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Abstract

This paper studies the short-term impact of public smoking bans on hospitalizations in Germany. It exploits the staggered implementation of smoking bans over time and across the 16 federal states along with the universe of hospitalizations from 2000-2008 and daily county-level weather and pollution data. Smoking bans in bars and restaurants have been effective in preventing 1.9 hospital admissions (-2.1%) due to cardiovascular diseases per day, per 1 million population. We also find a decrease by 0.5 admissions (-6.5%) due to asthma per day, per 1 million population. The health prevention effects are more pronounced on sunny days and days with higher ambient pollution levels.

Keywords: smoking bans; health effects; hospital admissions; second-hand smoke

JEL classification: D12, H19, I12, I18

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1. Introduction

In a recent report on trends in smoking prevalence, the World Health Organization (WHO) estimates that tobacco use is responsible for the death of around six million people worldwide each year (World Health Organization, 2015a). This includes about 600,000 people who are estimated to die each year due to exposure to second-hand smoke. Reducing smoking prevalence and exposure to environmental tobacco smoke is one of the key public health priorities of the WHO and many governments around the world.

This paper extends previous work on the causal health effects of smoke-free legislation in several important ways. First, we exploit variation in smoke-free laws across states and over time in Germany along with exceptionally rich high-quality register data to investigate the effects on hospital admissions. Our data cover the universe of more than 160 million hospitalizations between 2000 and 2008 in Germany. It enable us to separate time effects, state effects, and smoke-free legislation effects which makes it less likely that unobserved factors (coinciding with the introduction of public smoking bans) confound the estimates.

Second, we control more comprehensively than most existing studies for potentially important environmental factors that are likely to affect hospitalizations, such as local weather and local pollution conditions. To the best of our knowledge, our paper is one of the first to study potential interaction effects between these environmental factors and the effectiveness of public smoking bans. Accounting for such environmental interactions is important as the combination of smoking and exposure to second-hand smoke with, for example, high pollution levels might result in more hospitalizations due to cardiovascular diseases.

Third, we investigate objective health outcome measures (i.e., cardiovascular hospital admissions, asthma admissions) using high-frequency register data.[1] Most previous studies in the economics literature investigate changes in smoking behavior using survey data.[2] The findings of these studies are mixed. Whereas some studies find a reduction in tobacco

[1] A comprehensive literature documents the direct link between smoking, smoking intensity, exposure to second-hand smoke and cardiovascular events (see, for example, U.S. Department of Health and Human Services, 2006, 2014; Mons et al., 2015, and references therein).
[2] Shetty at al. (2011) is one exception and estimates the effects of US smoking bans on hospitalizations.

consumption following smoke-free laws (e.g. Evans et al., 1999 for the US and workplace smoking bans), others report no or only very small changes (Adda and Cornaglia, 2010 for the US; Anger et al., 2011 for Germany; Carpenter et al., 2011 for Canada; Jones et al. 2015 for the UK). Kuehnle and Wunder (2017) report improvements in self-assessed health among non-smokers following the introduction of smoking bans in Germany, but no effects among smokers. Exploiting variation over time and 40 European countries, Odermatt and Stutzer (2015) find that smoking bans increase the happiness of smokers who would like to quit. A similar finding has been reported by Gruber and Mullainathan (2005) who exploit cigarette tax variation in the US. More generally, our paper contributes to the rich reduced-form literature evaluating the causal effects of tobacco policies (mostly cigarette taxes) on smoking behavior (Gruber, 2001; DeCicca et al., 2002, 2008, 2013; Gruber et al., 2003; Gruber and Koszegi, 2004; Gruber and Frakes, 2006; Avery et al., 2007; Carpenter and Cook, 2008; Lovenheim, 2008; Courtemache, 2009; Goolsbee et al., 2010; Shetty et al., 2011; Wehby and Courtemanche, 2012; Kvasnicka and Tauchmann, 2012; Lillard et al., 2013; Callison and Kaestner, 2014; Friedman, 2015; Rozema and Ziebarth, 2017; Hansen et al., 2017).

Fourth, we study the consequences of smoking bans in a high-income country with a high smoking prevalence. The estimated age-standardized WHO prevalence rate among those aged 15 years and more is 31% in Germany, compared to 18% in the United States, 20% in the United Kingdom and Northern Ireland, and 13% in Australia (World Health Organization, 2015b). However, the latter countries have been researched most extensively in the literature (Cutler and Glaeser, 2009; World Health Organization, 2015b).

Finally, our setting provides a potential explanation for why it is so difficult to identify (objective) health effects following smoking bans. Even in a country like Germany with 82 million residents, a relatively high smoking prevalence, a high population density, low access barriers to the hospital infrastructure (universal insurance coverage and no provider networks), state-year variation in smoking bans, and data on the universe of around 17 million annual hospital admissions, we operate in a setting where statistical power becomes an issue. For example, our -0.19 point estimate for the largest disease category *cardiovascular admissions per 100,000 population* is still precisely estimated—even though the effect size is only two percent of the mean. However, trying to assess the effects for a *subset* of this disease category—such as heart attacks or deaths after cardiovascular admissions—is technically very challenging due to power issues. In Germany with about 15 heart attacks per day and 1 million residents, heart attacks are still a relatively rare event and small changes in these rates are very hard to identify when using rich sets of time and region fixed effects, even with register data.

Our findings show that, in the short run, cardiovascular admissions decreased by 1.9 cases per 1 million population (-2.1%) because of state-level smoking bans in Germany between 2007 and 2008. We also find a significant short-run reduction in hospital admissions due to asthma (-6.5%). Many countries around the world have not yet banned smoking in public. Our results suggest that these countries could achieve health improvements by banning public smoking. Our findings also suggest that health improvements can be expected even if countries are unable or unwilling to impose 100% smoke-free laws. Public smoking bans in Germany are not very strict. Exemptions exist (e.g., smoking bars and separate smoking rooms in some premises) and the bans are not always strictly enforced. On the other hand, in the only published economics paper that uses hospitalizations as an outcome, Shetty et al. (2011) do not find evidence for significant decreases in hospitalizations in the US. Bitler et al. (2010) study state-level clear indoor air laws in the U.S. and find evidence that these laws were strongly enforced in bars, but not in restaurants, private workplaces, schools, or government buildings.

This paper also enriches the previous literature by showing that the reduction in cardiovascular admissions is reinforced on sunny days. We discuss several potential mechanisms for these findings. Our estimates suggest that smoking bans are more effective under adverse environmental conditions (unrelated to tobacco smoke) that negatively affect the human body, such as high pollution levels.

The next section briefly describes the staggered implementation of the smoking bans in Germany. Section 3 describes the datasets, Section 4 discusses the empirical strategy, and Section 5 presents and discusses our findings. Section 6 concludes.

2. Smoking Bans in Germany

At a meeting in March 2007, the 16 state health ministers decided to ban smoking in bars and restaurants in all 16 German federal states. Shortly after, smoke-free policies were introduced over a time period of just 13 months (August 2007 to August 2008). Our empirical analysis exploits this state-time variation across the sixteen federal states. We distinguish states by the exact month when smoking bans in bars and restaurants were legally implemented. As Table 1 and Figure 1 show, the south-western state of Baden-Wuerttemberg was the first to introduce smoke-free legislation in August 2007. By the end of August 2008, all states in Germany had introduced public smoking bans (see Table 1).

Table 1:
Dates of Enforcement of State Smoking Bans in Germany

Federal State	Enforcement of State Smoking Ban
Baden-Wuerttemberg	August 2007
Bavaria	January 2008
Berlin	July 2008
Brandenburg	July 2008
Bremen	July 2008
Hamburg	January 2008
Hesse	October 2007
Lower Saxony	November 2007
Mecklenburg-West Pomerania	August 2008
North Rhine-Westphalia	July 2008
Rhineland-Palatinate	February 2008
Saarland	June 2008
Saxony	February 2008
Saxony-Anhalt	July 2008
Schleswig-Holstein	January 2008
Thuringia	July 2008

Notes: All smoking bans were enforced at the start of the month with the exception of Rhineland-Palatinate, which introduced the smoking ban on February 15, 2008. Information on individual states was compiled from original law texts and from a survey of state-level smoking ban legislation by the German Hotels and Restaurants Federation (DEHOGA, 2008).

Figure 1: Dates of Enforcement of State Smoking Bans in Germany

Notes: For further information, see notes to Table 1.

The German bans were less comprehensive than in other countries and allowed for exemptions. All states except Bavaria allowed smoking in separate “smoking rooms” in bars and restaurants and some states made additional exceptions. In practice, because of the bureaucratic regulations for separate smoking rooms, one can summarize that the ban was very effective in banning smoking in restaurants (see, for example, Baxmann and Eckoldt, 2007; NRauchSchG SH, 2007; LNRSchG, 2007). It was also effective in banning smoking in bigger and popular (tourist) bars. However, basically each state allowed small pubs to selfdeclare as “smoker pubs” where people could still smoke inside. In practice, almost every German city still had a small number of such “smoker pubs” that were typically attended by a large share of (local) smokers who also tend to drink heavily.[3] Germany does not have a general closing time for bars and that it was not unusual that such smoker bars were open 24/7. Moreover, smoking outside of bars and restaurants is not prohibited and still common in Germany.

Although tobacco control measures increased both in number and strictness since the early 2000s in Germany (for a review, see Göhlmann and Schmidt, 2008), their overall effectiveness remained low in comparison to other European countries (Joossen et al., 2011). Landmark policy initiatives include a federal law that made the protection of non-smokers in the workplace mandatory in 2002, and the introduction of a nation-wide smoking ban in federal public buildings and transportation in September 2007 as well as the concurrent increase of the minimum smoking age from 16 to 18. Note that our econometric models include month-year fixed effects which net out common time effects among all German states.

More detailed information on the smoke-free legislation in Germany can be found in Anger et al. (2011), Brüderl and Ludwig (2011), and Kuehnle and Wunder (2017). In particular, Anger et al. (2011) examine whether the timing of the implementation of the smoke-free German legislation is associated with various pre-ban characteristics at the state level. The authors do not find statistically significant associations with *(i)* the percentage of smokers in a state’s population, *(ii)* whether the state government is conservative, *(iii)* the average age of the state residents, *(iv)* the proportion of university graduates, *(v)* the proportion of singles in the state’s population, or *(vi)* the state’s GDP per capita. Hence, the variation in smoke-free legislation in Germany over time and states likely provides plausible exogenous variation to study the causal effects of public smoking bans.

3. Datasets

We make use of high-quality register data. We use the census of all German hospital admissions from 2000 to 2008 and link these data with weather measures, pollution measures, as well as socioeconomic background information at the county level. Being able

[3] Note that there exist no official figures for the number of “smoker pubs” in Germany.

to identify all health shocks that require inpatient treatment, this dataset allows us to study serious objective health effects of smoking (bans).

3.1 German Hospital Admissions Census (2000-2008)

The *German Hospital Admission Census* (Krankenhausstatistik – Diagnosedaten, 2000-2008), includes all hospital admissions from 2000 to 2008. By law, German hospitals are required to submit depersonalized information on every single hospital admission. The 16 German states collect this information and the research data centre (RDC) of the Federal Statistical Office and Statistical Offices of the Länder (*FDZ der Statistischen Ämter des Bundes und der Länder*) provides restricted data access for researchers. Germany has about 82 million inhabitants and registers about 17 million hospital admissions per year. We observe every single hospital admission from 2000 to 2008, i.e., a total of about 160 million hospitalizations.[4] In this data, hospital admissions include admissions requiring an overnight stay. It is not possible to separately track emergency room admissions; the data do not contain information on the admission route (i.e., ambulance, self-admitted). However, we observe the main diagnosis and the number of nights that the patient spent in the hospital.

To obtain our working dataset, we aggregate the individual-level admission data on the daily county level and normalize admissions per 100,000 or 1,000,000 population. As seen in the Appendix, besides others, we have information on age and gender, the day of admission, the county of residence, as well as the diagnosis in form of the 10th revision of the *International Statistical Classification of Diseases and Related Health Problems (ICD-10)* code. The total number of county-day observations in our main models is 1,429,196.[5]

Construction of Main Dependent Variables

Using the ICD information on the primary diagnosis, we generate the following dependent variables: *(a)* Aggregating over the total admissions on a given day in a given county, we obtain *admissions* representing the overall admission rate. *(b)* By extracting the ICD-10 codes I00-I99—diseases of the circulatory system—we generate *cardiovascular*

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

[5] If we had a stable set of 430 counties over all years, we would have 430*365*9 = 1,412,550 observations. However, due to county mergers, the number of counties decreased over time and varies from 442 (2000) to 413 (2008).

admissions. (c) Extracting the codes I20 and I21, we generate a third dependent variable, *heart attacks*. *(d)* A fourth variable measures hospital admissions due to asthma (ICD-10 code J45). *Cardiovascular admissions* and *asthma admissions* are our main dependent variables because tobacco smoke mainly triggers diseases of the circulatory system and asthma (U.S. Department of Health and Human Services, 2006, 2014). Admissions due to cardiovascular diseases are also the single most important subgroup of admissions (16% of all admissions).

Smoking bans change people's going out behavior to bars and restaurants (Anger et al., 2011) and might therefore influence (excessive) drinking behavior, hospital admissions due to alcohol intoxication, and traffic injuries. Adams and Cotti (2008), for instance, find an increase in fatal accidents involving alcohol following smoking bans in the U.S. because smokers drive longer distances to bars without smoking restrictions. Therefore, we also study *(e) alcohol poising* (code T51) and *(f) injuries* (codes V01-X59). Finally, we conduct falsification exercises and report estimates for the placebo outcomes *(g) drug overdosing* (ICD-10 code T40) and *(h) suicide attempts* (code T14).

Summary statistics for all dependent variables are provided in the Appendix. On a given day, we observe about 57.9 hospital admissions per 100,000 population in Germany.[6] On average, there are 9.1 *cardiovascular admissions* and *0.9 asthma admissions per 100,000 population*.

3.2 Merging Hospital Data with Weather, Pollution and Socioeconomic Data

We merge the *German Hospital Admission Census* with official daily weather and pollution data to exploit additional exogenous variation in weather and pollution conditions. This allows us to study the effectiveness of smoking bans under specific environmental conditions.

Weather Data. The weather data are provided by the German Meteorological Service (*Deutscher Wetterdienst (DWD)*). The DWD is a publicly funded federal institution and collects information from hundreds of ambient weather stations which are distributed across Germany. We have information on the minimum, average, and maximum

[6] Note that German data protection laws prohibit us from reporting minimum and maximum values.

temperature, as well as rainfall and hours of sunshine from up to 1,044 monitors and the years 2000 to 2008 (see Appendix for summary statistics). We extrapolate the point measures of the ambient weather stations into space using inverse distance weighting. This means that we use the measures 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 (Hanigan et al., 2006).

Pollution Data. The pollution data are provided by the GERMAN FEDERAL ENVIRONMENTAL OFFICE (*Umweltbundesamt (UBA)*). The UBA is a publicly funded federal agency that collects daily information on ambient air pollution. As for the weather data, we use data for 2000 to 2008 from up to 1,314 ambient monitors. As with our weather measures, we extrapolate the point measures into the county space on a daily basis. The Appendix shows all summary statistics.

Socioeconomic Background Data. Because the hospital data only contain gender and age information, we collect administrative data on the *unemployment rate*, the *number of hospitals in a county,* as well as the *number of hospital beds per 10,000 population* (see Appendix). Our empirical models control for these county-level characteristics. For example, Dehejia and Lleras-Muny (2004) find that smoking changes with the business cycle, and Ruhm (2007) reports a negative relationship between unemployment and deaths from coronary heart disease.[7]

4. Empirical Strategy

4.1 Empirical Model

To estimate the causal effect of smoking bans on hospitalizations, we estimate several variants of the following econometric difference-in-differences (DD) model:

$$y_{cd} = \beta_0 + \beta_1 Ban_{smt} + \varphi_w + \phi_m + \delta_t + \nu_s + X_{st}'\gamma + Z_{cd}'\theta + \varepsilon_{cd} \tag{1}$$

where y_{cd} stands for one of our dependent variables (normalized hospital admissions) and varies at the daily (*d*) county (*c*) level. The binary Ban_{smt} indicator is our main variable of interest. It indicates whether a bar/restaurant smoking ban was in effect in state *s* in month

[7] Similarly, Ruhm and Black (2002) and Ruhm (2005) report that smoking, drinking and excess weight decline in times of economic downturns.

m of year t. To net out persistent differences across states, we incorporate a set of state dummy variables ν_s. To control for seasonal and other time shocks, we additionally include sets of year (δ_t), month (ϕ_m), and week-of-year (φ_w) fixed effects. In the most saturated models employed, we replace the state, year and month fixed effects with month-year ($\phi_m \times \delta_t$) and state-year ($\nu_s \times \delta_t$) fixed effects. Note that one could easily rewrite the variable of interest in this DD model, $SmokingBan_{smt}$, as an interaction term between binary time-invariant state indicators and time variables that indicate when the ban became effective in each state.

Z_{cd} stands for a vector of controls that we generated from the individual-level hospital admission data; we aggregated those controls at the daily county level. For example, in the *German Hospital Admission Census*, we have information on patients' gender and age (reported in 17 different age groups).

Finally, we include a set of annual county-level covariates X_{st} that control for differences in the *unemployment rate*, the number of *hospitals in the county*, and the number of *hospital beds per 10,000 population* (see Appendix). The standard errors are clustered at the state level (Bertrand et al., 2004).

4.2. Identification

It is plausible to assume that the implementation of the German smoking bans across the 16 German states over time was exogenous to individual smoking behavior. Particularly helpful features of our setting are *(i)* that all German states eventually introduced smoking bans, *(ii)* that it all happened between August 2007 and August 2008, i.e., within only 13 months, and *(iii)* that we can exploit temporal variation in the implementation that ranges across all seasons of a year. Finally, Anger et al., 2011 have shown *(iv)* that the timing of the implementation across states shows no systematic relationship with a rich set of pre-ban state, among them the percentage of smokers in a state.

Our preferred specification in equation (1) does not only control for socio-demographic characteristics and the health care infrastructure at the county level, but also nets out week and month-year fixed effects and controls for persistent differences across states by including state-year effects. Such a rich specification does not leave much space for unobservables that could affect changes in admission rates which could be systematically correlated with the introduction of a smoking ban, but were not caused by it.

A general identification issue—but common to virtually all smoking ban papers (Adda and Cornaglia, 2006, 2010 being notable exceptions)—is that individual-level exposure to tobacco smoke is unknown. This means that smoking ban papers typically estimate a reduced-form effect of a smoking ban on the outcome variables of interest. Even if actual individual-level cigarette consumption could be measured without error, it is unclear whether (and if so, by how much) the actual consumption *intensity* changed (cf. Adda and Cornaglia, 2006).

Thus, the smoking ban-related change in individual-level exposure to environmental tobacco smoke—for smokers and non-smokers—is determined by *(a)* the population share of smokers and (their smoking intensity), *(b)* the (cultural) habits of smokers in terms of where they preferably smoke, *(c)* the details of the law banning smoking in certain locations, as well as *(d)* the specific implementation and enforcement of the law.

With respect to *(a)* to *(d)* above, one can summarize that *(a)* in the German population, the share of smokers is roughly one third across all cohorts, which is considerably larger than in the US (Cutler and Glaeser, 2009). *(b)* At least before the smoking ban, smoking was still to a large degree a social activity and not necessarily associated with a stigma as in the US. *(c+d)* The smoking bans mostly apply to indoor smoking in pubs and restaurants. Almost no exceptions exist for restaurants. However, as discussed in Section 2, in almost all states during the observation period, it was still possible to smoke in dive bars that self-declared as “smoker pubs.” On the other hand, the majority of pubs, particularly popular and touristic pubs, entirely banned indoor smoking.

5. Results

5.1 Main Estimates

Table 2 shows the results from regression models as in equation (1). Every column represents one model. The dependent variable in the first two columns is *all-cause* *admissions* per 100,000 population. Columns (3) and (4) use *cardiovascular admissions* per 100,000 population, columns (5) and (6) *heart attacks* per 100,000 population, and the final two columns report estimates for the dependent variable *asthma admissions* per 100,000 population. All models in the odd-numbered columns control for state, week, month, and year effects. All models in the even-numbered columns control for week, month-year, and state-year effects and control for socio-demographics.

Table 2: Main Estimates
Bar and Restaurant Smoking Ban Effect on Hospital Admission Rates

chnungsfläche	All-Cause Admissions		Cardiovascular Admissions[a]		Heart Attacks[b]		Asthma Admissions[c]	
	(per 100,000 pop.)		(per 100,000 pop.)		(per 100,000 pop.)		(per 100,000 pop.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ban	-1.0499**	-0.9565***	-0.0954	-0.1870***	-0.0453*	-0.0190	-0.0078	-0.0574***
	(0.4850)	(0.2248)	(0.1137)	(0.0434)	(0.0258)	(0.0203)	(0.0460)	(0.0183)
Mean of outcome variable	57.99	57.99	9.11	9.11	1.48	1.48	0.88	0.88
Change in %	-1.8	-1.6	-1.0	-2.1	-3.1	-1.3	-0.9	-6.5
State Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Month-Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
State-Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Socio-demographic daily controls	No	Yes	No	Yes	No	Yes	No	Yes
Annual county-level controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.1132	0.4132	0.1150	0.3834	0.0684	0.1532	0.0085	0.0123

Notes: [a] ICD-10 codes I00-I99. [b] ICD-10 code I20 and I21. [c] ICD-10 code J45. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. All models are variants of equation (1). All models have 1,429,196 county-day observations. The column headers indicate the dependent variable. The even and odd-numbered columns only differ by the sets of covariates included. *Ban* is the main variable of interest and varies at the month-year-state level. This dummy is one for states and months with a smoking ban in bars and restaurant and zero else.
Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The *"German Hospital Admission Census"* is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 for more details.

We learn the following from Table 2: First, following the implementation of a smoking ban, the all-cause admission rate decreased significantly by about 10 admissions per 1 million population, or 1.6% (column (2)). According to our preferred specification in column (4), the cardiovascular admission rate decreased significantly by 1.9 per 1 million population or by 2.1%. This is a small, but highly significant, effect. For the entire German population with its 82 million residents, 1.9 fewer people admitted due to heart problems per 1 million population translates into 156 fewer hospital admissions per day or about 56,867 fewer cardiovascular admissions per year. Applying the average health care costs of one hospital day of about €500, just these avoided cardiovascular admissions would yield a resource savings estimate worth €78 thousand per day (Gesundheitsberichterstattung des Bundes, 2012). For a comprehensive welfare loss estimate, one would need to add the patients' quality of life lost during hospital stays and the welfare loss of lost working days.

Could it be that the reduction in cardiovascular admissions is mainly driven by fewer hospitalization of employees in establishments that are newly smoke free (e.g., bartenders and waitresses)? According to the Federal Statistical Office, around 1.1 million worked in cafes, pubs, and bars in 2016 (Destatis, 2017). A decline by 1.9 cardiovascular hospital admissions per 1 million population per day among employees in these smoke-free venues would result in around 730 fewer admissions per year. This simple back-of-the-envelope calculation suggests that the reduction in cardiovascular admissions is very likely due to lower population exposure rather than a decline only among employees in venues directly affected by the smoke free laws.

Because our data contain information on whether people died in the hospital after having been admitted, we experiment with an additional outcome *death after cardiovascular admission* but do not find significant effects. The reason is likely that only 0.45 people per 100,000 population die after being hospitalized due to heart problems. This number only represents five percent of all cardiovascular admissions. Even with our high-frequency register data counting 17 million admissions per year, we operate in an underpowered setting. This illustrates a general structural issue for researchers trying to identify specific objective population health effects of anti-tobacco policies. If the *death after cardiovascular admission* effect was symmetric to the general *cardiovascular admission* effect, one would need to identify a 0.007 point estimate which is hardly possible even with register data.

Our next two models with the outcome *heart attack* admission rate (a subset of the overall *cardiovascular admission* rate) illustrates this point as well. Although we find consistently reductions in the heart attack rate in our specifications, only the estimate of the "parsimonious" DD model, with only state, week, month and year fixed effects in column (5) of Table 2 yields a marginally significant -0.05 point estimate, translating into a reduction in the heart attack rate of -3.1%. Our preferred saturated model estimate in column (6) is just -0.02 and not statistically significant any more. Relative to the mean of 1.48 heart attack admissions per 100,000 population and day, the estimate translates into a decrease of only

0.1%. This illustrates why many studies that intend to identify health effect estimates following smoking bans cannot provide precise estimates: even in a densely populated country with a very good health care infrastructure, short distances to the next hospital as well as a relatively high smoking prevalence, heart attacks are still a relatively rare event and small changes in the rates are very hard to identify, even with register data. It is also important to point out that the reduction in heart attack admissions in Germany is considerably smaller than what has been found in the study by Pell et al. (2008) following smoke-free legislation in Scotland. The authors report a reduction in acute coronary syndromes by 17%. However, methodologically Pell et al. (2008) compare hospitalizations before and after the smoke-free legislation was implemented in Scotland. Consequently, their findings are not directly comparable to our differences-in-differences model, which considers rich sets of time and regional fixed effects which net out seasonal as well spatial confounding factors.

The last two columns of Table 2 present the results for *asthma admissions*. In our preferred specification in column (8), we find a statistically significant decrease by around 0.06 fewer asthma admissions per 100,000 population and day. This is a considerable reduction as it implies a decline of nearly seven percent at the mean.

In unreported regressions (available upon request), we also estimate the smoking ban effects on *cardiovascular admissions* and *asthma admissions* separately by age group. Specifically, we ran our preferred model in columns (4) and column (8) of Table 2 for nine different age groups.[8] Furthermore, we explored potential heterogeneity in the treatment effect by gender. Overall, we did not find any significant differential impacts of public smoking bans on cardiovascular or asthma admissions by age group or gender.

[8] Ages 0-10, 11-20, 21-30, 31-40, 41-50, 51-60, 61-65, 66-75, and 75+.

Table 3: Main Estimates II
Bar and Restaurant Smoking Ban Effect on Selected Further Hospital Admissions Rates

	Alcohol Poisoning[a] (per 1 million pop.)		Injuries[b] (per 1 million pop.)		Drug Overdosing[c] (per 1 million pop.)		Suicide Attempts[d] (per 1 million pop.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ban	-0.0127	-0.0036	1.0493**	-0.3787	0.0045	-0.0016	-0.0126	-0.0039
	(0.0152)	(0.0145)	(0.4527)	(0.3209)	(0.0047)	(0.0055)	(0.0207)	(0.0161)
Mean of outcome variable	0.18	0.18	58.94	58.94	0.09	0.09	0.31	0.31
Change in %	-7.0	-2.0	1.8	-0.6	5.0	-1.8	-4.1	-1.3
State Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Year Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Month-Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
State-Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Socio-demographic daily controls	No	Yes	No	Yes	No	Yes	No	Yes
Annual county-level controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.0042	0.0093	0.0835	0.1477	0.0008	0.0017	0.0196	0.022

Notes: [a] ICD-10 code T51. [b] ICD-10 codes V01-X59. [c] ICD-10 code T40. [d] ICD-10 code T14. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. All models are variants of equation (1). All models have 1,429,196 county-day observations. The column headers indicate the dependent variable used. The even and odd-numbered columns only differ by the sets of covariates included. *Ban* is the main variable of interest and varies at the month-year-state level. This dummy is one for states and months with a smoking ban in bars and restaurant and zero else.
Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The *"German Hospital Admission Census"* is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 and Appendix for more details.

Table 3 presents the results for *alcohol poisoning*, *injuries*, and for the placebo outcomes *drug overdosing* and *suicide attempts*. Smoking bans might alter where people smoke and drink. They may drive longer distances by car to venues without smoking restrictions, increasing the risk of accidents and fatalities (Adams and Cotti, 2008). However, our results in Table 3 do not suggest a significant decline of *alcohol poisonings* or an increase in the number of *injuries* as a result of more car accidents. However, keep in mind that low means per 1 million population and that we may not have enough power to identify small changes, e.g., the point estimates for *alcohol poisonings* are consistently negative and between 2 and 7% of the mean.

Finally, columns (5) to (8) show the results for the falsification outcomes *drug overdosing* and *suicide attempts.* The estimates do not show consistent signs, are relatively close to zero and not statistically significantly different at conventional levels.

5.2 Robustness Checks

Table 4 provides a series of robustness checks for *cardiovascular admissions*. The first column is our preferred estimate from column (4) of Table 2 and serves as comparison. Column (2) clusters standard errors at the county level, which barely changes the standard errors. Column (3) includes 467 county fixed effects. As a result, the size of the coefficient decreases

to -0.08 but remains significant. Excluding the three early adopting states that implemented the ban in the second half of 2007 increases the estimate only slightly (column 4). In column (5), we run a placebo test and assume that the ban was implemented exactly one calendar year earlier than it actually was implemented. As seen, the point estimate is very small, positive, and not statistically significant. Finally, the regression in the last column in Table 4 excludes all counties that border Germany's neighboring countries Switzerland, Austria, Czech Republic, Poland, the Netherlands, Belgium, Denmark, Luxembourg or France. The point estimate of -0.183 is very close to the standard estimate suggesting that potential cross-border effects are unlikely to play a major role.

Table 4: Robustness Checks for the Outcome Variable Cardiovascular Admissions

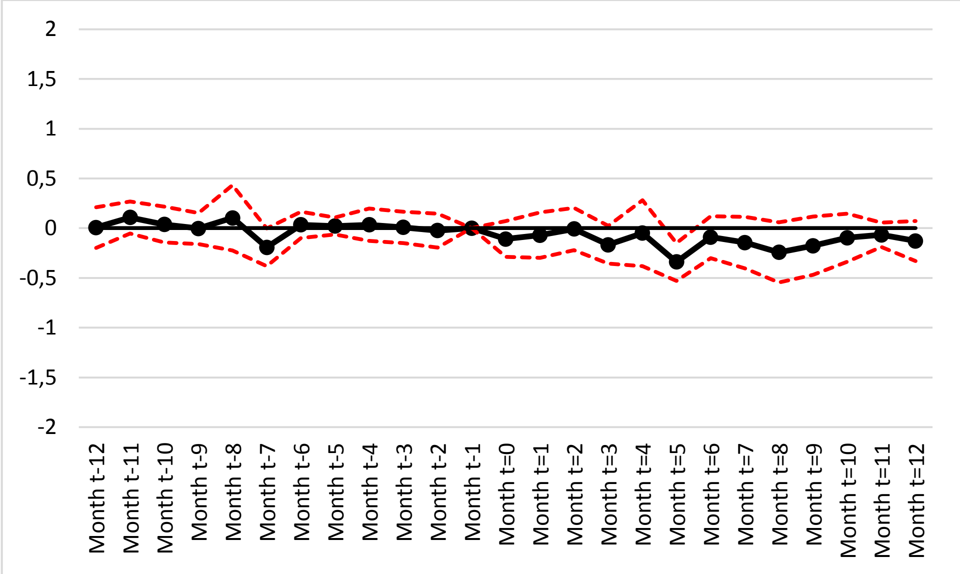
	Standard Estimate (1)	Cluster at County Level (2)	County-Level FE (3)	No Early Implementing States (4)	Placebo Treatment One Year Before (5)	No Border Counties (6)
Ban	-0.1870***	-0.1870***	-0.0765**	-0.2135**	0.0087	-0.1831***
	(0.0434)	(0.0442)	(0.0353)	(0.0967)	(0.0815)	(0.0489)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Daily and annual county controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3834	0.3828	0.3460	0.3666		0.3804
N	1,429,196	1,429,196	1,429,196	1,048,268	1,429,196	1,249,505

Notes: * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level (except for column (2)). All models are models as in equation (1) but using state-year and month-year instead of separate state, year, and month fixed effects. Ban varies at the month-year-state level and is one for states and months with a smoking ban in bars and restaurant and zero else. Column (1) equals column (4) in Table 2. Column (2) clusters the standard estimate at the county instead of the state level. Column (3) uses 467 county-level fixed effects. Column (4) excludes the three states that implemented the ban in 2007 (Baden-Wurttemberg, Lower Saxony, Hesse). Column (5) is a placebo check and assumes that the bans were implemented exactly one year earlier than they were actually implemented. Column (6) excludes the 67 counties that border a the neighboring country of Germany.
Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The "*German Hospital Admission Census*" is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 and Appendix for more details.

5.3 Event Studies

Next, we present event study graphs for our main outcome variables *cardiovascular admissions* and *asthma admissions*. We estimate our preferred saturated version of equation (1) with state-year, week, and month-year fixed effects, but interact Ban_{smt} with an indicator that counts the 12 months before and after the smoking ban implementation. Figures 2 and 3 plot the coefficient estimates of this indicator along with their 95% confidence intervals. The event studies illustrate how changes in admission rates evolve in the months before and after the smoking bans have been implemented.

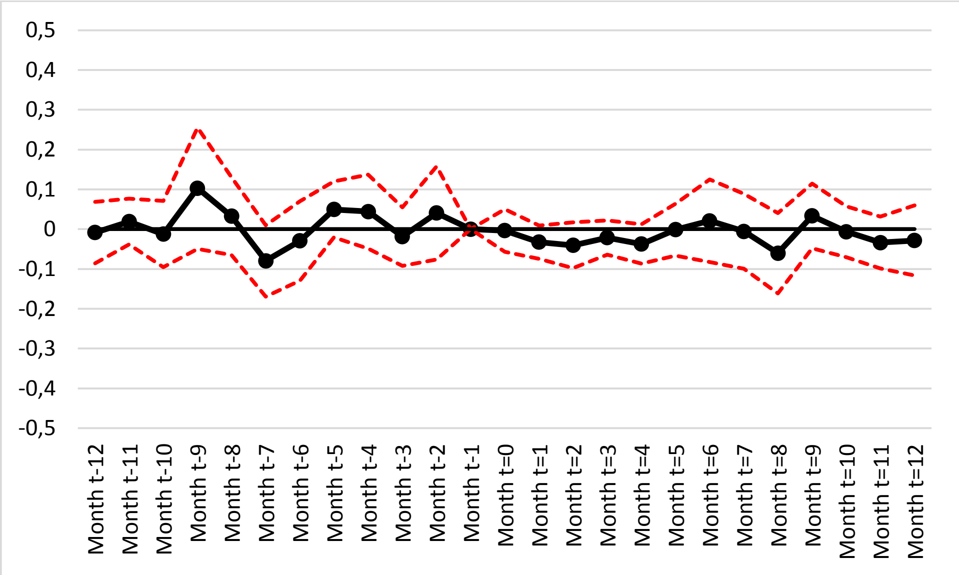
Figure 2: Event Study—Smoking Ban Effect on Cardiovascular Admissions per 100K pop.



Note: *German Hospital Admission Census*; Y-axis displays the mean change in ppt and x-axis the months before and after the smoking ban implementation. The solid black line represents the point estimates and the dotted line 95% confidence intervals. Regression is based on the saturated version of equation (1) and includes week, state-year and month-year fixed effects. Cardiovascular admissions are generated by extracting the ICD-10 codes I00-I99.

Figure 2 displays the event study for *cardiovascular admissions*. The pre-ban estimates are relatively flat and fluctuate around the zero line (8 positive, 3 negative point estimates); except for one, all confidence intervals include the zero line. In contrast, in post-ban months, we observe a smooth slight decrease in cardiovascular admission rates. Although most monthly point estimates are imprecisely estimated, *all* post-reform point estimates are negative. This pattern is suggestive of a persistent, albeit hard to quantify negative effect of smoking bans on cardiovascular admissions. In terms of relative size, the post-ban estimates lie between 0.7% and 3.8% of the mean with most estimates lying between -1% and -2%, which explains why it is hard to estimates these coefficients precisely.

Figure 3: Event Study—Smoking Ban Effect on Asthma Admissions



Note: *German Hospital Admission Census*; Y-axis displays the mean change in ppt and x-axis the months before and after the smoking ban implementation. The solid black line represents the point estimates and the dotted line 95% confidence intervals. Regression is based on the saturated version of equation (1) and includes week, state-year and month-year fixed effects. Asthma admissions are defined according to ICD-10 code J45.

Figure 3 shows the event study for asthma admissions. Similar to the results for cardiovascular admissions, the pre-ban point estimates fluctuate around zero (6 positive and 5 negative) and only one is statistically significant. In contrast, almost all post-ban estimates are negative (but imprecisely estimated). Although imprecisely estimated, Figure 3 suggests a short-term reduction in asthma admissions particularly in the first months after the ban. When estimating the event study using the basic model in equation (1) with separate week, state, month and year fixed effects, this suggestive evidence of a short-term effect is reinforced: In this specification, the four post-ban months estimates t=0 to t=3 all carry relatively large negative signs with effect sizes of almost 10% and all are statistically different from zero. However, for asthma admissions, there appears to be a rebound to the zero line after significant reductions in the first post-ban months. Further research on the longer-term health effects of smoking bans would be highly warranted.

5.4 Effectiveness of Bans by Weather Conditions

We now exploit exogenous variation in our weather data and use continuous measures of rainfall quantities, hours of sunshine, and temperature to stratify the estimates by weather conditions. Methodologically, we interact Ban_{smt} with the weather variable of interest (and its square), and also add the weather variable in levels and squares to the model. Table 5 reports our effect heterogeneity estimates by weather conditions.

Table 5: Effect Heterogeneity, Weather Conditions

	(1)	(2)	(3)	(4)	(5)	(6)
Ban*Rain	0.0205**	0.0199**				
	(0.0093)	(0.0092)				
Ban*Rain^2	-0.0011**	-0.0010**				
	(0.0005)	(0.0004)				
Ban*Sunshine			-0.0684**	-0.0685**		
			(0.0247)	(0.0243)		
Ban*Sunshine^2			0.0028	0.0029		
			(0.0023)	(0.0023)		
Ban*Temperature					0.0035	0.0012
					(0.0121)	(0.0114)
Ban*Temperature^2					0.0000	0.0001
					(0.0004)	(0.0004)
State-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Daily and annual county controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather and pollution controls	No	Yes	No	Yes	No	Yes
R^2	0.3828	0.3831	0.3829	0.3832	0.3831	0.3833
N	1,429,196	1,429,196	1,429,196	1,429,196	1,429,196	1,429,196

Notes: * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Each cell represents one model similar to Column (4) of Table 2. The dependent variable is always *cardiovascular admissions per 100,000 population*. The only difference to Column (4) of Table 2 is that we add interaction terms of the Ban indicator and our variable of interest (in levels and in squares) as indicated in the rows. In addition, we add the variable of interest (and its square) in levels. We do not report the level estimates for the sake of saving space.
Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The *"German Hospital Admission Census"* is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 for more details.

Whereas we do not find evidence that smoking ban laws are more or less effective with respect to the average temperature, there is evidence that for every additional *hour of sunshine* on a given day, admission rates additionally decrease by 0.068 (-0.7%) per 100,000 population. Similarly, with each additional hour of rain on a given day, cardiovascular admission rates increase by around 0.02 (+0.2%) per 100,000 population (ignoring the squared coefficient). This decrease (increase) in admissions on sunny (rainy) days could be due to several factors. For example, one could hypothesize that people spend more time outside when the sun shines. Because smoking bans only apply to places outside individuals' homes, this could explain the effect.

Note that the sunshine effect cannot be explained by the correlation between *hours of sunshine* and *temperature*—i.e., this is a true sunshine effect—because the estimate remains unchanged when we add *temperature* to the model. However, when creating an indicator of hot days with maximum temperatures of more than 30°C (86°F) instead of using the continuous temperature indicator (not shown), we also find a reinforcement of the health promotion effect, in line with the arguments above.

5.5 Effectiveness of Bans by Ambient Air Pollution

Table 6 analyzes whether high pollution levels reinforce or attenuate the smoking ban health effects. Again we add the pollutant of interest and its square to our baseline model in levels and in interaction with the Ban_{smt} indicator. Like hot days (cf. Karlsson and Ziebarth 2017; Deschênes and Moretti 2009), elevated ambient air pollution potentially induces stress for the human body and can trigger negative health effects. Tobacco smoke could reinforce this effect. Thus one could hypothesize that the health promoting effect of smoking bans should be reinforced under adverse environmental conditions.

Table 6: Effect Heterogeneity, Ambient Air Pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Ban*O3	-0.0047***	-0.0046***				
	(0.0011)	(0.0012)				
Ban*O3^2	0.0000***	0.0000***				
	(0.0000)	(0.0000)				
Ban*NO2			-0.0107	-0.0163		
			(0.0119)	(0.0134)		
Ban*NO2^2			0.0000	0.0001		
			(0.0001)	(0.0001)		
Ban*PM10					0.0308*	0.0185
					(0.0172)	(0.0149)
Ban*PM10^2					-0.0008*	-0.0006*
					(0.0004)	(0.0003)
State-Year Fixe Effects	Yes	Yes	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Daily and annual county controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather and pollution controls	No	Yes	No	Yes	No	Yes
R^2	0.3836	0.3929	0.3913	0.3941	0.3833	0.3919

Notes: * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Each cell represents one model similar to Column (4) of Table 2. All models have 1,429,196 county-day observations. The dependent variable is always *cardiovascular admissions per 100,000 population.* Each specification adds interaction terms of the *Ban* indicator and the pollution variable of interest (in levels and in squares) to the model in column (4) of Table 2, as indicated by the rows. The pollution variable of interest and its square is also added in levels. We do not report the level estimates to save space.
Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The "*German Hospital Admission Census*" is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 for more details.

The findings for O_3 and NO_2 are in line with this conjecture. First, the highly significant *Ban*∗ O_3 indicator in the first two columns implies that, on average, an additional 5 cardiovascular admissions per 10 million population are avoided by the German smoking bans when ozone levels are 10μ/m$_3$ higher (relative to a mean O_3 concentration of 46μ/m$_3$, see Appendix). Second, the sign of the estimates for NO_2 also suggest that the health promotion effects of smoke-free legislation are reinforced under adverse environmental conditions. However, even though the point estimates are relatively large, they are not statistically significant. In an alternative specification (available upon request), we generate pollution alert indicator variables that are one when the NO_2 concentration exceeds EU alert threshold levels. Replacing the continuous NO_2 measures with this dummy yields a highly significant -0.0088*** interaction term, suggestion that health effects of smoking bans are larger when pollution levels are critical. Finally, the main interaction terms for PM_{10} are not statistically significant.

6. Conclusion

Reducing smoking prevalence and exposure to environmental tobacco smoke remains a key public health priority of international health organizations and governments worldwide. Public smoking bans have become particularly popular in many countries in the last decade. Evidence on the effects of such bans on health outcomes, however, is still inconclusive. A lack of natural tempo-spatial variation and suitable treatment-control group designs—in combination with limited data availability to achieve enough statistical power and to control for potential confounders—additionally complicates identification.

This paper studies the short-run effects of the staggered implementation of state-level public smoking bans on hospital admissions in Germany. We contribute to the literature *(i)* by exploiting both time and regional variation in smoke free legislation in a high smoking prevalence country, *(ii)* by focusing on objective health measures and *(iii)* by using high-frequency administrative data in combination with auxiliary weather, pollution and socio-economic county data. This setting allows us to control more comprehensively than many existing studies for potentially important confounders. For example, in addition to being able to net out important seasonal confounders by employing rich sets of week, month-year, and state-year fixed effects, we also study the role of environmental pollution and weather effects.

We find that daily cardiovascular admissions decreased by about 1.9 per 1 million population (or by 2.1%) after the introduction of state-level smoking bans in Germany between 2007 and 2008. This translates into 57 thousand fewer cardiovascular admissions per year for the whole of Germany. Our findings hence suggests that sizable health gains can be achieved from such an anti-smoking policy—even if the law allows for exemptions and enforcement is imperfect.

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Appendix: Hospital Admission Data, Merged with Weather & Pollution Data

	Mean	*Std. Dev.*	*Min.*	*Max.*	*Obs.*
Outcome Variables					
All cause admissions per 100K pop.	57.987	25.709	N/A	N/A	1,429,196
Cardiovascular admissions per 100K pop.	9.112	4.922	N/A	N/A	1,429,196
Heart attack admissions per 100K pop.	1.481	1.362	N/A	N/A	1,429,196
Asthma admissions per 100K pop.	0.877	2.916	N/A	N/A	1,429,196
Alcohol poisoning per 1M pop.	0.1800	1.283	N/A	N/A	1,429,196
Injuries per 1M pop.	58.943	28.073	N/A	N/A	1,429,196
Drug overdosing per 1M pop.	0.0921	0.8743	N/A	N/A	1,429,196
Suicide Attempts per 1M pop.	0.3121	1.650	N/A	N/A	1,429,196
Daily County-Level Controls					
Female	0.539	0.0714	0	1	1,429,196
Age Group 0-2 years	0.062	0.043	0	1	1,429,196
….					1,429,196
Age Group above 74 years	0.003	0.008	0	1	1,429,196
Annual County-Level Controls					
Unemployment rate	10.465	5.277	1.6	29.3	1,429,196
Hospital beds per 10,000 pop.	1,208	1,586	0	24,170	1,429,196
Hospitals per county	4.828	5.472	0	79	1,429,196
Daily Weather & Pollution Controls					
Rainfall	2.225	4.215	0	144.98	1,429,196
Hours of sunshine	4.625	4.237	0	16.7	1,429,196
Temperature	9.557	7.305	-19	30.6	1,429,196
O_3 in μ/m_3	45.98	22.04	0.86	135.79	1,429,196
NO_2 in μ/m_3	26.89	10.63	0.31	80.31	1,429,196
PM_{10} in μ/m_3	24.31	11.46	2.06	64.63	1,429,196

Sources: RDC of the Federal Statistical Office and Statistical Offices of the Länder, [Krankenhausstatistik – Diagnosedaten 2000-2008], own calculations. The "*German Hospital Admission Census"* is administrative county-level data, daily weather data from the German Meteorological Service, daily pollution data from the German Federal Environmental Office, unbalanced panel at daily county level; see Section 3 for more details. N/A means not available due to legal restrictions and German data protection laws.

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