Winter cold wave	-0.002	0.000
		(0.004)	(0.002)
	TX10p – exports	0.009	0.015**
		(0.009)	(0.006)
	TX10p – imports	-0.003	-0.003
		(0.008)	(0.005)
RAIN	Days of rain (>10mm)	0.005	0.004
		(0.007)	(0.004)
	Days of rain (>20mm) – exports	0.000	0.000
		(0.008)	(0.005)
	Days of rain (>20mm) – imports	0.009	0.000
		(0.008)	(0.005)
STORM	Maximum average wind speed	0.010	-0.005
		(0.007)	(0.004)
	Storm – exports	0.004	-0.007
		(0.012)	(0.007)
	Storm – imports	0.017*	0.011**
		(0.009)	(0.005)
SNOW	Snow lying	0.004	0.004
		(0.004)	(0.003)
	Extreme winter – exports	0.024	-0.051
		(0.075)	(0.051)
	Extreme winter – imports	-0.013	0.009
		(0.051)	(0.032)
FLOOD	Flood – exports	0.010	0.002
		(0.014)	(0.008)
	Flood – imports	-0.018	-0.010
		(0.012)	(0.007)
DROUGHT	Consecutive dry days	-0.004	0.003
		(0.005)	(0.003)
	Drought – exports	0.015	0.006
		(0.041)	(0.026)
	Drought – imports	0.016	-0.013
		(0.024)	(0.015)
	Number of observations	36541	36535
	Number of firms	12264	12263
	R- squared	0.080	0.020

Notes: Each column represents one multivariate regression of labour productivity on the listed dependant weather variables. The first column reports fixed-effects regressions results and the second first differences. Year dummies are included. The last line reports R-squared. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Correlation of different weather variables

	Summer heat wave
Heating degree days	-1.908***
	(0.111)
Extreme temperature range	0.150***
	(0.001)
Cooling degree days	1.137***
	(0.005)
Consecutive dry days	0.145***
	(0.002)
Maximum temperature	0.103***
	(0.001)
Sunshine days	0.265***
	(0.002)

Notes: At the firm level, each cell represents the result of seven different regressions of alternative weather measures on summer heat wave duration over the sample of firms included in the main regressions.

Table 7: Robustness checks on Summer heat wave

	Labour productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Summer heat wave	-0.011**	-0.013**	-0.022**	-0.012*	-0.015**	-0.022**
	(0.006)	(0.006)	(0.009)	(0.006)	(0.007)	(0.009)
Dummy for summer heat wave				0.002	0.006	0.002
				(0.009)	(0.010)	(0.010)
Number of observations	40348	35714	36313	40348	35714	36313
Number of firms	13895	12691	13895	13895	12691	13895
Drop 2003	No	Yes	No	No	Yes	No
Drop top 10^{th} percentile of summer heat wave	No	No	Yes	No	No	Yes

Notes: Dependant variable is value added over employment for each of the six columns which each represent a regression with firm and year fixed effects. In columns 2 and 5, observations for 2003 are dropped. In columns 3 and 6, the top 10^{th} percentile of summer heat wave duration are dropped. In columns 4 to 6, a dummy for the presence of a summer heat wave is included.

Figure 4: Labour productivity and summer heat wave plot

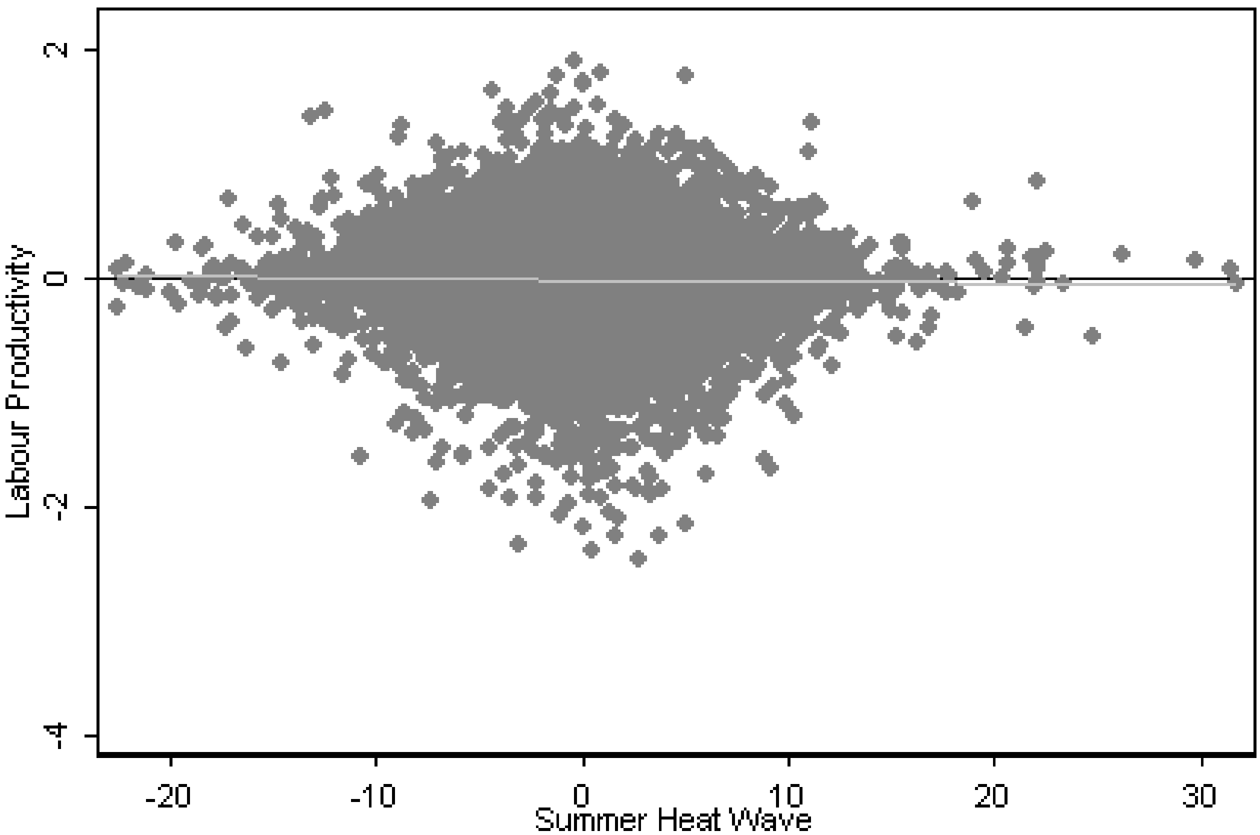
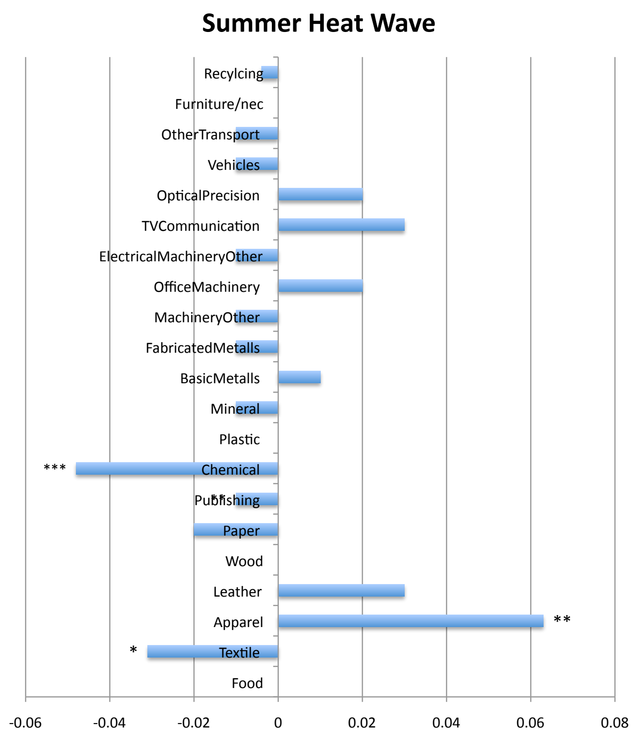


Figure 5: 2-digit first difference regression



Notes: Each bar represents the size of the coefficient of the summer heat wave duration as a dependent variable of a first difference regression of value-added per employee. Year fixed effects are included. The stars show the significance of this coefficient: *** p<0.01, ** p<0.05, * p<0.

Table 8: Summer heat wave effects by 2-digit sector

		Labour productivity				
		Univariate		Multivariate		
	UK SIC92	Fixed effect	First difference	Fixed effect	First difference	n. obs./n. firms
Food	15	-0.002	-0.008	-0.002	-0.004	4508
		(0.014)	(0.011)	(0.014)	(0.011)	1264
Textile	17	0.015	-0.028	0.011	-0.031*	1070
		(0.031)	(0.018)	(0.033)	(0.019)	377
Apparel	18	-0.004	0.061**	-0.001	0.063**	658
		(0.061)	(0.030)	(0.056)	(0.031)	250
Leather	19	-0.040	0.007	-0.048	0.026	376
		(0.066)	(0.042)	(0.063)	(0.043)	124
Wood	20	0.035	-0.002	0.041	-0.004	799
		(0.046)	(0.024)	(0.047)	(0.024)	385
Paper	21	-0.030	-0.013	-0.031	-0.017	1709
		(0.021)	(0.013)	(0.021)	(0.013)	495
Publishing	22	-0.039*	-0.018*	-0.035	-0.013	2529
		(0.022)	(0.011)	(0.023)	(0.010)	1082
Chemical	24	-0.063***	-0.043***	-0.066***	-0.048***	3091
		(0.023)	(0.015)	(0.023)	(0.015)	836
Plastic	25	0.000	0.002	0.004	0.004	2619
		(0.022)	(0.012)	(0.023)	(0.012)	1052
Mineral	26	0.020	-0.009	0.015	-0.009	1802
		(0.022)	(0.014)	(0.022)	(0.014)	562
Basic Metals	27	0.012	0.008	0.024	0.013	1197
		(0.037)	(0.020)	(0.039)	(0.020)	362
Fabricated Metals	28	-0.014	-0.005	-0.009	-0.006	2498
		(0.028)	(0.013)	(0.028)	(0.013)	1136
Other Machinery	29	-0.013	-0.010	-0.013	-0.008	4058
		(0.019)	(0.012)	(0.019)	(0.012)	1549
Office Machinery	30	-0.023	0.017	-0.015	0.016	409
		(0.052)	(0.037)	(0.053)	(0.036)	153
Electrical Machinery	31	-0.010	-0.007	-0.003	-0.008	1716
		(0.033)	(0.018)	(0.032)	(0.019)	638
TV and Communication	32	-0.006	0.021	-0.011	0.025	1063
		(0.033)	(0.024)	(0.034)	(0.024)	338
Optical Precision	33	0.017	0.020	0.017	0.020	1621
		(0.032)	(0.019)	(0.03)	(0.018)	582
Vehicles	34	-0.001	-0.008	-0.003	-0.014	1541
		(0.027)	(0.017)	(0.027)	(0.018)	484
Other Transport	35	0.009	-0.011	0.002	-0.007	1042
		(0.031)	(0.021)	(0.030)	(0.021)	316
Furniture/nec	36	0.012	0.002	0.011	0.000	2068
		(0.023)	(0.013)	(0.024)	(0.013)	797

Notes: Each panel represents the results of a regression of value-added per employee on weather variables. When the column is entitled univariate, the only weather variable included is the summer heat wave. In the multivariate case, all weather variables are included, but only the summer heat wave is reported. Year dummies are included. The last column reports the number of observations and firms for the first difference multivariate regressions.Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1

6 Potential aggregate effects

The previous sections established a significant relation at the level of individual firms between summer heat waves and labour productivity. A crucial question for policy are the economy wide aggregate consequences of such effects. Computing such aggregate effects is easy if we can assume that weather effects are homogenous for all firms in the economy. However, in practice it is more plausible that effects differ between different firms and that the effects we identify represent some weighted average across firms. For instance we have already documented that the effects differ greatly between different sectors. In further results[10] we have found that the effects differ between firms of different size. For instance we find that the heatwave effect occurs only in larger firms (i.e. firms with more than 50 employees): the coefficient on summer heat waves becoming insignificant and close to zero for small firms, and remains positive and significant. In the fixed-effects specification, the coefficient is -0.011 and significant at the 10% level, and for the first difference case, it is -0.010 and significant at the 5% level[11].

To estimate reliable aggregate effects we need to clearly identify the differential effects for the various sub-groups in our data. To see this consider that we have G different groups in our data for each of which we can assume that a weather impact on labour productivity β_g is homogenous within the group. Note that aggregate labour productivity is equal to labour productivity in each group times the employment share of each group.

$$\left(\frac{VA}{L}\right)_A = \sum_g \left(\frac{VA}{L}\right)_g \theta_g$$

where $\theta_g = \frac{L_g}{L_A}$. Because our regressions are in terms of log labour productivity, our parameter estimates can be interpreted as semi elasticities so that the coefficient β_W on a weather variable W_i gives us (approximately) the percentage change of labour productivity in response to a change of 1 standard deviation (σ_W) of the weather variable. Or to figure out by how many percent labour productivity would change if the weather variable changed by ΔW we would have to compute

$$\gamma_g(\Delta W) \approx \beta_{gW}\frac{\Delta W}{\sigma_W}$$

Hence can compute the (relative) impact on aggregate GDP/Value Added as

$$\theta_A = \sum_g \gamma_g(\Delta W)\,\theta_g$$

[10]More details available on request.

[11]Results available on request. One could refine this analysis by allowing the effects to vary more widely depending on a wider range of firm characteristics.

Table 9: Assessing the aggregate impact

Parameter	Small	Large	Total
Employment Share	0.720	0.280	1.000
Summer heat wave marginal impact	0.000	0.010	
Std. Summer heat wave			10.246
Mean Summer heat wave			10.295
Mean Summer heat wave 2003			21.949
Relative Impact for ΔW=Mean(2003)-Mean	0.00%	1.14%	0.32%
UK Manufacturing GDP 2009 [Million of £]			140,000
Absolute Impact [Million of £]			446

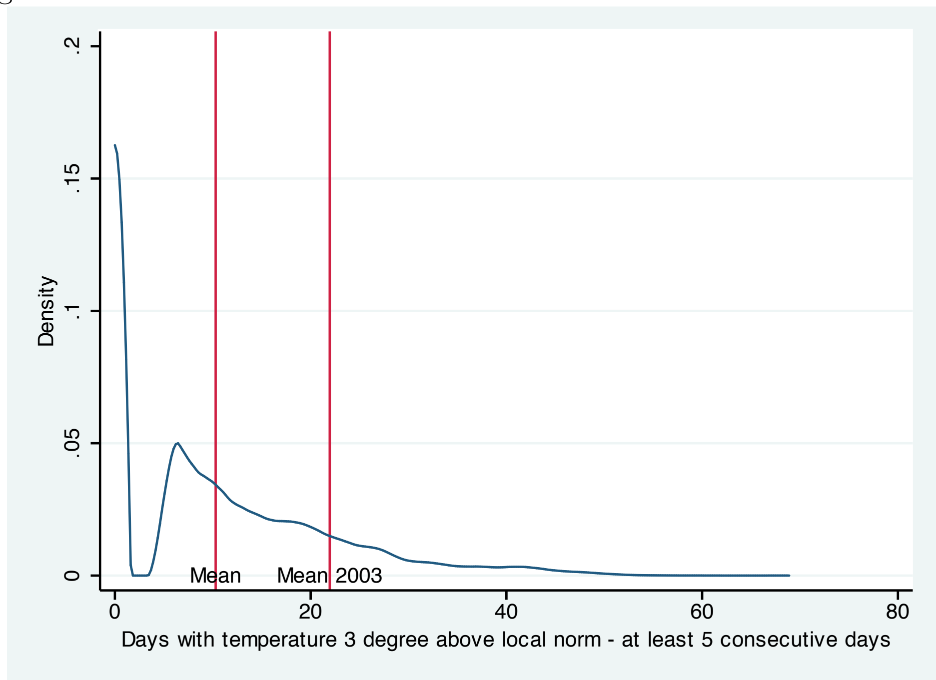
Finally, if we are willing to assume that weather has an impact only on value added but not on employment we can derive the impact on value added as

$$VA_A\theta_A$$

Thus, to work out the aggregate impact we need the employment weighted average impact, however in general we cannot estimate this average without separate regressions for each sub-group.[12] Further work is needed to establish relevant subgroups of firms in more detail. To have nevertheless a sense of the aggregate relevance of our results so far, we provide an extrapolation of our results to the aggregate in what follows. These figures should be taken as a preliminary gauge of the order of magnitude rather than a definite prediction. In doing so we allow for two sub-groups of firms: small firms where we assume an effect of zero and large firms for which we assume an effect of 1% for a standard deviation change in heat waves. Table 9 reports all necessary figures to compute these calculations. We examine the impact of the average summer heat wave of 2003 (one of the warmer years on record) relative to the mean of the summer heat wave variable (see Figure 6); i.e. on average across all UK locations there are 10.3 summer heatwave days. In 2003 this climbed to almost 22. Hence we have $\Delta W = 22 - 10.3 = 11.7$ which is roughly the same as the standard deviation of the summer heatwave variable as well. The proportional impact for large firms becomes consequently 0.32%. Considering that Manufacturing GDP was around £140 billion in 2009 this would translate into a loss of GDP of around £446 million.

[12]See DuMouchel and Duncan (1983) for a further discussion.

Figure 6: The distribution and means for the summer heat wave variable



Source: UKCP09 MetOffice

7 Conclusion

This is the first study to examine the impact of extreme weather events both in the UK and globally on businesses in the UK using a large sample of firm level performance data. Our initial results establish a significant and robust negative relationship between summer heat waves and labour productivity. We also find evidence that heat waves in countries the UK is importing more from in a given sector have a negative impact on the same sector, whereas the same figure for exports leads to a positive impact. We interpret this as evidence of upstream and downstream disruptions. According to this, upstream disruptions have a negative impact, whereas downstream disruptions have a positive impact. This could be the case if consumers abroad shift to UK suppliers in response to problems with their domestic producers.

We also find some evidence for a positive effect of storms in countries the UK imports from. This could reflect a shift of UK consumers away from foreign producers towards domestic ones.

We will investigate further the various drivers for the evidence based on international weather data using firm level data on imports and exports, which was not yet available for this study. Equally, in future work we will consider a richer set of outcome variables.

Another issue for additional research is to examine more closely the heterogeneity of weather impacts for different sub-sets of firms in the data. This is particularly important in order to make predictions about the aggregate impact of a given weather event. A very crude initial calculation we have conducted suggests that a heat wave as experienced in 2003 for example has an impact on the order of £400 to £500 million.

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