The Health Effects of Weather and Pollution: Implications for Climate Change [‡]

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Abstract

This paper estimates the effects of weather conditions and pollution levels on population health. We merge censuses of all hospital admissions and death records in Germany from 1999-2008 with rich weather and pollution data on a daily county level basis. This unique dataset includes 170 million ICD-10 coded hospital admissions and 8 million deaths along with the daily weather conditions and pollution levels from several hundred measurement stations. The data allow us to analyze in detail how specific weather conditions such as heat and cold waves interacting with variation in pollution levels affect human health.

Germany has one of the highest densities of hospital beds worldwide, universal health care coverage, and almost no access barriers for inpatient care treatments. This institutional setting makes it possible to comprehensively assess the effects of environmental conditions on population health and on demand for health care.

In a second step, using climate change scenarios, we predict how climate change might potentially affect human health in industrialized countries in the northern temperate climate zone.

Keywords: register data, hospitalization, mortality, weather and pollution, climate change

JEL classification: H51; I18; J22; J32

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1 Introduction

Over the last decade, the economics literature has seen a staggering rise in the number of studies that empirically estimate the impact of air pollution on population health. Certainly, the reason for this boom lies partly in an increaslingly sophisticated data collection and availability. On the other hand, without any doubt, researchers and policymakers understand that well-founded state-of-the-art empirical investigations may provide well-founded policy advice which in turn may lead to effective and welfare increasing policy regulation. Although thorough cost-benefit analyses are still scant, almost all studies in this substrand of the economics literature find that pollution negatively affects population health. This finding has been shown to hold particularly for vulnurable subgroups such as the newborn (Currie and Schmieder, 2009; Currie and Walker, 2011), children (Chay and Greenstone, 2003; Nilsson, 2009; Currie et al., 2009), or the elderly (Villena et al., 2008; Schlenker and Walker, 2011; Karlsson and Schmitt, 2011), but also for the population as a whole (Almond et al., 2009). Outcome measures are typically mortality statistics (Knittel et al., 2011), but some studies also rely on hospitalization data (Neidell, 2009; Lagravinese et al., 2013), school absence data (Currie et al., 2009), specific diagnoses (Hammitt and Zhou, 2006), or even self-reported health data (Evans and Smith, 2005; Edwards and Langpap, 2012). By construction or due to data availablity, the limitations of many of these studies are that they rely on *(i)* very narrowly defined outcome measures, *(ii)* very narrowly defined geographic locations, or *(iii)* single pollutant measures limiting the ability to model air pollution comprehensively (c.f. Joyce et al. (1989), Neidell (2004), Currie and Neidell (2005), Moretti and Neidell (2011), Zivin and Neidell (2012)). Most existing studies use data from industialized countries, although there has been an upswing in the work on developing countries in recent years (Quah and Boon, 2003; Greenstone and Hanna, 2011; Hanna et al., 2012).

A less popular but closely related subfield of the economics literature studies the impact of weather conditions on population health (Deschênes and Moretti, 2009; Deschênes et al., 2009; Deschênes and Greenstone, 2011).[1]. The relative small literature on weather and health is surprising, given the heated debates about the causes and consequences of climate change in the last 15 years. The famous Stern report states that the world's average temperature has

[1]The epidemiological literature on this topic is older and, thus, more diverse (Curriero et al., 2002; Basu and Samet, 2002)

risen by 0.74 °C (1.33 °F) over the past 100 years. It projects this trend to progress in the future. For the US, the predicted increase until the end of this century ranges between 2.2 and 6.1 °C (4 and 11 °F) (United States Global Change Research Program, 2009). Moreover, climate scientists project a significant increase in the number of hot days with temperatures above 30 °C (86 °F) as well as heat waves. The Intergovernmental Panel on Climate Change (IPCC) projects *"warmer and fewer cold days and nights"* and states: *"It is very likely that hot extremes, heat waves and heavy precipitation events will continue to become more frequent."* (Intergovernmental Panel on Climate Change (IPCC) (2007), p. 46, 53).

This study aims at comprehensively assessing the population health effects of pollution and weather. We base our findings on various rich high-quality administrative datasets over a time period of ten years. This allows us to consider a battery of pollution and weather indicators and to model specific weather conditions and nonlinear associations between weather and pollution more thoroughly than previous studies. We rely on 11 weather and 11 pollution measures collected by more than 2,350 ambient monitors on a daily basis. This very dense high-quality network of stations covers the whole 138,000 square miles of Germany over ten years.

More importantly, we also base our health outcome findings on two high-quality register datasets from 1999 to 2008. First, the official mortality statistic, containing all deaths on German territory. Second, the universe of all hospital admissions, containing more than 170 million hospital admissions. Most previous studies primarily focused on mortality effects. It is intuitively plausible that solely relying on deaths only allows to caputure a fraction of the total population health effects of pollution and weather. Relying on both, the universe of deaths and hospital admissions, should capture all serious adverse health effects to a large degree. To our knowledge, this paper represents the most comprehensive attempt to assess the population health effects of weather and pollution.

The institutional setting in Germany appears to be particularly well suited for our research setting. Germany has one of the highest densities of hospital beds worldwide, universal health care coverage, and virtually no barriers to access for inpatient care. In addition, Germany is the most populous country in Europe and counts 82 million residents. We argue that our findings can be seen as representative for industrialized countries in the North Temperate Climate Zone, where the majority of the world's population resides.

For our parametric analysis, we merge, aggregate, and analyze the universe of all hospitalizations and deaths on a daily county-level basis with the pollution and weather data from 2,350 ambient monitors. Our findings are in line with previous findings and allow us to model the interdependencies between comprehensive weather and pollution measures thoroughly and to disentangle singular pollutant and weather effects. In a second step, we apply the existing climate change scenarios to our empirical findings and monetize the health effects in forms of Quality Adjusted Life Years (QALYs) lost.

The findings can be summarized as follows. First, extreme heat events have a highly significant negative impact on population health and lead to more hospitalizations and deaths, mostly due to cardiovascular health shocks. We find (partly) support for the "harvesting hypothesis." The harvesting hypothesis interprets a significant subsequent drop in mortality rates *after* the occurance of heath waves as evidence that those humans who died during the heat event would have died soon anyways due to their generally faible health conditions.

Second, we find that extreme cold events likewise have a signficant negative impact on human health. Negative population health effects continue to persist over the duration of cold waves and we fail to detect any subsequent drop in mortality or hospitalization rates. This yield support for permanent adverse health effects triggered by cold waves, in line with previous studies. However, as compared to heat events, extreme cold events have a quantitatively smaller impact on population health.

Third, positive daily temperature shocks trigger negative population health effects, whereas drastic decreases in the maximum daily temperature trigger decreases in mortality and hospitalization rates. Drought periods and heavy precipitaion periods have a negative effect on health.

Fourth, shocks in outdoor air pollution are associated with large negative health effects. All five pollutant analyzed affect health negatively. Quantitatively, NO_2 and PM_{10} shocks lead to the largest adverse health effects. Interestingly, sharp daily increases in the air concentration of these pollutanty are also most common and observed during 12 percent of all county-day observations or an average of 44 days per year. Hence, despite the relatively tight environmental regulation by the European Union, air pollution shocks are still relatively common. To the degree that policymakers can actively bring down these spikes in pollution levels, our findings suggest that a more effective environmental regulation would also be effective in improving population health.

Finally, one needs to impose strong assumptions on how exactly climate change would affect specific weather conditions in order to be able to assess and monetize their population health effects. Applying back-of-the-envelope calculations to different climate change scenarios yields no conclusive result since the negative effects of heat events and the positive effects of cold events work in opposite directions. Without knowing the exact shift in the weather event distribution, no conclusive net effect of climate change population health can be derived. However, since the magnitude of the health effects is larger for heat as compared than cold events, it is likely that, on net, climate change will affect population health negatively. Also note that this study excludes all health effects that may occur due to a climate change-related increase in natural disasters such as flooding, hurricanes, or tornadoes.

We describe the various datasets in the next section. Moreover, Section 2 illustrate rich variations in our weather and pollution measures across space and time and discuss their interdependencies. Section 3 describes our estimation strategy and contains our empirical findings. In Section 4, we apply different climate change scenarios and attempt to calculate their impact on population health. Secion 5 concludes.

2 Datasets, Main Variables, and Descriptives

This paper makes use of a variety of different high-quality register datasets. First, we describe these datasets and explain how we generated our weather and pollution shock indicators. We also discuss descriptives and Then, we explain how we combine these single datasets to obtain our working dataset on the daily county level.

2.1 Hospital Admission Census: The Universe of all German Hospital Admissions 1999-2008

The first dataset comprises a census of all German hospital admissions from 1999 to 2008. By law, German hospitals are required to submit depersonalized information on every single hospital admission. The 16 German states collect these information and the German Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*) provides restricted data access for researchers.

Germany has about 82 million inhabitants and registers about 17 million hospital admission per year. We observe every single hospital admissions from 1999 to 2008, i.e., a total of more than 170 million hospitalizations.[2] To obtain our working dataset, we aggregate the individual-level data on the daily county level and normalize admissions per 100,000 population.[3] Appendix A shows all raw measures of the Hospital Admission Census as well as the descriptive statistics of our working dataset.

As seen in Appendix A, besides others, we have information on age and gender, the day of admission, length of stay, county of residence as well as the diagnosis in form of the 10$^{\text{th}}$ revision of the *International Statistical Classification of Diseases and Related Health Problems* (ICD-10) code.

Construction of Main Dependent Variables

Using the information on the primary diagnosis, we generate a series of dependent variables. Basically, we extract the first digit of the the ICD-10 code, e.g., J00-J99 refers to "diseases of the respiratory system." In some cases, the second and third ICD-10 digit are helpful to identify more specific conditions. For example, we generate a dummy variable *heart* that includes codes I00-I99 and "diseases of the circulatory system." In this case, in addition to the dummy *heart*, we also generate a dummy variable *heartattack* indicating I20 ("Angina pectoris") and I21 ("myocardial infarction").

Along with each main diagnosis indicator, we exploit the death and the length of stay information. Following up on our example from above, this means that we do not only make use of the *heartattack* dummy, but also generate a variable *heartattackdead* identifying people who died after they were admitted to a hospital due to a heart attack. Also we rely on *heartattacklengthstay*, indicating the number of nights a patient spent in a hospital after a heart attack. We use length of stay as an severity indicator.[4]

[2] This excludes military hospitals and hospitals in prisons.

[3] The remote access servers of the *Statistische Ämter des Bundes und der Länder* only provide a memory of 18 gigabytes per computer. The individual admission data is provided in files by calendar years. The memory capacities only allow us to merge and analyze two calendar years of hospitalizations on the individual admission level. Therefore, we have to restrict the working dataset to patients who were admitted after January 1 of a given year. In other words, we have to delete all admissions that led to stays over New Years. We have to do this since we first aggregate admissions on the daily county level and then merge the files by calendar years, resulting in duplicate observations for counties and days with admissions in t_0 and discharges in t_1. In robustness checks, we *(i)* draw a 10 percent subsample at the individual-admission level and merge the annual data files before we aggregate, *(ii)* run the analysis using only two calendar years but including stays over New Years. The results are robust to excluding over New Years hospitalized people.

[4] Note that this may not necessarily be the case if hospitals are capacity constraint. Times of high occupancy rates may be correlated with decreasing lengths of stay. Moreover, an increase in occupancy rates in one

Appendix A yields the summary statistic of our generated hospital admission variables.[5] They serve as dependent variables in our models below. We use official data sources on the annual county level to normalized the dependent variables at the daily county level per 100,000 population. For example, on a given day, we observe about 68 hospital admissions per 100,000 population in Germany. The incidence varies substantially over the daily county level; the standard deviation is 24. On average, a day triggers 536 hospital days, i.e., the 68 per 100,000 pop. admissions have an average length of stay of 7.9 days. The largest single group of diseases that contributes to the incidence of admissions is cardiovascular diseases (10 per 100,000 pop.); however, although making up only a fraction of the incidence, neoplasm is responsible for most days spent in hospitals (XXX days triggered on a given day per 100,000 pop.; 20 percent of total hospital days triggered on a given day).

2.2 Mortality Census: The Universe of all Deaths 1999-2008

Our second dataset is the official German Mortality Statistic provided by the German Federal Statistical Office. The register data include every death that occured on German territory. Per year, we observe approximately 800,000 deaths, i.e, about 8 million deaths in total. To obtain our working dataset, we aggregate the individual-level data on the daily county level and generate the mortality rate per 100,000 population. Appendix B shows all raw measures of the Mortality Statistic as well as the descriptive statistics of our working dataset on the daily county level.

As the Hospital Admission Census and listed in Appendix B, the Mortality Statistic contains information on age, gender, day of death, county of residence as well as the primary cause of death in ICD-10 form.

Construction of Main Dependent Variables

We generate four dummy variables that indicate the cause of death. Similar to the hospitalization data above, we use the first digit of the ICD-10 code to group the reason of death by

department may lead to decreases in occupancy rates in others. However, in Germany, occupancy rates are structurally low. For acute care hospitals, the average occupany rate lies at around 75 percent (German Federal Statistical Office, 2012a). In addition, there is not much empirical evidence that length of stay is determined by workforce restrictions or is systematically correlated with occupany rates (XXX QUOTE).

[5] Note that the strict German data protection laws prohibit us from reporting min and max values.

disease category, e.g., *respiratory disease*, *cardiovascular disease*, *neoplasm*, and *infectious disease*. The summary statistics of the mortality rates are in Appendix B. Again, we normalize by 100,000 population at the daily county level, which yields an average of 2.8 deaths per 100,000 population—1.3 of which are caused by cardiovascular diseases, i.e., almost 50 percent.

2.3 Using Hospitalization and Mortality Censuses to Identify Population Health Effects

Note that while we are able to observe every single hospital admission, data protection laws prohibit us from analyzing panel data. This means that we are unable to observe hospital readmissions.[6]

Also note that we only observe inpatient treatments, i.e., hospital admissions that require the patient to stay overnight. This excludes mild conditions that were treated in outpatient settings. Since this paper intends to assess the population health effects of weather and pollution, the underlying assumption is that negative health effects not requiring an overnight stay are negligible relative to inpatient treatments and mortality effects. Clearly, this assumption essentially means that we obtain a lower bound total population health effect triggered by weather and pollution.

In addition, we implicitly assume that all severe health effects triggered by weather and pollution eventually lead to hospital admissions or death. We believe that this is a reasonable assumption. German geography, combined with the institutional setting of the German health care system, reinforces that assumption. First of all, the German population density is relatively high. Germany counts 82 million residents and has the size of the US state Montana. The average German population density is about seven times as high as the US population density (231 vs. 32 people per km^2) (Bureau, 2012; German Federal Statistical Office, 2012b). Consequently, not surprisingly, the hospital bed density is also much higher. Per 100,000 population, Germany's health care infrastructure offers 824 hospital beds, while the US has only 304 (OECD, 2012). Germany counts a total of 2,045 hospitals while Montana has only 70

[6] According to representative SOEP data, about 13 percent of all Germans were admitted to a hospital in 2010. About 2 percent (15 percent conditional on an admission), had more than one hospital stay in 2010 (Wagner et al., 2007). Not being able to identify readmissions would be particularly worrisome if we were interested in treatments of chronic diseases such as diabetes were patients are obliged to return to the hospital in regular intervals. Using the age, gender and county-level information, we could apply propensity score matching methods to probabilistically identify readmissions.

hospitals (German Federal Statistical Office, 2012a). This illustrates that geographic access barriers, such as travel distances, are significantly lower in Germany. Lastly, the uninsurance rate in Germany is below 0.5 percent. The public health care system covers 90 percent of the population and copayment rates in the public scheme are uniform and low.[7] The overwhelming majority of hospitals can be accessed independent of insurance status; provider networks are almost unknown in Germany.

2.4 Weather: Daily Weather Data from 1,044 stations 1999-2008

The weather data is provided by the German Meteorological Service (*Deutscher Wetterdienst (DWD)*). The DWD is a publicly funded federal institution and uses information from 1,044 meteorological stations which are distributed all over Germany. Figure 1 shows the distribution of all ambient monitors along with county borders. It is easy to see that the German weather station network is very dense.

[Insert Figure 1 about here]

We obtain official measurement data from all existing weather stations in a given year. As described in Section 2.7, we extrapolate the point measures into county space on a daily basis.

Weather Variation Across Space and Time

Summary statistics of all raw weather measures on the daily county level are given in Panel A of Appendix C. Due to the public interest and the obvious connection to climate change as well as the previous literature, our most important plain weather indicators are certainly *temperature*, *hourssunshine*, and *precipitation*.

The mean daily air **temperature** is 9.6 ° C (49.2 ° F), averaged over the whole time period and all counties. Note the extremely rich variation in the average daily temperature across German counties and over ten years: it ranges from -19 ° C (-2.2 ° F) to 30.6 ° C (87.1 ° F). The minium daily temperatures on the county level vary from -25 ° C (-13 ° F) to 23.8 ° C (74.8 ° F). The maximum daily temperatures vary from -14.1 ° C (6.6 ° F) to 39.1 ° C (102.3 ° F).

Analogously to the temperature measures, hours of sunshine also exhibits a great deal of

[7] If total out-of-pocket expenditures do not exceed 2 percent of the individual's income (1 percent for people with chronic conditions), the daily copayment for inpatient stays is €10 in the public system.

variation with 4.6 hours as the national 10-year average, but daily county values ranging from 0 to 16.7 daily hours of sunshine. Precipitation levels range from a daily average of 0 (mm) to 144.9 (mm). Indicators for storm and wind force as well as air and vapor pressure exhibit similarly rich variation across space and time.

Figure 2 shows boxplots of the mean temperature, the sunshine duration, and the precipitation level over the twelve months of a year (averaged over all ten years). Essentially this graph illustrates the cross-county as well as seasonal variation in weather. First, the variation across counties is stunning. Second, we observe a clear increase in average temperatures and sunshine duration during the summer months. Interestingly, precipitation does not seem to follow a strong seasonal pattern, but variation is huge.

[**Insert Figure 2 about here**]

Figure 3 shows the daily cross-county temperature, sunshine, and precipitation variation over 10 years. We observe the typical seasonal trends along with a lot of noise in the high-frequency data. Later in the regression models, we will exploit and rely on the many positive and negative weather shocks across space and time. Deviations in daily weather variations are plausibly exogenous to individuals' health.

[**Insert Figure 3 about here**]

Interestingly, Figure 3 also indicates slightly positive temperature and sunshine trends over a time period of just 10 years. This might be interpreted as suggestive evidence for a permanent change in climate. Note that the precipitation trend is negative. Also note that the weather *variation* does not seem to increase over time.

Finally, Figure 4 plots a scatter matrix for our three main weather indicators. The positive association between sunshine and temperature as well as between temperature and precipitation is easy to grasp. However, temperature and precipitation level do not exhibit any strong relationship. In the regression models below, to model the nonlinear associations, we include the weather indicators in levels, add quadratic and cubic terms as well as interaction terms between the indicators.

[**Insert Figure 4 about here**]

Main Variables of Interest: Construction of Weather Condition Indicators

Next, we follow the recommendations of the *World Meteorological Organisation (WMO)* and the *Working Group of Climate Change Detection*. These experts developed and identified a list of simple and feasible indices to define specific weather conditions and monitor climate change (Frich et al., 2002). Out of the list proposed, we select and generate the following indicators:

- **Frost Day (*FD*)**: day with absolute minimum temperature <0 ° C.
- **Intra-Day Extreme Temperature Range (*ETR*)**: difference between the highest and lowest temperature observation of any given calendar day.
- **Growing Season Length (*GSL*)**: period in days between *(i)* average temperature >5 ° C for >5 days and *(ii)* average temperature <5 ° C for >5 days.
- **Heat Wave Duration Index (*HWDI*)**: maximum period > 5 consecutive days with max. daily temperature >5 ° C above the average monthly max. temperature.
- ***R10***: day with precipitation >10 mm $d^{-}1$.
- ***CDD***: maximum period > 5 Consecutive Dry Days (Rday < 1 mm).

One great advantage of these indicators is that they are not highly correlated, but rather contain independent information. In addition, these indicators are considered relatively robust and not very noisy.

We also generate the following indicators that we consider as helpful for our purposes:

- **Hot Day (*HD*)**: day with max. temperature >30 ° C (86 ° F).
- **Heat Wave (*HW*)**: maximum period > 3 consecutive days with max daily temperature >30 ° C (86 ° F).
- **Cold Day (*CD*)**: day with min. temperature < -10 ° C (14 ° F).
- **Cold Wave (*CW*)**: maximum period > 3 consecutive days with min. daily temperature <-10 ° C (14 ° F).
- **Positive Temperature Shock (*PTS*)**: average temperature in t_1 exceeds average temperature in t_0 by at least 10 ° C (14 ° F).
- **Negative Temperature Shock (*NTS*)**: average temperature in t_0 exceeds average temperature in t_1 by at least 10 ° C.

Panel B of Appendix C shows the descriptive statistics for our generated weather condition indicators. As seen, 2 percent of all days are "hot days" with the maximum daily county level temperatures exceeding >30 ° C (86 ° F). This translates into 7.3 days or about one week of hot days per year. *HW* indicates days *after* three consecutive hot days. On average, a year counts about one such day, i.e., per year we measure about four days belonging to a heat wave. *HWDI* is similarly constructed but measures the number of days following 5 consecutive days with the maximum temperature exceeding the maximum monthly temperature by at least 5 $^\circ$C. There are slightly more than fours such days per year. Note the relatively large standard deviations of all these measures—they are about seven times larger than the mean. Over ten years, we observe 638 positive temperature shocks where the average daily temperature was at least 10 $^\circ$C (14 $^\circ$F) larger than the average temperature of the preceeding day. Negative temperature shocks occur much more often, on almost 4,000 of our 1.5 million county-level days.

Turning to the other temperature extreme, we note that 22 percent of all days are "frost days" with temperatures below 0 $^\circ$C in Germany. Days were the minimum temperature falls below -10 $^\circ$C are much more rare. We count only 3.6 days per year. Even rarer are cold waves with more than 3 consecutive cold days—between one and zero occur per year. However, over ten years, we still count 2,870 county-level days of which the preceeding three days had minimum temperatures of less than 10 $^\circ$C (14 $^\circ$F).

About 20 days per year, or 5.4 percent of all days, are heavy precipitation days. Climate change scenarios predict an increase in the number of those days—as they predict an increase in the number of dry periods without rain. The latter are already relatively common in Germany– in 20 percent of all days, the previous 5 days were dry as well.

2.5 Pollution: Daily Pollution Data from 1,314 stations 1999-2010

The pollution data is provided by the German Federal Environmental Office (*Umweltbundesamt (UBA)*). The UBA is a publicly funded federal agency that operates 1,314 ambient monitors as Figure 1 illustrates. As with our weather measures and described in Section 2.7, we extrapolate the point measures into the county spaceon a daily basis over 10 years. Panel A of Appendix D shows all raw pollution measures on a daily county level basis.

5 Different Pollutants: Occurance, Health Hazards, and Variation Across Space and Time

(i) Nitrogen Dioxide (NO_2)

Nitrogen dioxide is a red-brown toxic gas that is formed by oxidation of nitrogen monoxide (NO). NO_x–describing the sum of NO and NO_2—is a product of combustion processes under high temperature that happen in automobile enginges or fossil fuel power plants; it is an important intermediate in the chemical industry. Since NO_x is one main ingredient in the formation of O_3 (see below) and highly correlated with the other pollutants, isolating its single impact on human health is challenging. Thanks to the various underlying high-quality register datasets, one main purpose of this study is to disentangle the health effects of the pollutants from each other and weather conditions. Experts by the WHO and the EU warn that "epidemiological studies of NO_2 exposures from outdoor air are limited in being able to separate these effects" (World Health Organization (2003), p. 46; European Environment Agency (2012), p. 39). Evidence for negative health effects mainly comes from indoor toxicological studies showing that NO_x has a negative effect on respiratory functions (cf. Blomberg et al. (1999); C Barck (2002)).

The NO_2 concentration is measured in $\mu g/m^3$. The European Union (EU) applies a long-term threshold of 40 $\mu g/m^3$ and an hourly alert threshold of 400 $\mu g/m^3$. If exceeded for more than three hours, authorities are required to implement short-term action plans (European Environment Agency, 2012).

Figure 5a shows a boxplot of the mean daily NO_2 levels across German counties and over the twelve months of a year (averaged over 10 years). There is some seasonal variation with lower NO_2 levels during the summer month, but most striking is the huge variation within months across counties.

[**Insert Figures 5 and 6 about here**]

Figure 5b shows the mean, minimum, and maximum daily NO_2 levels over the time period from 1999 to 2008. First, we observe a significant difference between minimum and maximum daily values throughout the years. Second, there seems to exist a slightly increasing trend in NO_2 levels over the 10-year period.

Figure 6 reveals the relationship between NO_2 and some of the weather indicators discussed above. We observe a slightly negative correlation between NO_2, temperature and wind speed. On the other hand, humidity levels of more than 80 percent seem to be positively correlated with NO_2. The is no association with the hours of sunshine.

(ii) Ground-Level Ozone (O_3)

Ozone is an oxidant and may lead to respiratory hazards. It is called a "secondary pollutant" since it is formed by various photochemical reactions between carbon monoxide (CO), nitrogen oxides (NO_x) and free oxygen molecules (O) (European Environment Agency, 2013). The ground-level ozone concentration is measured in μg/m^3. According to the European Union (EU), values below 100 μg/m^3 do not pose a threat to human health. Very high ozone concentrations of more than 240 μg/m^3 may lead to asthma, bronchitis, chest pain, coughing, throat irritation, or congestion, but also to more severe conditions such as heart attacks or other cardiopulmonary problems (cf. **?**Broeckaert et al. (2000)).

In the EU, an hourly concentration of more than 180 μg/m^3 requires that the population is officially informed by the national authorities. The health alert threshold requires the hourly concentration to exceed 240 μg/m^3. The EU Air Quality Directive specifies that a daily maximum 8-hour average of 120 μg/m^3 should not be exceeded by the member states to avoid health hazards (European Environment Agency, 2012).

As shown in Table A of Appendix D, in Germany, the average ozone level is 45.98, but average daily values vary from 0.86 to 135.87. Minimum daily values vary from 0 to 79.6, whereas maximum daily county averages range between 1.17 and 192.15 μg/m^3.

[Insert Figures 7 and 8 about here]

Again, we first look at the O_3 variation across counties and calendar months (Figure 7a). And again, we find enormous variation in levels across counties within months. Ozone levels increase significantly over the summer months. This can be traced back to the fact that ground-level ozone is highly and positively correlated with both temperature and sunshine and thus negatively correlated with humidity (Figure 7b). Over the time period from 1999 to 2008, both variation and levels of ozone seem to be stable (Figure 8).

In the following, we refrain from discussing detailed space-time variation for the other three pollutants. They all have in common that they *(i)* exhibit some seasonal pattern, *(ii)* exhibit nonlinear, but modest, associations with the weather indicators, and most importantly for identification purposes: *(iii)* exhibit strong daily variation across counties and over time.

(iii) Carbon Monoxide (CO)

Carbon monoxide is a colorless odorless gas that is toxic to humans in higher concentrations.

The typical concentration in the athmosphere is about 0.1 parts per million (ppm). Incomplete burning of carbon-containing materials, such as smoke from fire, is one main source of high CO concentrations. However, in industrialized countries, automobile fuel combustion is responsible for a large fraction of CO concentration in the air. CO concentrations of more than 100 ppm are considered health damaging, although individual tolerance levels vary significantly (Omaye, 2002).

According to the *Centers for Disease Prevention and Control (CDC)*, in the US, about 450 people die every year from "accidental, non-fire related exposure to this toxic gas." CO decreases decreases the blood oxygen transmission. CO poisoning would require medical care for thousands more (Centers for Disease Control and Prevention, 2012). Omaye (2002) notes that CO poising may be the main cause of more than 50 percent of all fatal poisonings in industrialized countries and that many situations would remain un- or missreported. The EU and WHO 8-hour threshold values are 10 $\mu g/m^3$ (or 8.7 parts per million (ppm)) (European Environment Agency, 2012).

Appendix D shows that the average daily carbon monoxide (CO) concentration in parts per million (ppm) is 0.43, ranging from 0.002 to 1.31. The daily average county-level minimum concentration is 0.23 and the average maximum concentration is 0.81. The latter varies between 0.03 and 2.8. A boxplot of daily CO levels shows the typical seasonal variation with lower CO levels during the summer month. Over the last decade, average CO concentrations have slightly decreased, but standard deviation remain high illustrating positive and negative CO shocks.

(iv) Sulphur Dioxide (SO_2)

Sulphur dioxide is a colorless toxic gas emitted by sulphur containing fuels when burned. Industrial processes lead to SO_2 emissions as do domestic heating and transportation. For example, coal contains sulphur and thus coal combustion lais off SO_2 unless the sulphur components are removed before the burning process. Oxidation of SO_2 may lead to H_2SO_4 and acid rain. SO_2 is also a precusor for particular matter (see below). While SO_2 is still one of the main air pollutants in developing countries, due to environmental regulation, SO_2 emissions decreased significantly over the last decades in industrialized countries (World Health Organization, 2000; **?**).

Epidemiological and experimental studies with small numbers of volunteers show that SO_2 concentrations may primarily result in adverse respiratory health effects. It disrupts the ciliary function, slows the ciliary transport of mucus and may lead to coughing, asthma and chronic bronchitis. Moreover, for people with heart diseases and among vulnurable populations SO_2 shocks my lead to hospitalizations, premature birth, and even deaths (Lawther et al., 1975; Horstman DH, 1988; Shah and Balkhair, 2011).

Natural SO_2 concetrations in rural areas are around 5 $\mu g/m^3$. The EU treshold for daily SO_2 concentrations is 125 $\mu g/m^3$. The hourly alert threshold is 500 $\mu g/m^3$ and action plans have to be implemented when exceeded in three consecutive hours. As Panel A of Appendix D illustrats, all SO_2 concetration values measured in all German counties from 1999-2008 are significantly below these thresholds. The average concentration is 3.7 $\mu g/m^3$ and the maximum concentration is 12.5 $\mu g/m^3$. Boxplot graphs (not displayed) show significant variation across counties with average values slightly lower in the summer months. Plotting values over time illustrates a significant decline in SO_2 concentrations from 1999 to 2008.

(v) Particular Matter (PM_10)

Particular matter (PM) is a generic term and describes aerosol particles, or athmospheric aerosol, which can be of different size and chemical composition. PM_10 refers to particles with a diameter of at most 10 micrometres. PM may either have a "natural" origin and stem from sea salt, dust, pollen or ash of volcans. However, PM may also result from fuel combustion, e.g., burning of wood, domestic heating, road dust due to traffic, or power generation. Then it is typically formed from oxidation and transformation of "primary" pollutants such as SO_2 or NO_2 (European Environment Agency, 2012).

Health effects of PM are caused through lung inhalation and physicial as well as chemical reactions with lung cells. A plentitude of epidemiological studies demonstrate a strong link between PM exposure and cardiovascular mortality in particular (cf. C et al. (2002); Li et al. (2012). For example, Abbey et al. (1999) found a signficant impact of PM_10 on respiratory deaths as well as lung cancer. However, studies that intend to measure the effects of long-term exposure to PM obviously suffer from various methodological challenges, such as selection into regions and a high permanent correlation with other pollutants.

The EU short-term limit value is a 24 hour concentration of 50 $\mu g/m^3$. Effective January 2005, this concentration ought not to be exceeded on more than 35 days per year. However, various European cities regulary exceed that threshold (European Environment Agency, 2012). The WHO sets the same daily air quality guideline value in addition to an annual mean value of

20 μg/m^3 and states: "The aim is to achieve the lowest concentration possible. As no threshold for PM has been identified below which no damage to health is observed [...]" (World Health Organization, 2011).

Panel A of Appendix D shows, that the average daily PM_10 concentration is indeed relatively high in Germany, namely 24.3 μg/m^3 and thus lies above the WHO annual guideline value. The maxium daily mean is 64.6 μg/m^3. Nevertheless, plotting the daily PM_10 concentrations over a decade, it becomes clear that they decreased between 1999 and 2008 (graph not shown). Interestingly, seasonaly trends in PM_10 concentration are only very weak as a boxplot by months demonstrates (not shown).

Associations Between All 5 Pollutants

Lastly, Figure 9 shows the association between all five air pollutants discussed above. NO_2 is positively correlated with SO_2 and PM_{10}, but negatively correlated with O_3. The same is true for CO. O_3 exhibits only very noisy and weak associations with SO_2 and PM_{10}. However, SO_2 and PM_{10} themselves show a strong and positive association.

[Insert Figure 9 about here]

Main Variables of Interest: Construction of Pollution Shock Measures

In our regression models, we make use of all raw pollution measures listed in Panel A of Appendix D *(i.)* in levels, *(ii)* in quadratic, and *(iii.)* in cubic terms. In addition, we generate various interactions terms between both, pollutants itself as well as pollutants and our weather indicators above.

We also intend to replicate the health impact of crossing the EU thresholds discussed above.[8] Hence, we generate the following indicator variables (European Environment Agency, 2012)[9] The descriptives are shown in Panel B of Appendix D.

- **O_3 Shock (*O3S*)**: day with maximum O_3 level >120 μg/m^3.
- **NO_2 Shock (*NO2S*)**: day with average NO_2 level >40 μg/m^3.
- **SO_2 Shock (*SO2S*)**: day with average SO_2 level >8 μg/m^3.

[8] This is not always exactly feasible since we rely on daily county averages, whereas some EU thresholds rely on hourly averages.

[9] Note that we omit CO since the maximum value of the maxiumum daily county-level CO value is 2.8 ppm, which is significantly below the EU and WHO 8-hour threshold of 8.7 ppm. Although all SO_2 values also lie significantly below the maximum daily EU threshold of 125 μg/m^3, we decided to nevertheless model a SO_2 shock when *average* daily values lie above 8 μg/m^3 since we have no data on *maximum* values.

- **PM_{10} Shock (*PM10S*)**: day with average PM_{10} level >50 $\mu g/m^3$.

According to these definitions, 12 percent of all 1.6 million county-day observations are NO_2 and PM_{10} shock days. This translates into 44 days per year. 34 days per year are days with high O_3 concentration and 5.5 days have high SO_2 concentration.

2.6 Other: County-Level Background Information 1999-2010

We collected additional time varying county-level data provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (2012) (*Bundesinstitut für Bau-, Stadt- und Raumforschung*) in their INKAR (*Indicators and Maps on Spatial Development*) database. The data vary by year. [10] To normalize our outcome measures, we collected total population counts and population counts by gender and agegroups. In addition, we collected information on per capita GDP and the unemployment rate to compensate for the lack of individual-level socioeconomic background information in the register datasets. Supply-side constraints are captured by the physician and hospital bed density. Appendix E shows the summary statistics of these variables.

2.7 Interpolation of Weather and Pollution Measures, Aggregation and Merging at the Daily County Level

To obtain our two working datasets, we *(i)* had to interpolate the point measures of the weather and pollution monitors into the county space, *(ii)* merge the register databases with the pollution, weather, and socioeconomic database at the daily county level, *(iii.)* aggregate all information at the daily county level. Thus, assuming that the number of counties would be time-invariant and 400, we would end up with $400 \times 365 \times 10 = 1,460,000$ rows, each representating one county at a given day.

In each row, we observe the daily weather and pollution indicators along with the socioeconomic county measures that only vary at the calendar year level. Most importantly, we

[10] The hospitalization and mortality data contain the county of residence according to the county codes and boundaries of the specific year. In contrast, the INKAR database contains all information according to the county codes and boundaries as of January 1, 2012. From 1999 to 2008, various county reforms, mostly mergers between two counties, led to changes in the county codes and boundaries. Consequently, the number of counties varies across years from 442 (1999) to 413 (2008). For counties with county reforms, we imputed pre-reform values using the post-reform boundary data as of January 1, 2012. In addition to reforms, not all information listed above has been collected in every single calendar year. We imputed missing values for these cases. See notes to Table E1 for more details.

observe how many county residents—normalized per 100,000—were hospitalized or died on that specific day. Plus, we can work with all additional information listed above such as age, gender, ICD-10 codes etc.

When extrapolating the weather and pollution point measures into county space, we relied on Hanigan et al. (2006). Hanigan et al. (2006) discuss and compare different approaches of how to calculate population exposure estimates of daily weather and pollution conditions from monitors. We choose an approach that makes use of the geographical centroid of each county: We calculate he weather and pollution conditions for every county and day as the inverse distance weighted average of all ambient monitors within a radius of 60 km (37.5 miles) of the county centroid.[11]

3 Regression Model and Results

3.1 Econometric Approach

$$Y_{it} = \alpha + \beta\, W_{it} + \theta\, X_{it} + \sum_{j=1}^{11} \sigma_j\, month_{jt} + \sum_{k=2000}^{2008} \eta_k\, year_{kt} + \nu_i + \epsilon_{it} \tag{1}$$

Y_{it} :	hospital admissions or mortality rate per 100,000 inhabitants in county i at time t.
W_{it} :	denotes a specific weather conditions, e.g., a hot day dummy with the maximum temperatur exceeding 30 $^\circ$ C, OR a vector of weather conditions.
X_{it} :	is a vector that includes additional control variables
X_{it} :	is a vector that includes additional control variables, such as the average hospital size in the county, the county GDP or the age and sex structure of the patients.
$month_{jt}$	a vector of dummy fixed effects
$year_{kt}$	a vector of year fixed effects
ν_i :	a vector of county fixed effects
ϵ_{it} :	time varying stochastic error term.

[11] This implies that monitor measures become less important the farer away they lie from the county centroid. In case that there was no monitor within a radius of 60 km, measurements come from the next closest monitor.

3.2 Identification of Pollution and Weather Effects

From an identifcation point of view, the ultimately appealing aspect of using weather and pollution shocks to estimate their impact on health is that weather and pollution seems to be orthogonal to the error term in equation 1 above. It is indeed very plausible that climate *shocks* are exogenous to individuals.

However, there are at least three concerns that have been put forward by some researchers in this context: *(i)* based on (un)observables, people may self-select into specific regions, *(ii)* pollution *levels* may be correlated with economic activities which, in turn, may affect health outcomes, *(iii)* individual-level exposure to weather and pollution conditions is unknown and adaption behavior may downward bias the true causal effects.

A few recent papers try to assess these concerns by using variation in traffic as an instrument for CO, PM10, and O3 exposure (Knittel et al., 2011; Moretti and Neidell, 2011). While we view these approaches as stimulating and worthwhile to persue, as we discuss below, we also believe that our approach is superior to instrumenting pollution levels with traffic activity. One reason is that traffic activity itself may impact population health. Another could be that increased economic activity—the main reason for instrumenting—is probably correlated with traffic.

We are confident that our approach sufficiently addresses all of the above mentioned concerns. With respect to *(i)*: It is of course true that people with specific characteristics may self-select into specific regions. This is of particular concern for studies that rely on small geographic regions—one may question the external validity of the findings. One particular strength of our approach is that we rely on the universe all all hospital admissions and deaths for the most populous European country over 10 years. In addition, using the German Socio-economic Panel Study (SOEP), we show that moving across regions is relatively rare in Germany. More importantly, we do not find any evidence that people sort into pollution or weather shock regions based on their characteristics.

As far as *(ii)* is concerned: is obvious that the *level* of regional economic activity and the regional pollution *level* may be correlated. This is particularly worrisome when pollution and health outcome data are merged on a highly aggregated level, e.g., when the unit of observation is the year or month and studies do not or cannot account for year-region fixed effects. However, recall that we rely on high-frequency data on a *daily* county-level basis over 10 years. We do not only consider county-fixed effects, but also week (of the year) fixed-effects, as well as county-level time trends. Moreover, we generate several indicators that specifically indicate weather and pollution shocks. Econometrically, this means that we exclusively focus on (exogenous) daily county-level deviations in weather and pollution, i.e., pollution and weather shocks. Economic activity does not fluctuate strongly on a daily county-level basis. Lastly, as a robustness check, we analyze whether our pollution and weather shock measures have a significant impact on hospitalizations that may stem from an increased economic activity: treatments due to physical injuries caused by accidents.

Finally, with respect to *(iii)*, we argue that we intentionally want to estimate an effect that would equal an "intention-to-treat" estimate in other settings. We believe that the parameter that we estimate is the crucial and relevant parameter for policymakers and any policy action should be based on this parameter. We do not deny that people engage in avoidance behavior and spend less time outdooer when pollution levels and temperatures are extreme. We are just questioning that the policy-relevant parameter would be any that measures the health effets of a theoretical 24 hours exposure to high pollution level or heat waves. Isn't the relationship we would like to unfold the following: given people adjust their behavior to climatic conditions, how would a decrease in the number of annual days with heavy ambient air pollution affect population health? Or: given that people have the capacity to adjust, how would climate change affect population health?

3.3 Econometric Results

4 Implications of Climate Change

to be written

4.1 Climate Change Scenarios

4.2 Climate Change Scenarios & Population Health

4.3 Health-Related Welfare Effects of Climate Change

5 Conclusion

to be written

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Figure 1: Distribution of German Ambient Weather and Pollution Monitors

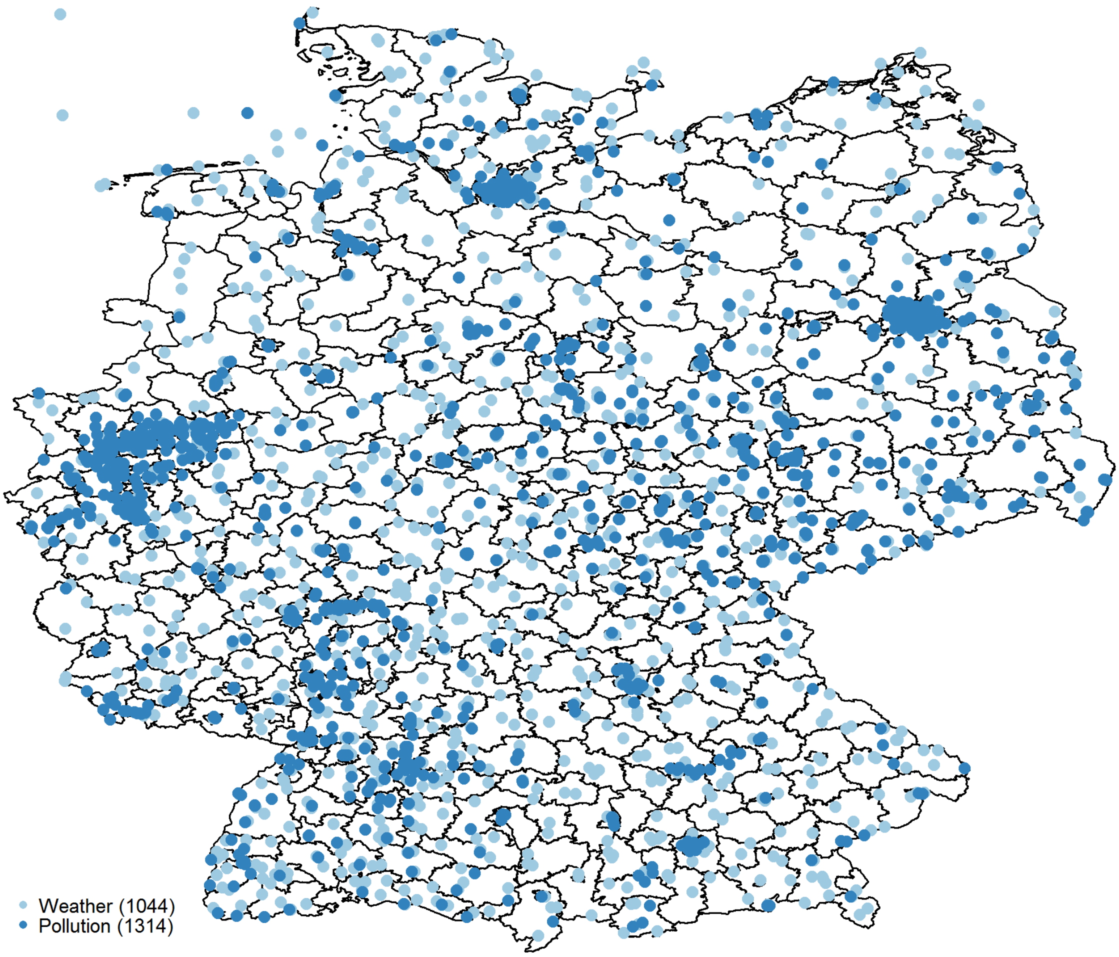

Figure 2: Boxplots of Mean Temperature, Sunshine, and Precipation Showing Variation Over Counties and Months

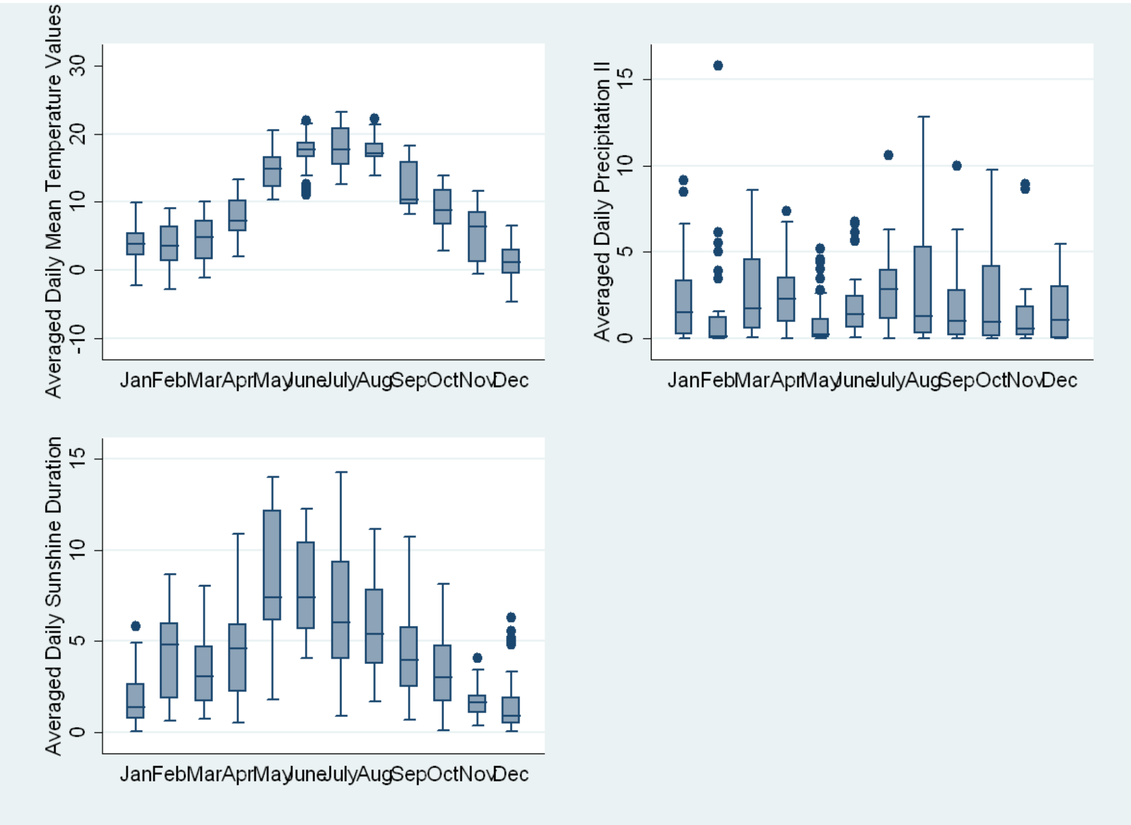

Figure 3: Temperature, Sunshine, and Precipation Variation Over 10 Years

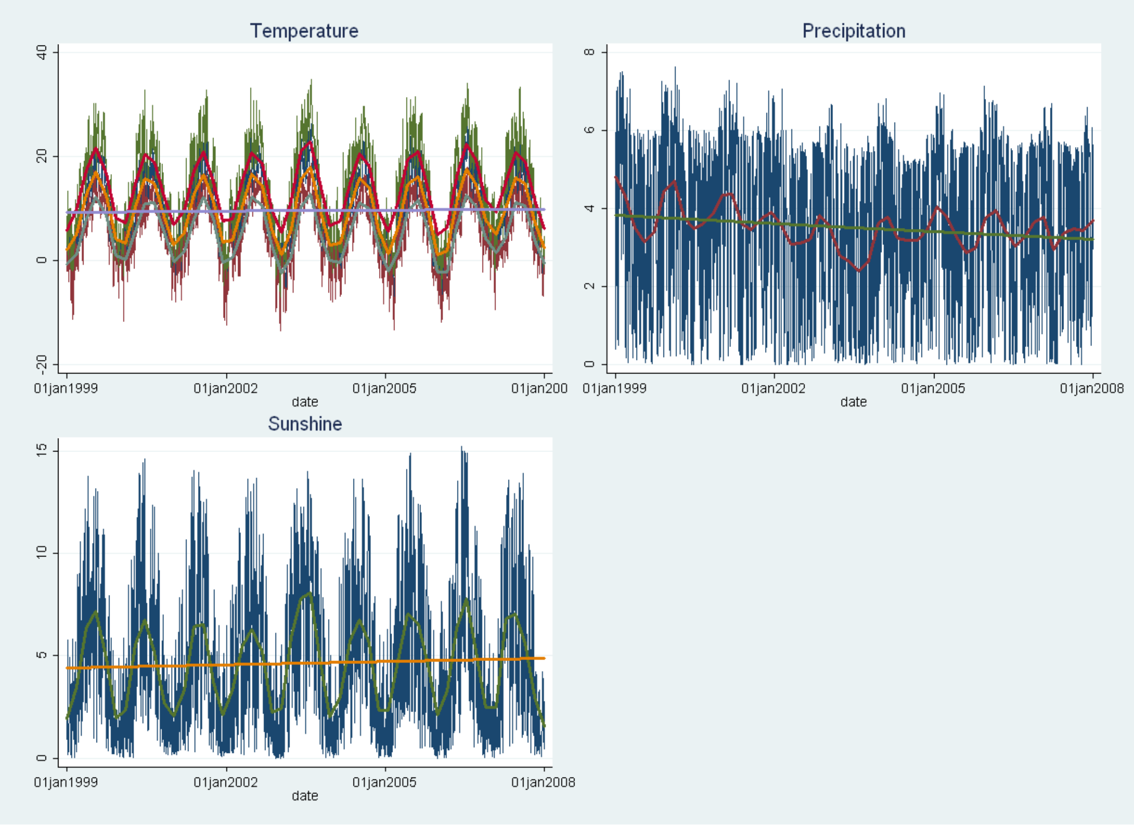

Figure 4: Scatter Matrix Illustrating Associations Between Temperature, Sunshine, and Precipation

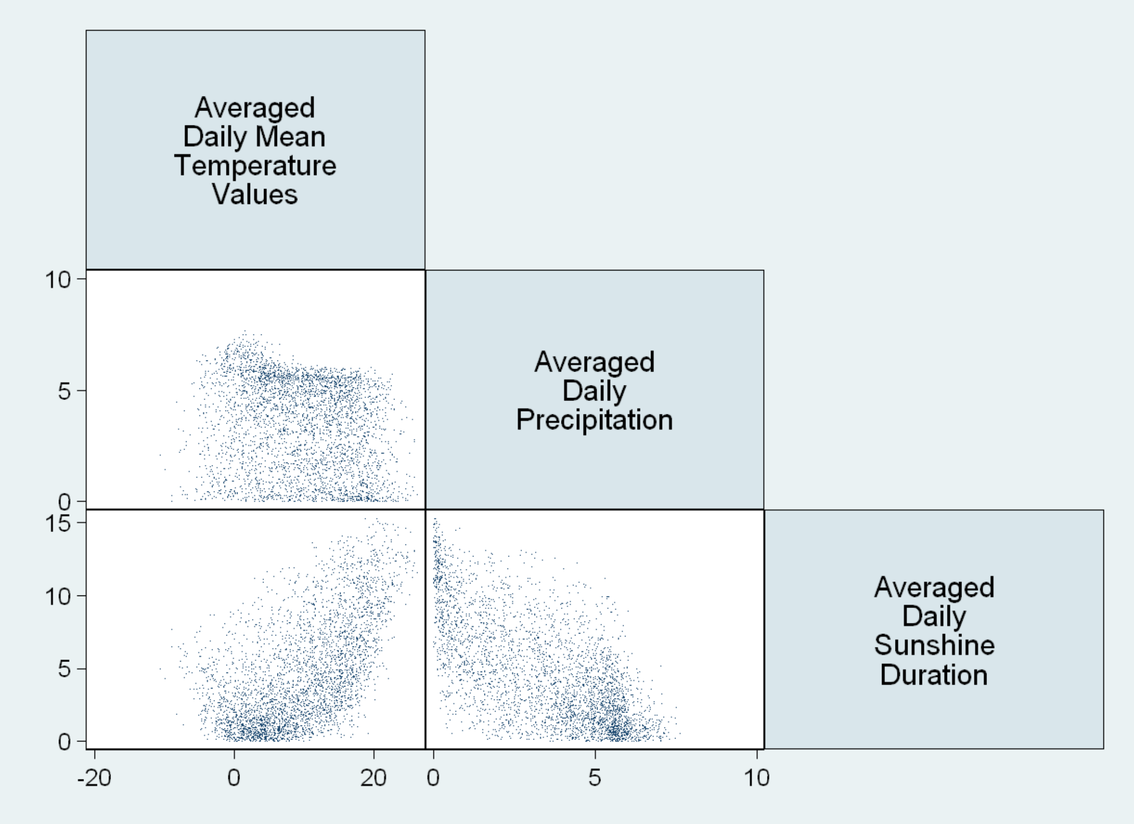

Figure 5: Nitrogen Dioxide (NO_2) Variation Across Counties and Over Time

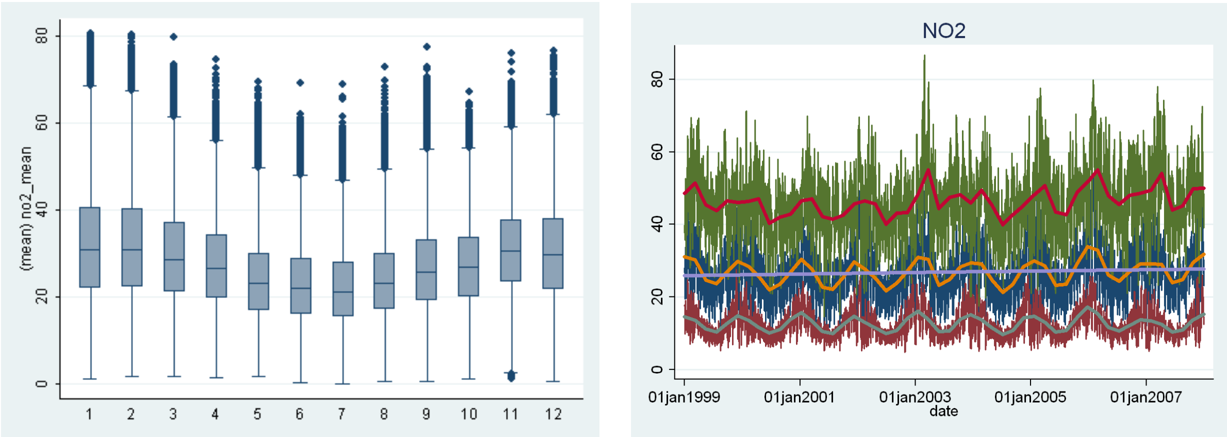

Figure 6: Association Between Nitrogen Dioxide (NO_2) and Weather

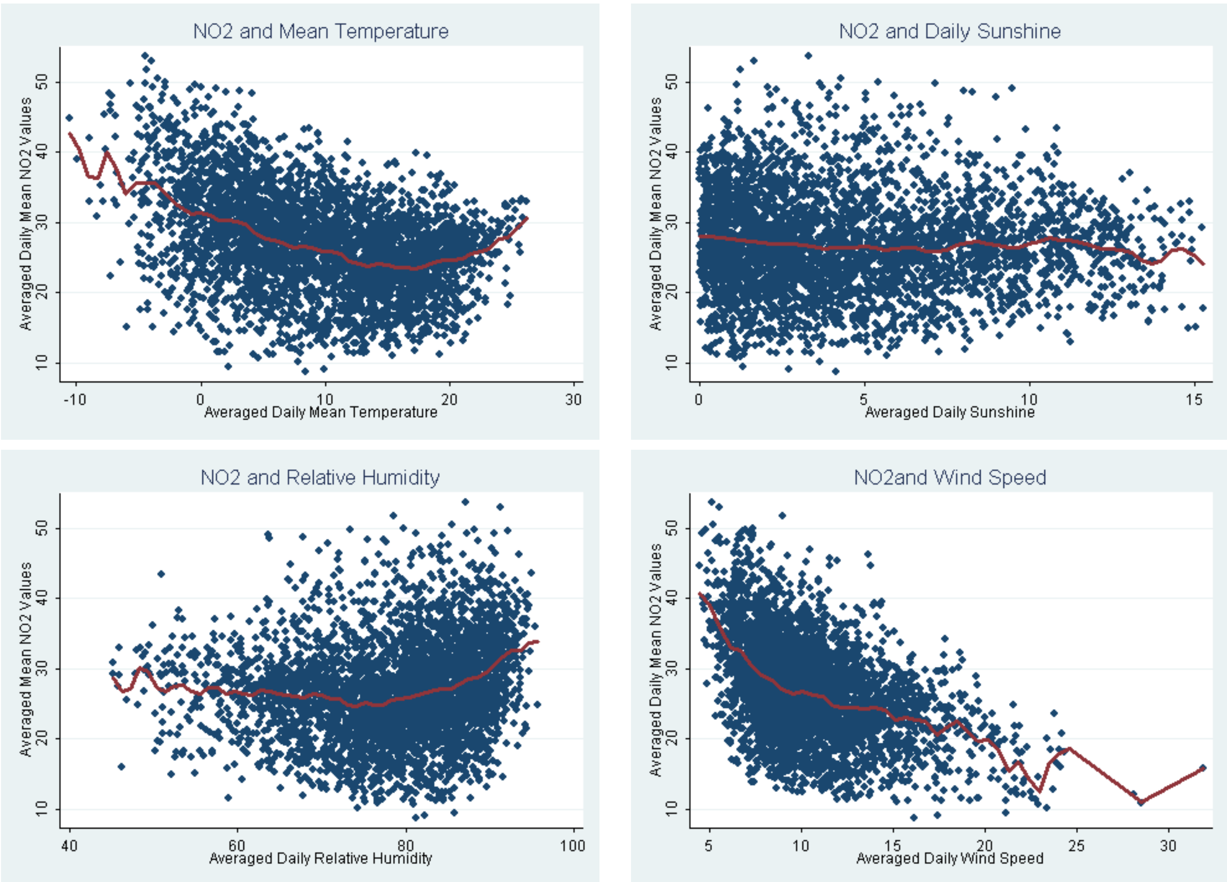

Figure 7: Ozone (O_3) Variation Across Counties and Over Time

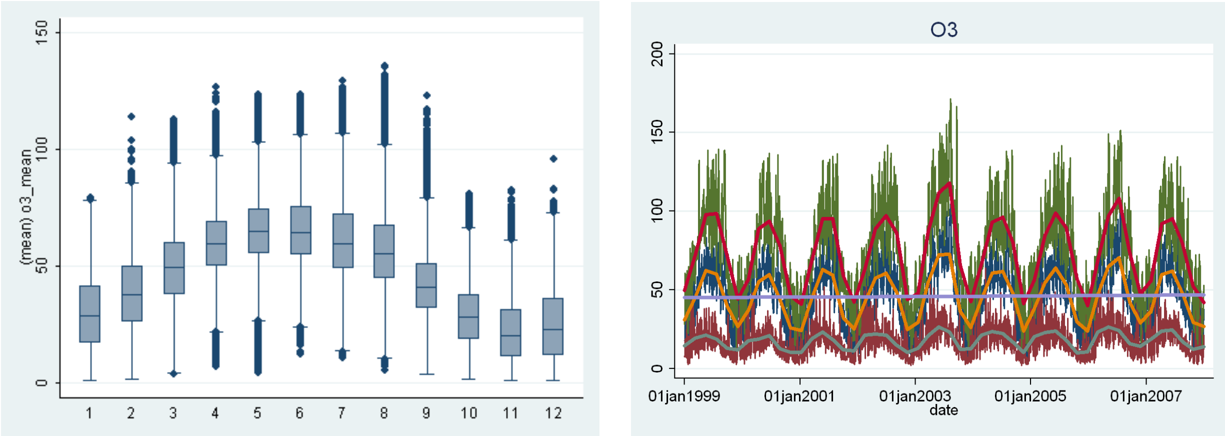

Figure 8: Association Between Ozone (O_3) and Weather

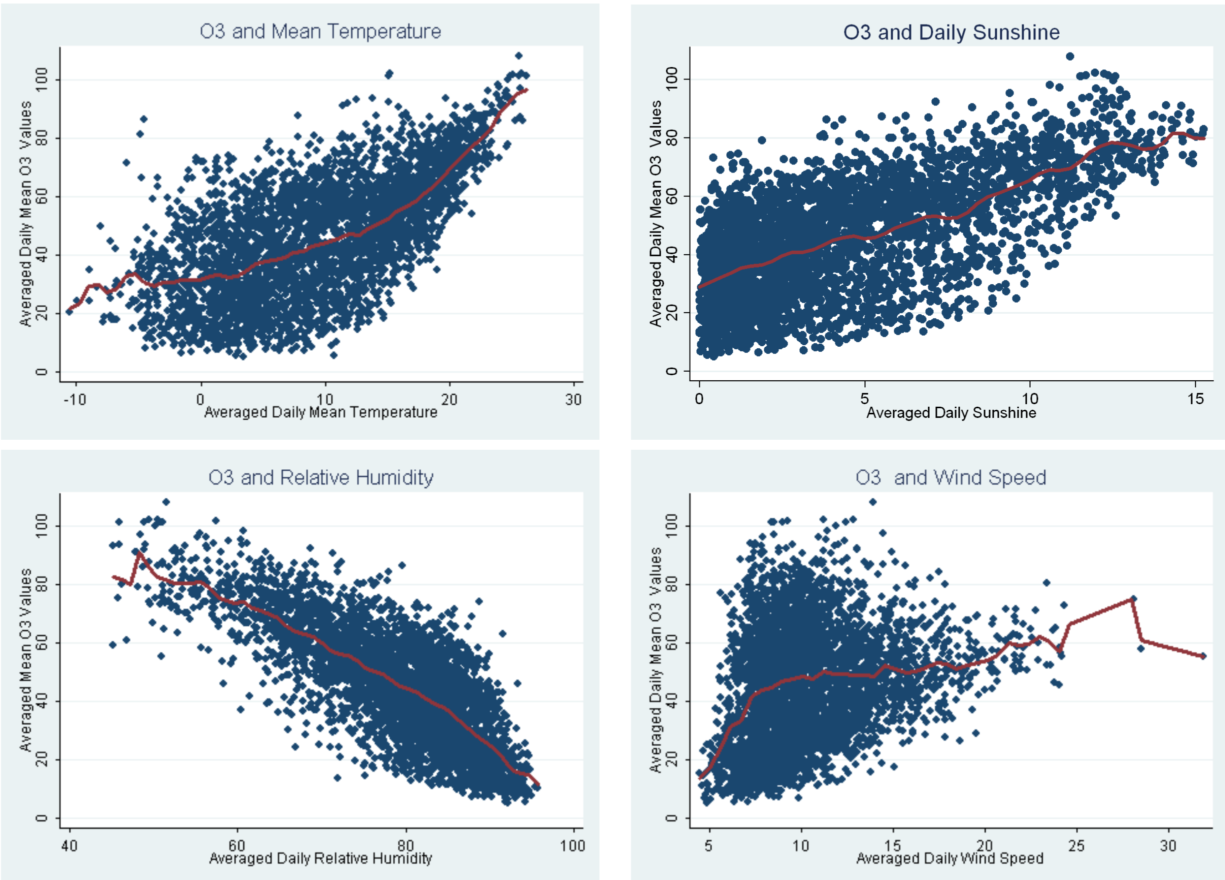

Figure 9: Scatter Matrix Illustrating Associations Between Pollutants

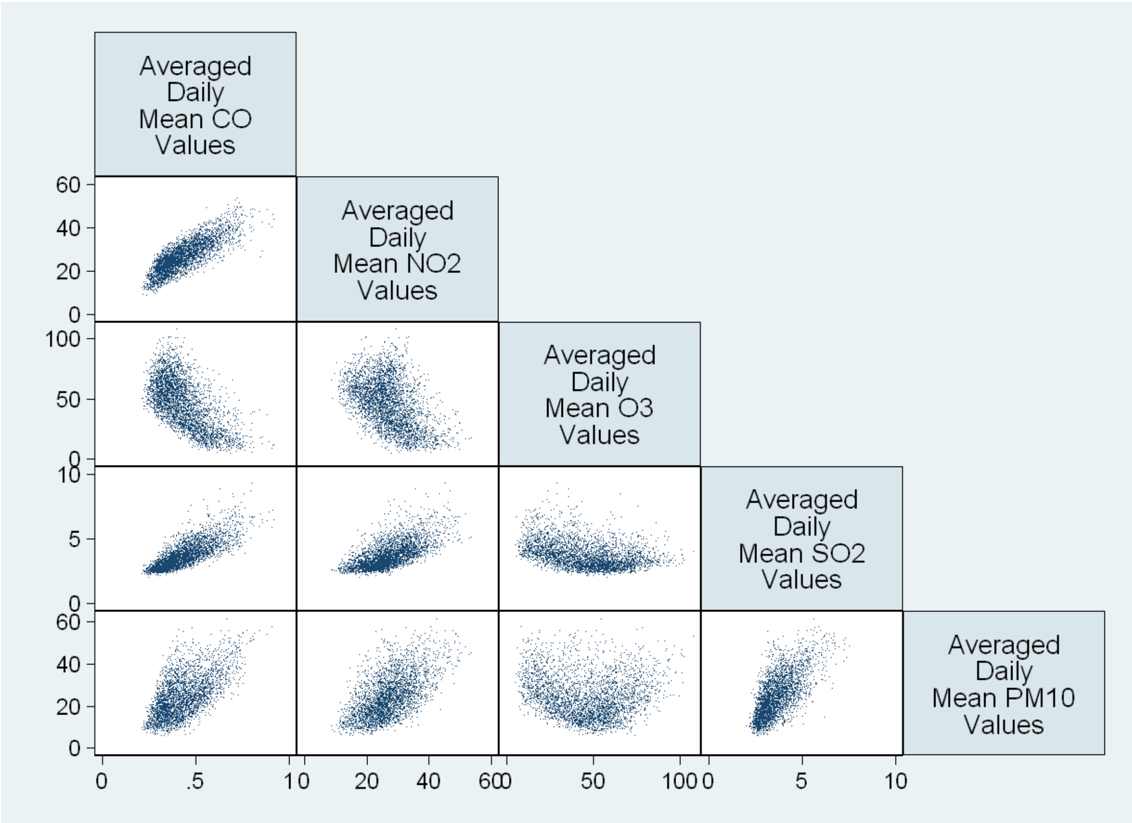

Table 1: The Impact of Weather Conditions on Hospitalizations ence)

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	3.2144***				4.4624***	
	(0.2368)				(0.2792)	
Heat Wave		-13.1214***			-4.8739***	
		(0.2683)			(0.2918)	
Cold Day			5.9751***		4.9005***	
			(0.3744)		(0.4289)	
Cold Wave				6.4371***	3.2080***	
				(0.7106)	(0.8420)	
Pos. Temp. Shock					15.5885***	
					(1.6383)	
Neg. Temp. Shock					-29.2322***	
					(1.6323)	
>5 CCDs					0.5474***	
					(0.0946)	
R10					1.1836***	
					(0.1612)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the daily incidence of hospital admissions per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 68.35, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 4.5 additional hospital admissions per 100,000 pop. This represents an increase by 6.6% and translates into 3,690 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 1.5 per hospital. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 2: The Impact of Pollution Shocks on Hospitalizations (Incidence)

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	0.8573***				0.3527**	
	(0.1306)				(0.1480)	
NO_2 Shock		8.2379***			8.1046***	
		(0.1547)			(0.1601)	
SO_2 Shock			2.3760		-0.1521	
			(17.8284)		(21.66)	
PM_{10} Shock				7.4912***	4.7253***	
				(0.3513)	(0.3626)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the daily incidence of hospital admissions per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 68.35, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 8.1 additional hospital admissions per 100,000 pop. This represents an increase by 12.9% and translates into 6,650 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 2.7 per hospital. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 3: The Impact of Weather Conditions on Hospital Days (Severity)

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	24.29***				35.92***	
	(2.0305)				(2.3576)	
Heat Wave		-110.29***			-36.74***	
		(3.1573)			(2.8394)	
Cold Day			32.37***		27.59***	
			(3.4887)		(3.8956)	
Cold Wave				36.45***	17.14**	
				(6.3043)	(7.4332)	
Pos. Temp. Shock					109.84***	
					(13.96)	
Neg. Temp. Shock					-229.59***	
					(14.18)	
>5 CCDs					7.8458***	
					(0.8205)	
R10					9.1665***	
					(1.3252)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the total number of hospital days that was triggered on a given day through all hospital admission on that specific day per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 536, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 36 additional hospital days per 100,000 pop. This represents an increase by 6.7% and translates into 29,520 additional hospital days for the whole of Germany with its 82 million inhabitants, or roughly 12 days per hospital. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 4: The Impact of Pollution Shocks on Hospital Days (Severity)

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	5.1931**				0.8539	
	(1.2070)				(1.3558)	
NO_2 Shock		71.0018***			70.1066***	
		(1.2501)			(1.2945)	
SO_2 Shock			3.2005		-19.1602	
			(111.07)		(144.2410)	
PM_{10} Shock				58.1866***	34.3368***	
				(3.2091)	(3.3067)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the daily incidence of hospital admissions per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 536, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 70 additional hospital days per 100,000 pop. This represents an increase by 13.1% and translates into 57,400 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 23 days per hospital. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 5: The Impact of Weather Conditions on Cardiovascular Hospitalizations (Incidence)

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	0.1269***				0.4354***	
	(0.0442)				(0.0506)	
Heat Wave		-2.1319***			-0.7867***	
		(0.0481)			(0.0509)	
Cold Day			0.9242***		0.8221***	
			(0.0708)		(0.0764)	
Cold Wave				1.0199***	0.5203***	
				(0.1332)	(0.1491)	
Pos. Temp. Shock					2.8698***	
					(0.2977)	
Neg. Temp. Shock					-4.9254***	
					(0.3013)	
>5 CCDs					0.0831***	
					(0.0171)	
R10					0.1744***	
					(0.0293)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. Dependent variable is always the daily incidence of hospital admissions due to cardiovascular diseases per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 10.22, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 0.44 additional cardiovascular hospital admissions per 100,000 pop. This represents an increase by 4.3% and translates into 361 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 0.14 per hospital. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 6: The Impact of Pollution Shocks on Cardiovascular Hospitalizations (Incidence)

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	-0.0612**				-0.1401***	
	(0.02503)				(0.0271)	
NO_2 Shock		1.2806***			1.2682***	
		(0.0271)			(0.0277)	
SO_2 Shock			-0.3143		-0.7466	
			(3.3638)		(3.9630)	
PM_{10} Shock				1.1228***	0.6968***	
				(0.0722)	(0.0726)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the daily incidence of hospital admissions per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 10.22, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 1.3 additional cardiovascular hospital admissions per 100,000 pop. This represents an increase by 12.7% and translates into 1066 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 0.43 per hospital. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 7: The Impact of Weather Conditions on Cardiovascular Hospital Days (Severity)

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	0.4791				3.2817***	
	(0.4498)				(0.5003)	
Heat Wave		-19.5994***			-5.9984***	
		(0.7708)			(0.6274)	
Cold Day			6.0778***		5.6513***	
			(3.4887)		(0.8173)	
Cold Wave				6.8509***	3.3097**	
				(1.2953)	(1.4286)	
Pos. Temp. Shock					18.5294***	
					(3.1543)	
Neg. Temp. Shock					-40.1456***	
					(3.2254)	
>5 CCDs					1.4030***	
					(0.1729)	
R10					1.2228***	
					(0.2894)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the total number of hospital days that was triggered on a given day through all hospital admission on that specific day per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 85, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 3.3 additional hospital days per 100,000 pop. This represents an increase by 3.9% and translates into 2,706 additional hospital days for the whole of Germany with its 82 million inhabitants, or roughly one day per hospital. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 8: The Impact of Pollution Shocks on Cardiovascular Hospital Days (Severity)

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	-0.8874***				-1.5466***	
	(0.2605)				(0.2773)	
NO_2 Shock		10.7428***			10.681***	
		(0.24071)			(0.2452)	
SO_2 Shock			-4.9239		-8.6464	
			(30.866)		(35.9291)	
PM_{10} Shock				8.3391***	4.7633***	
				(0.7874)	(0.7907)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the daily incidence of hospital admissions per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 85, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 11 additional hospital days per 100,000 pop. This represents an increase by 12.6% and translates into 8,774 additional admissions for the whole of Germany with its 82 million inhabitants, or roughly 3.5 days per hospital. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 9: The Impact of Weather Conditions on Cardiovascular Hospitalizations Followed by Death (Severity)

Panel A: Weather Conditions	(1)	(2)	(3)	(4)	(5)	(6)
Hot Day	0.0301***				0.0366***	
	(0.0063)				(0.0067)	
Heat Wave		-0.0542***			-0.0053	
		(0.0051)			(0.0069)	
Cold Day			0.0566***		0.0385***	
			(0.0093)		(0.0097)	
Cold Wave				0.0959***	0.0679***	
				(0.0187)	(0.0196)	
Pos. Temp. Shock					0.0166	
					(0.0483)	
Neg. Temp. Shock					-0.1139**	
					(0.0479)	
>5 CCDs					0.0058***	
					(0.0019)	
R10					0.0019	
					(0.0019)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the incidence of deaths after hospital admissions due to cardiovascular diseases per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 0.4268, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 3.7 additional cardiovascular hospital admissions per 10,000,000 pop. This represents an increase by 8.6% and translates into 30 additional admissions for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 10: The Impact of Pollution Shocks on Cardiovascular Hospitalizations Followed by Death (Severity)

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	0.0100**				0.0084***	
	(0.031)				(0.0031)	
NO_2 Shock		0.0276***			0.0267***	
		(0.0022)			(0.0022)	
SO_2 Shock			-0.0158		-0.0228	
			(0.1073)		(0.1201)	
PM_{10} Shock				0.0291***	0.0197*	
				(0.0102)	(0.0102)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
Hospital-level controls	yes	yes	yes	yes	yes	yes
N	495,280	495,280	495,280	495,280	495,280	495,280

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always the incidence of deaths after hospital admissions due to cardiovascular diseases per 100,000 population at the county level (see Appendix A). The mean of the dependent variable is 0.4268, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 2.9 additional cardiovascular hospital admissions followed by death of the patient per 10,000,000 pop. This represents an increase by 6.3% and translates into 22 additional deaths for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 11: The Impact of Weather Conditions on Mortality

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	0.3760***				0.366***	
	(0.0132)				(0.0067)	
Heat Wave		0.6667***			-0.0053	
		(0.0287)			(0.0069)	
Cold Day			0.0591***		0.0385***	
			(0.0148)		(0.0097)	
Cold Wave				0.0728***	0.0679***	
				(0.0258)	(0.0196)	
Pos. Temp. Shock					0.0166	
					(0.0483)	
Neg. Temp. Shock					-0.1139**	
					(0.0479)	
>5 CCDs					0.0058***	
					(0.0019)	
R10					0.0019	
					(0.0019)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
N	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. The data comprise the official German mortality census and include all deaths on German territory from 1999-2008. The mortality census is merged on the daily county level with official weather information from the German Meteorological Service (1,045 ambient monitors). All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always deaths on a given day per 100,000 population at the county level (see Appendix B). The mean of the dependent variable is 2.82, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 3.8 additional deaths per 1,000,000 pop. This represents an increase by 13.3% and translates into 308 additional deaths for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 12: The Impact of Pollution Shocks on Mortality

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	0.1654**				0.1596***	
	(0.0066)				(0.0066)	
NO_2 Shock		0.0619***			0.0454***	
		(0.0053)			(0.0053)	
SO_2 Shock			0.1228***		0.1015***	
			(0.0269)		(0.0269)	
PM_{10} Shock				0.0779***	0.0543***	
				(0.0089)	(0.0090)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
N	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. The data comprise the official German mortality census and include all deaths on German territory from 1999-2008. The mortality census is merged on the daily county level with official pollution information from the German Federal Environmental Office (998 ambient monitors). All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always deaths on a given day per 100,000 population at the county level (see Appendix B). The mean of the dependent variable is 0.4268, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 2.9 additional cardiovascular hospital admissions followed by death of the patient per 10,000,000 pop. This represents an increase by 6.3% and translates into 22 additional deaths for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Table 13: The Impact of Weather Conditions on Cardiovascular Mortality

Panel A: Weather Conditions	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Hot Day	0.0284***				0. 366***	
	(0.0046)				(0.0067)	
Heat Wave		0.0524***			-0.0053	
		(0.0076)			(0.0069)	
Cold Day			0.0149**		0.0385***	
			(0.0064)		(0.0097)	
Cold Wave				0.0156	0.0679***	
				(0.0139)	(0.0196)	
Pos. Temp. Shock					0.0166	
					(0.0483)	
Neg. Temp. Shock					-0.1139**	
					(0.0479)	
>5 CCDs					0.0058***	
					(0.0019)	
R10					0.0019	
					(0.0019)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
N	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651

* $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. The data comprise the official German mortality census and include all deaths on German territory from 1999-2008. The mortality census is merged on the daily county level with official weather information from the German Meteorological Service (1,045 ambient monitors). All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always deaths on a given day per 100,000 population at the county level (see Appendix B). The mean of the dependent variable is 1.32, i.e., a Hot Day—defined as the max. temperatur exceeding 30—triggers 2.8 additional deaths per 10,000,000 pop. This represents an increase by 2.2% and translates into 23 additional deaths for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 2% of all days are Hot Days in Germany, between 7 and 8 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix C.

Table 14: The Impact of Pollution Shocks on Cardiovascular Mortality

Panel B: Pollution Shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
O_3 Shock	0.0152***				0.0149***	
	(0.0022)				(0.0023)	
NO_2 Shock		0.0051**			0.0055**	
		(0.0026)			(0.0027)	
SO_2 Shock			-0.0249**		-0.0276**	
			(0.0140)		(0.0142)	
PM_{10} Shock				0.0026***	-0.0001	
				(0.0032)	(0.0032)	
County Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Month Fixed Effects	yes	yes	yes	yes	yes	yes
Individual-level controls (age, gender,...)	yes	yes	yes	yes	yes	yes
County-level controls	yes	yes	yes	yes	yes	yes
N	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651	1,202,651

* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the county level. Data sources are discussed in Section 2. The data comprise the official German mortality census and include all deaths on German territory from 1999-2008. The mortality census is merged on the daily county level with official pollution information from the German Federal Environmental Office (998 ambient monitors). All specifications estimate the model in equation (1) by OLS. Each column represents one model. The dependent variable is always deaths on a given day per 100,000 population at the county level (see Appendix B). The mean of the dependent variable is 1.32, i.e., a NO_2 Shock—defined as a day with the average NO_2 level exceeding 40 $\mu g/m^3$—triggers 5.5 additional cardiovascular hospital admissions followed by death of the patient per 100,000,000 pop. This represents an increase by 0.4% and translates into 4.5 additional deaths for the whole of Germany with its 82 million inhabitants. As shown in Appendix C2, about 14.4% of all days are NO_2 Shock Days in Germany, 52.6 per year. Weather conditions are specified and defined as explained in Section 2 and Appendix D.

Appendix A

Our first register dataset contains the universe of hospital admissions from 1999 to 2008. This is a restricted access dataset provided by the German Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*). We observe every single of the more than 17 million annual hospital admissions. The data contain the following information on the individual admission level:

- age in 18 age groups
  (0-2 yrs., 3-5 yrs., 6-9 yrs., 10-14 yrs.,..., 60-64 yrs., 65-75 yrs., >75 yrs.)
- gender *(binary indicator)*
- county of residence *between 442 (1999) and 413 (2008) counties*
- day of admission
- length of stay *(censored at 85 days)*
- died in hospital *(binary indicator)*
- primary diagnosis *(ICD-10, 3 digit)*
- surgery needed *(binary indicator)*
- primary hospital department *(43 categories)*
- #hospital beds *(12 categories)*
- hospital location *(federal state level; 16 states)*
- private hospital *(binary indicator)*
- hospital identifier

As described in Section 2.7, we normalize, aggregate, and merge this dataset with the other datasets on the daily county level. As such, we obtain the following descriptive statistics for the hospital admission data.

Table A1: Descriptive Statistics Hospitalization Outcome Variables (County-Level, 1999-2008, Daily)

Variable	Mean	Std. Dev.	Min.	Max.	N
Hospitalizations (**Incidence**) *(on given day per 100,000 pop.)*	68.35	23.98	N/A	N/A	1,594,154
Hospital days (**Severity**) *(trigged on given day per 100,000 pop.)*	536.03	207.45	N/A	N/A	1,594,154
Cardiovascular hospitalizations (**Incidence**) *(on given day per 100,000 pop.)*	10.22	4.45	N/A	N/A	1,594,154
Cardiovascular hospital days (**Severity**) *(trigged on given day per 100,000 pop.)*	85.01	42.49	N/A	N/A	1,594,154
Cardiovascular deaths (**Severity**) *(after hospitalization on given day per 100,000 pop.)*	0.4286	0.5058	N/A	N/A	1,594,154

Source: German Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*). This census of all hospitalizations in German hospitals includes the county of residence and the day when the patient was hospitalized. *Hospitalizations per 100,000 pop.* just counts the daily incidence of hospitalizations per 100,000 pop. on the county level. *Hospital days* is the sum of all hospital days that were triggered on a given day, i.e., it is the product of the incidence and the length of stay of each patient. *Hospital deaths* counts the number of deaths per 100,000 pop. on the county level. Reference point is always the day when the patient was hospitalized. In this case, the patient died sometime after being admitted, but not necessarily on the day of admission.

Appendix B

Our second register dataset contains the universe of deaths on German territory from 1999 to 2008. This is a restricted access dataset provided by the German Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*). We observe every single of the 0.8 million annual deaths. The data contain the following information on the individual admission level:

- age in years
- gender *(binary indicator)*
- county of residence *between 442 (1999) and 413 (2008) counties*
- day of death
- primary cause of death *(ICD-10, 3 digit)*

As described in Section 2.7, we normalize, aggregate, and merge this dataset with the other datasets on the daily county level. As such, we obtain the following descriptive statistics.

Table A1: Mortality Outcome Variables (County-Level, 1999-2008, Daily)

Variable	Mean	Std. Dev.	Min.	Max.	N
Mortality rate *(on a given day, per 100,000 pop.)*	2.8	XXXX	N/A	N/A	1,594,154
Cardiovascular mortality rate *(on a given day, per 100,000 pop.)*	1.3	XXX	N/A	N/A	1,594,154
Heart attack mortality rate *(on a given day, per 100,000 pop.)*	XXX	XXX	N/A	N/A	1,594,154

Source: German Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*). The mortality statistic includes the county of residence and the day of death. *Mortality rate per 100,000 pop.* counts the daily mortality rate per 100,000 pop. on the county level.

Appendix C

Our third register dataset contains daily weather measures from up to 1,044 ambient weather stations. The data are provided by the German Meteorological Service (*Deutscher Wetterdienst (DWD)*). It cover the years from 1999 to 2008. The following weather measures have been surveyed on a daily basis:

- average temperature in $^{\circ}$C [measured *2 m (6'7") above ground*]
- minimum temperature in $^{\circ}$C [measured *2 m (6'7") above ground*]
- maximum temperature in $^{\circ}$C [measured *2 m (6'7") above ground*]

- total hours of sunshine
- precipitation level in mm per day

- average humidity in percent
- average storm force
- max. wind speed in km per hour (Beauford scale)
- average cloud coverage in percent
- vapor pressure in hectopascal (hPa)
- min. air pressure in hectopascal (hPa) measured [*5 cm (2 inches) above ground*]

As described in Section 2.7, in a first step, we extrapolate the point measure into the county space. Then we merge the weather dataset with the other datasets on the daily county level.

Panel A shows the descriptive statistics for the raw measures. Panel B contains the generated weather indicators, i.e., our main variables of interest in the regression models.

Table C1: Descriptive Statistics Weather (County-Level, 1999-2008, Daily)

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Raw Measures					
Average temperature in $^\circ$C *(2 m (6'7") above ground)*	9.552	7.3066	-19	30.6	1,594,154
Minimum temperature in $^\circ$C *(2 m (6'7") above ground)*	5.4632	6.4985	-25.01	23.8	1,594,154
Max temperature in $^\circ$C *(2 m (6'7") above ground)*	13.8851	8.5627	-14.1	39.07	1,594,154
Total hours of sunshine	4.6238	4.2369	0	16.7	1,594,154
Precipitation level	2.2259	4.2179	0	144.98	1,594,154
Average humidity	78.3241	11.4285	10	100	1,594,154
Average cloud coverage	5.3131	2.1538	0	8.23	1,594,154
Average storm force	3.609	2.0944	0	26.3	1,594,154
Max. wind speed	10.5008	4.4572	0	54	1,594,154
Vapor pressure	9.8858	3.9986	0.5	25.9	1,594,154
Min. air pressure *(5 cm (2 inches) above ground)*	3.8421	6.5310	-29.01	22	1,594,154
B. Generated Weather Condition Indicators					
HD: Hot Day (max temp. >30°C)	0.0197	0.1391	0	1	1,594,154
HW: Heat Wave (>3 hot days)	0.0032	0.0568	0	1	1,594,154
HWDI: Heat Wave Duration Index (>5 days with max temp. >5 monthly av.)	0.0115	0.1067	0	1	1,594,154
PTS: Positive Temperature Shock (max temp. t_{-1} to t_0: +10°C)	0.0004	0.021	0	1	1,594,154
ETR: Intra-Day Temperature Range (max temp.- min temp.)	8.4219	4.0548	-7	26.1	1,594,154
FD: Frost Day (min temp. <0°C)	0.2138	0.4099	0	1	1,594,154
CD: Cold Day (min temp. <-10°C)	0.0124	0.1108	0	1	1,594,154
CW: Cold Wave (>3 cold days)	0.0018	0.0422	0	1	1,594,154
NTS: Negative Temperature Shock (max temp. t_{-1} to t_0: -10°C)	0.0025	0.0504	0	1	1,594,154
> 5 CDD: Consecutive Dry Days (Rday < 1 mm)	0.2058	0.4043	0	1	1,594,1524
R10 (precipitation >10 mm $d^{-}1$.)	0.0543	0.2265	0	1	1,594,154

Source: German Meteorological Service (*Deutscher Wetterdienst (DWD)*). The information was recorded on a daily basis by up to 1,044 ambient weather monitors that are distributed across the German counties (see Figure 1). The number of counties and weather stations vary from year to year. The measures displayed cover the years 1999 to 2008. As described in Section 2.7, all point measures from the stations are extrapolated into the county space by means of deterministic extrapolation. Level of analysis is the day×county level. Hence, with exactly 400 counties in each year, we would obtain $400 \times 365 \times 10 = 1,460,000$ observations. However, as explained in Section 2.7, the number of counties varies across years from 442 (1999) to 413 (2008).

Appendix D

Our fourth register dataset contains daily pollution measures from up to 1,314 ambient stations. The data are provided by the German Federal Environmental Office (*Umweltbundesamt (UBA)*). It cover the years from 1999 to 2008. Measures of the following pollutants have been recorded on a daily basis:

- average concentration of carbon monoxide (CO) in parts per million (ppm)
- minimum concentration of carbon monoxide (CO) in ppm
- maximum concentration of carbon monoxide (CO) in ppm

- average concentration of ozone (O_3) in micrograms per cubic meter of air ($\mu g/m^3$)
- minimum concentration of ozone (O_3) in $\mu g/m^3$
- maximum concentration of ozone (O_3) in $\mu g/m^3$

- average concentration of nitrogen dioxide (NO_2) in $\mu g/m^3$
- minimum concentration of nitrogen dioxide (NO_2) in $\mu g/m^3$
- maximum concentration of nitrogen dioxide (NO_2) in $\mu g/m^3$

- average concentration of sulphur dioxide (SO_2) in $\mu g/m^3$
- average concentration of particular matter (PM_{10}) in $\mu g/m^3$; since 2000

As described in Section 2.7, in a first step, we extrapolate the point measure into the county space. Then we merge the pollution dataset with the other datasets on the daily county level. Panel A of Table D1 shows the descriptive statistics for the raw measures. Panel B contains our generated pollution shock indicators. The thresholds are modelled after the alert threshold of the European Union (see Section 2.5 and European Environment Agency (2012).

Table D1: Descriptive Statistics Pollution (County-Level, 1999-2008, Daily)

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Raw Measures					
Average CO in ppm	0.4342	0.1794	0.0023	1.3083	1,594,154
Min. CO in ppm	0.2326	0.0911	0	0.6	1,594,154
Max. CO in ppm	0.8145	0.38	0.025	2.8	1,594,154
Average O3 in μg/m^3	45.9786	22.0423	0.8612	135.79	1,594,154
Min. O3 in μg/m^3	17.9888	13.8282	0	79.6	1,594,154
Max. O3 in μg/m^3	73.7943	31.5263	1.1673	192.15	1,594,154
Average NO2 in μg/m^3	26.8907	10.6284	0.0278	80.3095	1,594,154
Min. NO2 in μg/m^3	12.6384	5.9959	0	39.5	1,594,154
Max. NO2 in μg/m^3	46.4607	16.3252	0.5	132.1	1,594,154
Average SO2 in μg/m^3	3.7256	1.6115	0.0654	12.5435	1,594,154
Average PM10 in μg/m^3	24.3097	11.4625	2.0625	64.625	1,432,822
B. Generated Pollution Shock Indicators					
O3S: O_3 Shock (max level >120 μg/m^3)	0.0929	0.2903	0	1	1,594,154
NO2S: NO_2 Shock (av. level >40 μg/m^3)	0.1194	0.3243	0	1	1,594,154
SO2S: SO_2 Shock (av. level >8 μg/m^3)	0.0151	0.1218	0	1	1,594,154
PM10S: PM_{10} Shock (av. PM_{10} level >50 μg/m^3)	0.1278	0.3339	0	1	1,594,154

Source: German Federal Environmental Office (*Umweltbundesamt (UBA)*). The information was recorded on a daily basis by up to 1,317 ambient pollution monitors that are distributed across the German counties (see Figure 2). The number of counties and weather stations vary from year to year. The measures displayed cover the years 1999 to 2008. As described in Section 2.7, all point measures from the stations are extrapolated into the county space by means of deterministic extrapolation. Level of analysis is the day×county level. Hence, with exactly 400 counties in each year, we would obtain $400 \times 365 \times 10 = 1,460,000$ observations. However, as explained in Section 2.7, the number of counties varies across years from 442 (1999) to 413 (2008). CO stands for "carbon monoxide" and ppm for "parts per million." NO2 stands for "nitrogen dioxide," O3 stands for "concentration of ozone," SO2 stands for "sulphur dioxide," and PM10 stands for "particular matter." $\mu g/m^3$ stands for micrograms per cubic meter of air. The shock thresholds are modelled after the alert thresholds by the European Union (European Environment Agency, 2012) and Section 2.5.

Appendix E

We collected the following information provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (2012) (*Bundesinstitut für Bau-, Stadt- und Raumforschung*) in their INKAR (*Indicators and Maps on Spatial Development*) database. The data vary in the county level by year. As seen, on average, a German county counts about 190,000 residents. The average per capita income is €25,000 p.a.[12], but varies between 11,282 and 86,728 across counties and over years. A similarly strong variation is observed for the county unemployment rate which varies between 1.6 and 29.3 percent with an average of 10.5 percent.

An average county has 5 hospitals. However, in some counties there exist no hospital and one county counts a staggering 76 hospitals. Consequently, the number of hospital beds per 10,000 residents and county varies between 0 and 24,170. Later, we can test the hypothesis that there is a trade-off between outpatient and inpatient treatments using the outpatient physician density, which varies between 69 and 394 doctors per 10,000 residents of a county.

Table E1: Descriptive Statistics Other (County-Level, 1999-2008, Annual)

Variable	Mean	Std. Dev.	Min.	Max.	N
Unemployment rate	10.47	5.28	1.6	29.3	4,356
GDP per residents	24971	10146	11,282	86,728	4,354
# hospitals in county	4.84	5.49	0	76	4,354
Hospital beds per 10,000 residents	1211.19	1593.88	0	24,170	4,354
Outpatient care physicians per 10,000 residents	152.72	52.59	69	394	4,358
Total population	189,450	219,753	34,525	3,431,675	4,361
Male 0 to 2 years	2,575	3,034	331	47,489	4,361
Male 3 to 5 years	2,697	2,968	328	42,964	4,361
Male 6 to 9 years	3,776	3,972	409	60,320	4,361
Male 10 to 14 years	5,151	5,277	525	92,611	4,361
Male 15 to 17 years	3,280	3,323	366	55,698	4,361
Male 18 to 19 years	2,241	2,323	383	38,669	4,361
Male 20 to 24 years	5,613	6,704	987	111,475	4,361
Male 25 to 29 years	5,708	7,926	1,007	134,581	4,361
Male 30 to 34 years	6,628	9,117	881	164,445	4,361
Male 35 to 39 years	7,991	10,168	1,056	172,517	4,361
Male 40 to 44 years	8,089	9,634	1,347	164,928	4,361
Male 45 to 49 years	7,195	8,082	1,157	149,742	4,361
Male 50 to 54 years	6,274	7,021	926	116,102	4,361
Male 55 to 59 years	5,589	6,749	845	129,022	4,361
Male 60 to 64 years	5,745	6,929	817	119,554	4,361
Male 65 to 74 years	9,210	10,096	1,108	187,669	4,361
Male > 75 years	4,882	5,087	658	81,884	4,361
Female 0 to 2 years	2,442	2,882	295	44,660	4,361
Female 3 to 5 years	2,561	2,824	313	41,049	4,361
Female 6 to 9 years	3,584	3,770	406	57,060	4,361
Female 10 to 14 years	4,887	4,997	492	88,234	4,361
Female 15 to 17 years	3,109	3,147	358	52,753	4,361
Female 18 to 19 years	2,135	2,275	377	37,463	4,361
Female 20 to 24 years	5,431	7,071	939	117,108	4,361
Female 25 to 29 years	5,516	8,044	828	137,220	4,361
Female 30 to 34 years	6,331	8,559	699	152,632	4,361
Female 35 to 39 years	7,578	9,364	1,046	158,939	4,361
Female 40 to 44 years	7,714	9,012	1,204	153,034	4,361
Female 45 to 49 years	6,998	7,868	1,270	140,548	4,361
Female 50 to 54 years	6,232	7,188	906	117,351	4,361
Female 55 to 59 years	5,634	6,939	855	127,897	4,361
Female 60 to 64 years	5,959	7,239	838	123,874	4,361

Continued on next page...

[12] In 2012 values.

... Table E1 continued

Variable	Mean	Std. Dev.	Min.	Max.	N
Female 65 to 74 years	10,689	11,874	1,952	214,713	4,361
Female > 75 years	10,006	11,110	1,964	164,217	4,361

Source: Federal Institute for Research on Building, Urban Affairs and Spatial Development (2012). The information varies across counties and years on an annual basis. Some information has not been surveyed every calendar year. In addition, in contrast to the register databases in Appendix A and B, the INKAR data refers to the county codes and boundaries as of January 1, 2012. Since we saw various county reforms between 1999 and 2008, we had to impute information for pre-reform counties with post-reform data if possible. For example, if counties A and B simply merged to county C and we only had the GDP per capita for county C, we would impute the GDP per capita values for A and B using the population information on A and B which is available for all years and counties. If, as another example, data was survey in every other year, we took the mean value of t_0 and t_2 to impute information for t_1. However, we were unable to impute values for all measures and all counties in every year according to the boundaries of that specific year, which is why the number of observations slightly varies between the meausures.