The Political Fallout of Air Pollution*

Luna Bellani
Stefano Ceolotto
Benjamin Elsner
Nico Pestel

This version: March 30, 2022

This paper studies the effect of air pollution on voting outcomes. We use data from 60 federal and state elections in Germany from 2000 to 2018 and exploit plausibly exogenous fluctuations in ambient air pollution within counties across election dates. Higher air pollution on election day shifts votes away from incumbent parties and towards opposition parties. An increase in the concentration of particulate matter (PM10) by $10\mu g/m^3$ – around two within-county standard deviations – reduces the vote share of incumbent parties by two percentage points, which is equivalent to 4% of the mean vote share. We generalize these findings by documenting similar effects with data from a weekly opinion poll and a large-scale panel survey. We provide further evidence that emotions are a likely mechanism: the survey data show that poor air quality leads to greater anxiety and unhappiness, which may reduce the support for the political status quo. Overall, these results suggest that poor air quality affects decision-making in the population at-large, which has far-reaching knock-on effects on society.

Keywords: Pollution, Decisions, Voting
JEL Codes: D70, D72, D91, Q53

* L. Bellani (luna.bellani@uni-konstanz.de) University of Konstanz, the Institute of Labor Economics (IZA) and AXA Research Lab on Gender Equality of Dondena Research Center; S. Ceolotto (ceolotts@tcd.ie) Trinity College Dublin; B. Elsner (corresponding author; benjamin.elsner@ucd.ie) University College Dublin, IZA and CReAM; N. Pestel (n.pestel@maastrichtuniversity.nl) Maastricht University (ROA), IZA and CESifo. We are grateful to Philip Carthy, Olivier Deschênes, Paul Devereux, Joshua Graff Zivin, Stefanie Haller, Fabrice Kämpfen, Steffen Künn, Kate Laffan, Armando Meier, Matthew Neidell, Andrew Oswald, Margaret Samahita, Nora Strecker and Till Weber for their helpful comments. We would like to thank Paul Fiedler, Marie-Sophie Houben and Anthony Jordan for providing outstanding research assistance.

1 Introduction

Poor air quality affects many domains of life. Besides well-documented adverse effects on human health (Graff Zivin and Neidell, 2013), there is growing evidence of "non-health" impacts, such as negative effects on labor market outcomes or cognitive performance, as well as changes in behavior and decision making (see Lu, 2020, Aguilar-Gomez et al., 2022, for recent reviews). By changing how people work, behave and make decisions, exposure to air pollution can have important knock-on effects. For example, when exposed to high air pollution, students perform worse on high-stakes exams, leading to lower subsequent earnings (Ebenstein et al., 2016); or people are more willing to take out health insurance (Chang et al., 2018), which affects their subsequent health; or stock traders trade differently, which affects returns on investments (Huang et al., 2020, Dong et al., 2021). However, the knock-on effects found in the existing literature mainly affect individuals or fairly small groups. What remains unclear is whether air pollution can have broader and more profound effects on society as a whole.

In this paper, we study the impact of air pollution on decisions with a far-reaching impact on society, namely voting decisions. The outcome of an election arguably has profound political, social and economic consequences for all people living in a country. At the same time, election outcomes are the result of the decisions of many individuals, and these decisions may be affected by people's exposure to air pollution. In the paper, we focus on Germany, a democracy with a multi-party system, proportional representation, and frequent elections that decide on the government of single states or the federal government. Our data set contains county-level election results for 60 federal and state election between 2000 and 2018, which we match with daily information on air pollution and weather conditions. To measure air pollution we use the daily average concentration of coarse particulate matter (PM10), a frequently used measure of suspended particles in the air.

To capture the effect of pollution on voting through several plausible pathways, we choose the vote share of the incumbent parties as the main outcome. Voting for incumbent parties can be seen as an expression of support for the status quo. Relative to voting for opposition parties, it also represents the less risky option, as voters have experienced the incumbent government in power. Therefore, if air pollution affects either people's support for the status quo or their willingness to take risks, it may affect voting for the incumbent parties. *A priori*, this effect could work in either direction: if pollution reduces the willingness to take risks, we would expect greater support for the incumbent parties, while if pollution worsens people's mood and increases anxiety, these emotions may reduce the support for the status quo, resulting in a lower vote share for the incumbent parties. Which of these effects dominates is an empirical question.

We identify a causal effect based on idiosyncratic variation in air pollution within the same county across election dates, by exploiting deviations from the typical level of pollution in a given county. The identification assumption underlying this strategy is that within a given county, the level of air pollution on election day is independent of the local political situation or any other factors that determine individual voting behavior. While politics can influence air pollution in the long run through environmental policies, it is nearly impossible to affect pollution on election day. We isolate within-county variation by including county and election date fixed effects, which absorb average differences in air pollution and election results across counties as well as trends that are common to all counties. In addition, we control for weather conditions that could simultaneously affect voting decisions and pollution levels. Moreover, to alleviate concerns about potentially endogenous exposure to poor air quality, we perform a series of robustness and placebo tests.

We find that high air pollution on election day shifts votes from the incumbent to the opposition parties. An increase in the ambient concentration of PM10 by ten micrograms per cubic meter ($\mu g/m^3$) – around two within-county standard deviations – reduces the vote share of the incumbent parties by two percentage points, which is equivalent to 4% of the mean vote share of incumbent parties. We find that the result is not driven by changes in turnout.

These effects appear strong when compared to changes in the incumbent vote share in federal elections. A useful benchmark is the change in the incumbent vote share when Angela Merkel was elected as chancellor in 2005. Relative to the previous election in 2002, the incumbent center-left government lost 4.8 percentage points of its vote share. Compare that to the effect of a higher concentration in air pollution on election day by $5\mu g/m^3$ – one within-county standard deviation, and thus not uncommon – which reduces the vote share of the incumbent by one percentage point. This means that a commonly observed increase in air pollution on election day leads to a reduction in the incumbent vote share equivalent to 20% of the observed drop in the incumbent's share in 2005.

How plausible is it that large numbers of voters change their mind shortly before an election? One has to consider that in Germany the share of undecided voters is typically large. For example, in the last federal election in September 2021, a representative survey has shown that a couple of weeks before the election around 40% of the eligible voters planning to vote were still undecided on which party to vote for (Koecher, 2021). The large number of undecided voters can be explained by the existence of many parties that are similar in terms of political agenda, and by the fact that governments, both at the federal and at the state level, are mostly results of post-election coalitions. It is thus common that voters decide whom to vote for shortly before the election.

To corroborate our identification assumptions and exclude the notion that our results are spurious, we perform balancing tests, placebo tests and pursue an instrumental variable strategy. Balancing tests show that air pollution neither predicts changes in population nor local GDP nor local employment rates. To further rule out that our results are contaminated by omitted variables or time trends, we perform placebo tests based on pollution levels on days before and after the actual election. We find that the effects of air pollution are sizable and statistically significant on days before the election but are very small and mostly insignificant on days immediately following the election day. Significant effects several days before the election are plausible because people may make their voting decisions before the election. These results suggest that our identification strategy uncovers a real effect: they show that pollution only matters on days when it *can* affect decision-making but not on days when it cannot. Likewise, when we run permutation tests and assign each observation the pollution level from the same county on different election dates, we consistently obtain estimates close to zero and far away from our estimates based on the correct election dates. This suggests that our estimates pick up a real effect. In a further step, we perform an instrumental variable analysis that exploits daily variation in wind directions, following Deryugina et al. (2019). The idea behind this strategy is that wind directions have an effect on daily levels of air pollution, but they are independent of local political or economic factors that could determine voting. The instrumental variable estimates confirm our main findings, suggesting that our results are not contaminated by omitted variable bias.

We generalize our results by documenting similar effects in two large-scale representative surveys. The first is a monthly opinion poll – *Politbarometer* – carried out on behalf of the German public television since 1977. On days with higher pollution in a respondent's region, we find that respondents report a weaker intention to vote for the incumbent federal government, and a stronger intention to vote for the opposition. At the same time, the results indicate a weaker approval of the current government's policies, while approval of the opposition is unaffected. A second piece of evidence comes from the German Socio-Economic Panel (SOEP). The panel structure of the SOEP allows us to exploit fluctuations in air pollution across interviews by the same respondent. Again, on interview days with higher air pollution, respondents show weaker identification with the current federal government and stronger identification with the opposition.

In theory, our findings can be explained by two behavioral channels. One is that voters rationally punish the incumbent for a high local level of air pollution. Another is a behavioral bias: voters subconsciously vote for the opposition because air pollution happens to be higher on election day. Given the variation in air pollution that we exploit as well as the nature of particulate matter, we view our results as evidence of a behavioral bias. The difference in pollution levels *between* places may be salient for voters; they likely notice that a large industrial city is more polluted than a rural area. However, we exploit variation *within* the same place, namely that on election day the level of air pollution happens to be higher or lower than it would normally be in the same place. Unlike variation in rainfall or temperature, such fluctuations in air pollution are hardly noticeable. Therefore, our results are in line with air pollution having an unconscious effect; for example, by affecting a person's emotions or health, which in turn affects how they process information and make decisions. Using the survey data, we find evidence that emotions are an important underlying channel. On days with elevated levels of air pollution, respondents are more likely to feel angry and sad, and they are less likely to feel happy. By contrast, we find no evidence that air pollution affects people's perceptions of the current state of the economy or their own economic situation.

This paper contributes to three strands of literature. First, it provides novel insights in the broader societal consequences of air pollution. While earlier work has mainly focused on the effect of air pollution on health and the environment (Graff Zivin and Neidell, 2013), recent evidence shows that its impact unfolds in many domains of life – often referred to as "non-health" effects (Aguilar-Gomez et al., 2022). Even short-run fluctuations in air quality have measurable consequences.[1] Several studies show that poor air quality reduces the productivity of workers in manual and cognitive tasks (Graff Zivin and Neidell, 2012, Chang et al., 2016, Lichter et al., 2017, He et al., 2019, Chang et al., 2019) and increases the frequency of worker absences (Hanna and Oliva, 2015, Aragón et al., 2017). Moreover, poor air quality has substantial consequences for education by increasing absences (Currie et al., 2009, Chen et al., 2018, Balakrishnan and Tsaneva, 2021), reducing academic (Stafford, 2015, Ebenstein et al., 2016, Heissel et al., 2021, Graff Zivin et al., 2020, Roth, 2021) as well as cognitive performance (Zhang et al., 2018, Sager, 2019, Heyes and Zhu, 2019, Bedi et al., 2021). The novelty of our study is documenting an effect of air pollution on *political* outcomes. Our analysis yields a

[1] The studies summarized here consider the impact of *short-run* fluctuations in air pollution. There is a separate literature on the impact of *long-run* exposure to air pollution – often during pregnancy or early childhood – on later-life outcomes. See Graff Zivin and Neidell (2013) for a review.

strong effect of air pollution, suggesting that high levels of air pollution may tip the scale in favor of opposition parties. Therefore, pollution may have a substantial impact on people's lives by affecting which parties are in government.[2]

Second, the paper provides new evidence on the role of incidental factors in high-stakes decisions. Numerous studies have shown that factors that are unrelated to a given decision influence important decisions, often through subconscious changes in behavior (for reviews, see DellaVigna, 2009, Lerner et al., 2015). An example is judges' decisions in court cases: research has shown that sentencing decisions are influenced by temperatures (Heyes and Saberian, 2019), wins of the local football team (Eren and Mocan, 2018), or whether a decision is made before or after a judge's lunch break (Danziger et al., 2011). Similar influences of incidental factors have been documented in other contexts, such as stock trading (Hirshleifer and Shumway, 2003, Kamstra et al., 2003, Edmans et al., 2007) or students' enrollment decisions (Simonsohn, 2010). By affecting emotions and decision-making, air pollution can be seen as an incidental factor. However, despite many studies documenting an effect of ambient air pollution on health and well-being (e.g. Manisalidis et al., 2020, Zhang et al., 2017), there is limited evidence of its effect on high-stakes decisions. Perhaps the most compelling evidence is provided by studies on specific groups such as stock traders (Levy and Yagil, 2011, Heyes et al., 2016, Meyer and Pagel, 2017, Huang et al., 2020, Dong et al., 2021), chess players (Klingen and van Ommeren, 2022, Künn et al., 2021), baseball umpires (Archsmith et al., 2018), or criminals (Herrnstadt et al., 2021, Burkhardt et al., 2019, Bondy et al., 2020). Although these studies point to systematic biases in decision-making, there is scant evidence of air pollution affecting decision-making in the population at large.[3] Our paper adds important evidence to this literature by documenting significant behavioral effects among millions of people going to the ballot on the election day. We use elections as a real-world laboratory to show that air pollution has profound societal consequences, and provide evidence that affective emotions are an important mechanism through which this effect operates.

Third, this paper contributes to the literature on the determinants of voting. While large parts of voters' choices are determined by political factors such as party programs or the popularity of candidates, there is growing evidence that incidental factors outside the political or economic sphere – often irrelevant for the voting decision itself – can affect voting decisions. A commonly-studied incidental factor is rainfall, which may affect the cost of voting as well as voters' emotions (Gomez et al., 2007, Hansford and Gomez, 2010, Arnold and Freier, 2016, Meier et al., 2019). Studies have also shown that voters respond to events such as natural disasters (Healy and Malhotra, 2010, Eriksson, 2016), shark attacks (Achen and Bartels, 2017, ch.5), or wins of the local football team (Healy et al., 2010). Although some of these results are contested (Fowler and Montagnes, 2015, Fowler and Hall, 2018), the overall evidence points to an important impact of incidental factors in voting, because either past events trigger negative emotions or voters deliberately punish the government for these events. Our paper contributes to this literature by identifying air pollution as an important determinant of voting outcomes. On days with high air pollution, voters are systematically less likely to vote for

[2]To our knowledge, one of the few papers on air pollution and politics is Heyes et al. (2019), who use text analysis to show that on days with high air pollution members of parliament give speeches of lower quality.

[3]Exceptions are Chang et al. (2018), who show that air pollution affects people's health plan choices in a way that is inconsistent with rational choice theory, and Qin et al. (2019), who show that homes in Beijing sell for significantly more on days with high air pollution.

the incumbent parties compared to days with lower pollution. However, the nature of the effect is different from the effect of natural disasters or rainfall, which are salient. In contrast, air pollution is not salient, and the fact that we find an effect highlights that incidental factors can affect voting behavior even if voters do not observe them.

2 Conceptual Framework: Air Pollution and Voting Behavior

In this section, we summarize the state of knowledge regarding the impact of air pollution on decision making and explain why air pollution may plausibly affect voting outcomes.

The literature in medicine, epidemiology and psychology highlights several plausible channels through which air pollution can affect decision-making. Broadly speaking, these can be split in two categories, namely conscious and subconscious reactions to air pollution. If people notice that air pollution is high, they may make a conscious decision to change their behavior. For example, they may punish the current government for not doing enough to reduce air pollution, and thus vote for an opposition party. However, even if people do not notice air pollution, it can prompt them to subconsciously change their behavior, for example by affecting their emotions or their cognitive functioning. In this case, ambient air pollution is an incidental influence in the decision process; it is a transient factor that is unrelated to the decision itself yet indirectly affects the decision (Loewenstein et al., 2003). Examples of incidental influences include environmental factors such as the weather, or emotional cues such as whether one's favorite football team has won a match, or whether a decision occurs on a person's birthday. Although in most contexts these factors are unrelated with the decision, there is ample evidence of people deciding differently on sunny days or days after their football team has won. With respect to air pollution, the literature has highlighted physiological as well as psychological pathways through which it affects decisions (see Chen, 2019, for a comprehensive review).

Given our empirical strategy and the nature of particulate matter, our estimation results are more likely to represent a subconscious reaction to air pollution rather than a deliberate choice. At levels commonly observed in Germany, people cannot see or smell air pollution, but rather feel it indirectly through symptoms such as cough or irritation of the airways. Only at high levels of air pollution – such as levels observed in parts of China or India – is air pollution actually observable to humans (Barwick et al., 2019). Moreover, we exploit variation in air pollution within the same county across election dates. This means that any effect that we may find is due to air pollution being higher or lower than its normal level in the same place. Because such fluctuations of PM10 are hardly noticeable for voters, it is unlikely that voters deliberately punish the government simply because air pollution happens to be higher on the election day than it normally is.

Daily fluctuations in air pollution can affect people's decision-making through three main channels, namely physiological effects, emotions, and cognitive functioning.

Physiological effects. Air pollution has both immediate and chronic effects on human health, which in turn may affect a person's decision-making. Air pollution may affect several different systems and organs, ranging from minor irritations of the upper respiratory tract to chronic respiratory and heart disease, lung cancer, acute respiratory infections and asthmatic attacks (Kampa and Castanas, 2008). The general consensus from medical studies indicates that the mechanisms of air pollution-induced health effects involve an inflammatory response and oxidative stress in the lungs, the vascular system, the heart tissues and the central nervous system (Lodovici and Bigagli, 2011). These effects are stronger among older people and tend to be stronger for people in worse general health (Bell et al., 2013). In the short run, these health effects can lead to fatigue and lower well-being, which can affect decision-making.

The role of emotions. Recent studies have explored pathways through which air pollution influences the human brain and affects mental health. Pre-clinical and clinical studies have shown that air pollution induces oxidative stress and increases the occurrences of headaches and depression (Lim et al., 2012, Salvi and Salim, 2019, among others). This can have knock-on effects on people's mental health. It is well documented that exposure to high levels of air pollution has a negative effect on people's mood, reduces people's happiness (Levinson, 2012, Li et al., 2014, Zhang et al., 2017, Zheng et al., 2019) and well-being (Luechinger, 2009), and increases anxiety (Trushna et al., 2020).

In turn, the link between mental health, emotions, and decision-making has been documented in a large body of literature in psychology. A review by Lerner et al. (2015) and a meta-analysis by Angie et al. (2011) cite many examples of incidental factors that lead to systematic biases in decision-making. These effects are mostly non-conscious: an incidental factor like air pollution affects a person's emotions, which changes their judgment, and in turn affects their decision-making.

Cognitive functioning. An additional channel through which air pollution can affect decision-making is cognitive functioning. Exposure to air pollution can cause inflammation and oxidative stress, which may affect the development and operation of brain cells, and in turn affect how people process information and make judgments. Although the literature has not yet reached a consensus on the exact biological mechanisms, there is ample evidence that long-run exposure to high levels of air pollution impairs cognitive functioning (e.g. Weuve et al., 2012, Zhang et al., 2018). In particular, it slows down the cognitive development among young people and accelerates the cognitive decline among older people (Clifford et al., 2016). Studies also show that short-run fluctuations in air pollution can affect cognitive performance. Examples include Künn et al. (2021), who find that chess players make more erroneous moves on days with high air pollution, and Archsmith et al. (2018), who find that baseball umpires make significantly more incorrect calls. Other studies document negative effects in cognitive tests. Powdthavee and Oswald (2020) use a representative survey in England and show that people exposed to higher levels of NO_2 on the day of an interview perform significantly worse on a memory test. Bedi et al. (2021) document similar effects among students undertaking cognitive tests in Brazil: a higher concentration of particulate matter significantly reduces performance on a fluid reasoning test.

Main outcome: incumbent vote share. We choose voting for the incumbent government parties as the main outcome, as it reflects voters' support for the current political status quo and may be indicative of voters' risk preferences. If air pollution increases negative emotions, this may affect voters' willingness to change the status quo, which has implications for the support for the incumbent government. In general, the status quo operates as a reference point from which change is considered and people assign more weight to losses than to equally-sized gains (Kahneman and Tversky, 1979). The higher the loss aversion, the more sizable the status quo bias, increasing the relative support for the status quo (Attanasi et al., 2017, Alesina and Passarelli, 2019). Given that increased unhappiness fosters impatience and induces a desire to change (e.g. Lerner et al., 2004, 2013), this might reduce loss aversion and the status quo bias. In the context of voting decisions, this implies withdrawing support from the incumbent government. Consistent with this reasoning, there is evidence that happier people are more likely to vote for incumbents (Ward, 2015, Liberini et al., 2017), whereas unhappy people are more likely to vote for the opposition (Ward et al., 2020, Nowakowski, 2021).

It has also been shown that anxiety has a direct impact on citizens' political behavior, determining the strategies that they use to construct their political judgments (Marcus et al., 2000, 2007, Valentino et al., 2008). Voters who are anxious are found to reduce their reliance on political habits and heuristics (e.g., party identification) and devote more attention to contemporary information.

Negative emotions may also have an indirect effect on voting behavior through their impact on risk attitudes (Hockey et al., 2000, Lerner and Keltner, 2001, Kliger and Levy, 2003, Grable and Roszkowski, 2008, Bruyneel et al., 2009, Lepori, 2015, Otto and Eichstaedt, 2018, Meier, 2021, among others).

As Shepsle (1972) posits, "*the act of voting, like that of gambling or purchasing insurance, is one involving 'risky' alternatives*". Following this view, a substantial body of literature in political science has analyzed the link between risk aversion and candidate choice, *incumbent advantage* (Morgenstern and Zechmeister, 2003, Kam and Simas, 2012, among others), and policy choices, *status quo bias* (Ehrlich and Maestas, 2010, Eckles and Schaffner, 2011, among others). In particular, more recently Eckles et al. (2014) have shown empirically that citizens who are more risk averse are more likely to support incumbent candidates in US congress elections, while citizens who are more risk tolerant are more likely to vote for challengers. Similarly, Sanders and Jenkins (2016), Morisi (2018), Liñeira and Henderson (2019) show that more risk-averse individuals are more likely to vote for the "status quo" policy in the recent UK "*Leave*" and Scotland "*Independence*" referenda, respectively.

Summary. In sum, the literature shows that air pollution has impacts on the human body at various levels. By affecting the brain and increasing oxidative stress, it can negatively affect people's mood and emotions. These feelings in turn affect individuals' decision-making. Overall, we should expect that exposure to air pollution has *some* effect on voting outcomes. However, whether it increases or reduces support for the incumbent government is an empirical question. If air pollution increases risk aversion, we would expect a positive effect. On the other hand, if it mainly affects voters' mood, increasing their unhappiness and anger, we would expect a negative effect.

3 Main Data and Descriptive Statistics

To study the effect of air pollution on voting outcomes, we focus on parliamentary elections in Germany. The country has regular elections at the federal and state level, and elections at both levels have important consequences for all political domains. For our analysis, we combine county-level data on federal and state elections with data on pollution, weather conditions and socio-economic characteristics. The sample period runs from 2000 – the first year in which pollution measures are available – to 2018, the most recent year in which GDP data is available.

3.1 Election Data

We use county-level voting data from the German Federal Statistical Office (*Statistisches Bundesamt*), which covers five federal and 64 state elections from 2000 to 2018. Both election types are administered by municipalities in a uniform procedure. The national parliament (*Bundestag*) is elected for a four-year term, with elections typically taking place on a Sunday in September or October. The state parliaments (*Landtage*) are elected for five years.[4] State elections are typically held on a Sunday in spring or fall. In the sample period, there have been five early elections, one at the federal (2005) and four at the state level (Hamburg in 2004, Northrhine-Westphalia, Saarland and Schleswig-Holstein in 2012).[5]

In all elections, voters have two votes: the first vote is cast for a direct candidate in a local electoral district, and the second for a state-wide party list. The seats in parliament are distributed to directly elected candidates as well as candidates on the party lists. With some minor exceptions, the proportionality of parties in parliament is governed by the second vote (*Zweitstimme*). Voters do not need to give both votes to the same party. It is allowed — and not uncommon — that people give their first vote to a candidate from one party and the second vote to another party. In our analysis, we focus on the second votes because they are representative of people's party preferences, whereas the first votes are often strategically given to candidates from large parties who have a higher chance of winning. For each election, we observe the date and type, the number of eligible, valid and invalid votes as well as the number of votes for each party.

The vast majority of votes are cast at the polling stations on election day. However, it is possible to vote by mail, and this option has become increasingly popular in recent years. For example, in federal elections the share of mail voters increased from 13.4% in 1994 to 28.6% in 2017 (Bundeswahlleiter, 2017). Our data do not contain separate county-level information on the voting behavior of ballot voters vs. mail voters. In Appendix B, we discuss the implications of mail voting for our estimation.

To test whether air pollution leads to changes in voting decisions, we consider as main outcome the vote share for *Incumbent parties*, i.e., parties that are part of the governing coalition on the day before the election.[6] At the federal level, we consider incumbent parties that form the federal government, and analogously at the state level we consider parties that form the state government. Besides the

[4] The exception is Bremen, where the term is four years.

[5] There was also an early election for the *Landtag* in Hesse in 2009. The regular election took place in 2008, but the negotiation for the formation of a government failed and new elections were held in 2009. Since no government came out of the 2008 elections — i.e. no incumbent and opposition — we do not consider the 2009 elections in our analysis. See Appendix A.2 for the list of all elections taking place in the 2000-2019 period and their distribution across calendar months.

[6] In additional analyses, we also look at the *established opposition* parties, that form the opposition on the day of election and that have been regularly represented in the German Bundestag over the sample period, as well as *other parties*, i.e., smaller opposition parties, many of which are not frequently represented in the federal or state parliaments. The exact classification depends on whether the election is at the federal or state level (the complete breakdown is reported in Appendix A.1).

vote share, we also consider turnout, which may explain the observed changes in voting patterns. We estimate the effect of pollution on turnout and subsequently use turnout as a control variable when estimating the effect of pollution on vote shares.

Based on the county-level election data, we construct a panel dataset for all counties and elections. In thirteen out of sixteen states, the definition of counties remained stable over the sample period. Three states – namely, Mecklenburg-Vorpommern, Saxony, and Saxony-Anhalt – had territorial reforms between 2007 and 2011, during which some counties were merged or dissolved, meaning that county-level data from before and after the reform are not comparable. To obtain consistent panel data for these three states, we apply the post-reform county definition and construct the vote shares for pre-reform years based on municipality-level voting data.[7] We explain the construction of the pre-reform data in greater detail in Appendix C.2, where we also perform robustness checks omitting these three states from the analysis.

3.2 Pollution and Weather Data

The pollution data is provided by the German Federal Environment Agency (*Umweltbundesamt*) and it comprises geo-coded daily average measures of ground-level concentration of several pollutants from 1,170 measuring stations. Our measure for air pollution is the daily average concentration of particles smaller than ten micrometers in ambient air (PM10), one of the most frequently-used measures for suspended particles in the air (World Health Organization, 2005).[8] Particulate matter is a broad definition used to characterize a mixture of solid and liquid particles that significantly vary in their size. PM10 includes particles with an aerodynamic diameter smaller than ten micrometers (μm). The World Health Organization (WHO) and the European Environmental Agency (EEA) recommend a 24-hour average concentration of no more than 50 $\mu g/m^3$ (European Environment Agency, 2016). Across Germany, PM10 has been consistently monitored since 2000 and measurements are conducted through gravimetry, which is the standard method in the EU.

Next to particulate matter, there are several other air pollutants that are regulated in the European Union as well as many other places around the world, for example nitrogen oxides (NOx), sulphur dioxide (SO2) or carbon monoxide (CO). As these pollutants typically stem from the same or very similar emission sources (industry, power generation, traffic), their concentrations are typically highly positively correlated with PM concentrations. Hence, we treat the measurement of PM10 as a proxy for overall air pollution. The only exception is ozone (O3). Unlike PM10, ozone is not directly emitted into the atmosphere but emerges from certain combinations of temperature and solar radiation.[9] Therefore, in our preferred specification, we control for ozone levels. Ozone concentrations tend to

[7]The same is applied for demographic and socio-economic characteristics when the original datasets do not already include observations for the post-reform county definitions.

[8]Our analysis is based on measurements of PM10 concentrations in ambient air. We do not use the concentration of PM2.5, which only captures the concentration of very fine particles with a diameter not exceeding 2.5 μm and therefore most harmful for the human body by being able to penetrate very deep in the lungs and brain. Unfortunately, the measurement of PM2.5 in Germany only started in 2008 and with a much lower geographic coverage than PM10, which substantially reduces our sample size. However, the concentration of PM10 also captures fine particles and is consequently strongly correlated with PM2.5.

[9]The WHO suggests a maximum daily eight-hour mean concentration of 100 $\mu g/m^3$, while the EEA's target is set at 120 $\mu g/m^3$, not to be exceeded on more than 25 days per year (European Environment Agency, 2016). Measurement is carried out by UV absorption.

be particularly high during summer months, whereas particulate matter is lowest in summer. Given that most elections happen in spring or autumn, the level of ozone is negatively correlated with PM10, and thus may confound the estimation of the effect of PM10.

In order to control for weather, we obtained geo-coded weather data from the German Meteriological Service (*Deutscher Wetterdienst*). These comprise various measures of temperature (°C), relative humidity (%), wind (m/s), precipitation (mm/m^2), solar radiation (h), air pressure (hpa) and dew point (°C). As documented by a large body of literature in the natural and social sciences, meteorological conditions affect concentration levels of pollution as well as voting behavior, which is why we include these variables as controls (see, for example Eisinga et al., 2012a,b, Sforza, 2014). All pollution and weather variables are measured as 24-hours averages, apart from precipitation, which is the total amount over 24 hours.

We link the election, pollution and weather data based on the county centroid and the election date. For each county, we calculate the pollution and weather measures at the centroid as the inverse distance-weighted average across all stations within a certain radius. The choice of the radius comes with a trade-off between the accuracy of the measurement within a county and the number of counties that can be included. A smaller radius yields more accurate measures at each centroid but some centroids would not be sufficiently close to any measuring station and therefore cannot be included in the dataset. In our main analysis, we choose a radius of 30km.[10]

3.3 Demographic and Economic Data

We also collect data to control for demographic and economic characteristics that could simultaneously affect the concentration of PM10 as well as voter preferences. The data are provided by the Federal Statistical Office and include county-level observations of population by gender and age group, gross domestic product and gross value-added by economic sector as well as employment by sector for the 2000–2018 period. In our preferred specification, we control for total population, GDP per capita, and the employment rate as the ratio of the total number of employed persons over the population aged between 15 and 65 years. Note that this ratio may exceed 100% for counties characterized by a high share of inbound commuters.

3.4 Estimation Sample and Descriptive Statistics

We restrict our estimation sample to all county-election observations for which PM10, voting, weather, demographic and economic data are available. For our preferred data linkage based on a radius of 30km, this leaves us with 2770 observations (356 counties and a total number of 60 elections).[11]

Table 1 reports the descriptive statistics of the main variables in our analysis. The within-standard deviation is the standard deviation of the residuals after conditioning on election and county fixed effects. The table reveals a strong degree of variation in the voting and pollution data. The variation

[10]In Appendix C.3 we replicate our main analysis using alternative radiuses. The results are quantitatively and qualitatively identical to those we obtain with a radius of 30km.

[11]For some counties, we do not have observations for one or more of the pollution or weather variables for the entire sample period. In addition, most state elections in the county-states of Berlin and Hamburg are singletons, and they are thus dropped from the fixed effect estimation. This explains why we consider 60 instead of 69 elections that took place over the sample period.

in the number of eligible voters and valid votes reflects the fact that the population per county strongly differs between rural and urban areas. Large cities such as Berlin, Hamburg, Munich or Cologne coincide with counties, whereas other counties comprise the surroundings of large cities or rural areas. The average turnout is 69%, with little variation. The statistics for incumbent parties show that their average share in any election is higher than that of the established opposition, although the vote share considerably varies from 17% to 79%.

Table 1: Descriptive Statistics

	Mean	SD(total)	SD(within)	min	max	N
Voting data						
Eligible voters	159,376	159,294	5,247	26,396	2,505,718	2,770
Valid votes	109,548	116,304	16,955	13,132	1,872,133	2,770
Turnout	0.69	0.09	0.02	0.38	0.87	2,770
Share incumbent parties	0.48	0.10	0.07	0.17	0.79	2,770
Share established opposition parties	0.42	0.12	0.07	0.13	0.82	2,770
Share other parties	0.10	0.07	0.02	0.01	0.44	2,770
Pollution data						
PM10 ($10\mu g/m^3$)	1.90	0.85	0.47	0.26	6.79	2,770
Ozone ($10\mu g/m^3$)	4.20	1.54	0.81	1.36	16.21	2,770
NO2 ($10\mu g/m^3$)	2.18	1.20	0.59	0.00	9.25	2,762
Weather data						
Temperature (°C)	11.22	4.01	0.83	-7.60	21.12	2,770
Relative humidity (%)	80.02	9.12	4.45	47.40	99.58	2,770
Wind speed (m/s)	2.72	1.63	0.84	0.10	11.87	2,770
Precipitation (mm)	1.34	3.18	2.14	0.00	34.80	2,770
Demographic and economic data						
Population	214,510	228,459	10,663	34,084	3,613,495	2,770
GDP per capita	31,128	14,902	3,417	12,481	172,437	2,770
Employment rate	0.76	0.22	0.03	0.37	1.97	2,770

Notes: This table displays the descriptive statistics for the estimation sample. SD(within) represents the standard deviation of the residuals after removing election and municipality fixed effects. Pollution and weather measurements are computed based on a radius of 30 km. The employment rate is based on yearly average number of employed persons in a given county divided by its total population .

3.5 Variation in Air Pollution Levels and Incumbent Vote Shares

The descriptive statistics on the ambient concentration of PM10 in Table 1 show that the mean on election days (always on a Sunday) is $19\mu g/m^3$ and also indicate a strong variation in pollution. The within-standard deviation – which is close to our identifying variation – accounts for more than 50% of the total variation in PM10 and around 25% of its mean. Day to day variation in ambient concentrations of particulate matter in a specific location results from a combination of emissions from various sources and local atmospheric conditions.[12] This means that short-term variation in local pollution does not simply reflect variation in the amount of air pollutants emitted to ambient air (e.g., from industrial activity or traffic volumes) but also crucially depends on fluctuations in local weather conditions. For a given level of emissions, exposure to pollution is significantly lower on rainy or windy days as precipitation and wind reduce ambient concentrations of particles. Also, during temperature inversion episodes warmer air at higher altitude traps air pollutants emitted at the ground (Jans et al., 2018). In addition, depending on the direction from where the wind blows, particles emitted at other locations may be transported over long distances and increase air pollution independently of local economic activities (Deryugina et al., 2019).

Figure 1 shows the variation in PM10 on the days of election for deciles of average air pollution. The graph illustrates a significant degree of variation in all deciles – regardless of the average level of pollution, there is a large amount of variation in pollution levels *within* each decile. Despite the substantial variation in daily average concentrations of PM10, the levels we observe in Germany over the period under investigation do not exceed $70\mu g/m^3$. These levels are low in global comparison and substantially lower than, for example, in highly polluted industrial cities in India or China. In particular, the levels observed in Germany are substantially lower than levels that inhibit visibility, such that it is essentially impossible for voters to visually observe pollution levels they are exposed to.[13] This means that, different from what has been shown for weather conditions such as rainfall, sunshine, temperature or wind speed (Gomez et al., 2007), pollution levels are not at all salient in our setting and we can thus confidently exclude the notion that there may be a selection of specific types of voters going to the polls on more polluted days compared to low pollution days.

In Appendix C.1, we present further illustrations of the variation in PM10 within and across counties. The results show that the average level of PM10 fluctuates considerably from year to year, although it appears to be on a decreasing trajectory over the sample period. We also document the extent of within-county variation in PM10, which represents our identifying variation. Counties differ in their within-variation, but in most counties the within-standard deviation across election dates lies between 5 and $10\mu g/m^3$. Overall the descriptive analysis shows that our estimation strategy relies on a large amount of identifying variation that is spread across the country.

Figure 2 illustrates the typical fluctuations in voting for the incumbent parties in federal elections since the 1980s. Each bar indicates the change in the vote share of the incumbent government in a given election relative to the previous election. In most elections, the incumbent government performed considerably worse than in the previous election. In some years, these losses led to a change in government. An example is the change from Chancellor Gerhard Schröder's center-left (SPD/Greens) to Angela Merkel's Grand Coalition (CDU/CSU/SPD) government in 2005, following a drop in the vote share of the incumbent parties by close to five percentage points.

[12] While particulate pollution may have natural sources (e.g. wildfires, sandstorms or volcano eruptions), there are various man-made emission sources such as automobile exhaust, fossil-fueled electricity generation or any other industrial activity involving combustion processes.

[13] Research in atmospheric sciences has documented a non-linear relationship between visibility and particulate pollution which may differ by the level of relative humidity. Sun et al. (2020) report that the negative relationship between visibility and PM2.5 concentrations becomes particularly strong beyond a threshold of $76\mu g/m^3$ and $49\mu g/m^3$ for relative humidity levels from 60% to 80% and from 80% to 90% respectively. Over the period from 2010 to 2020 the mean PM2.5 concentration was in the range of 10 to $20\mu g/m^3$, see `www.umweltbundesamt.de/publikationen/luftqualitaet-2020` (page 11, last accessed: 19 Oct, 2021).

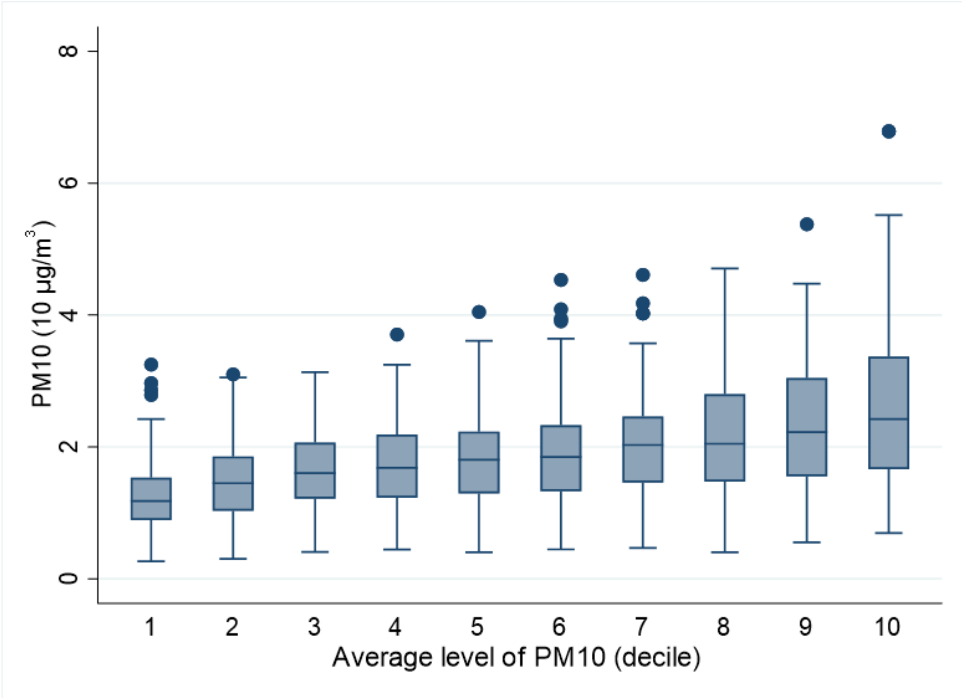


Figure 1: Variation of PM10 by Decile of the Average Level of PM10

Notes: This graph displays box plot charts visualizing the variation of particulate matter (PM10) on the day of election across different counties grouped by the average level of PM10. The average level of PM10 refers to the average across all election dates in the sample.

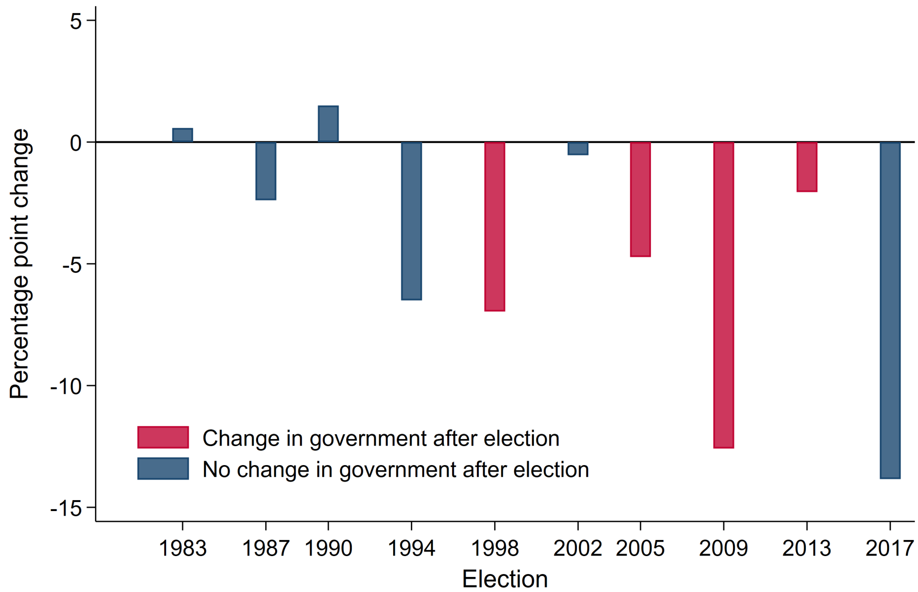


Figure 2: Changes in Incumbent Vote Shares in Federal Elections

Notes: This graph displays the change in the vote share of the incumbent parties in federal elections. The change is measured for the incumbent parties on the day of the election relative to the vote share of the same parties in the previous election. Red bars indicate a change in the government coalition. In 1998 and 2005, the change in the government coalition coincided with a change of the chancellor. Source: own calculations based on data from the German Statistical Office.

4 Empirical Strategy

Our goal is to study the effect of poor air quality on the election day on voting outcomes. In an ideal experiment, we would randomly assign air pollution levels on the election day to local areas. In this case, we could interpret the difference in voting results between areas with a high and low levels of air pollution as a causal effect. In the absence of such an experiment, we exploit quasi-experimental variation in pollution levels within counties over time. The underlying thought experiment is that on a given election day – for random reasons – the level of air pollution in a county is higher or lower compared to its normal level. This strategy allows us to identify a causal effect under the maintained assumption that the variation in pollution across election dates within a county can be considered as good as random. In this section, we explain our identification strategy under this assumption and point to some potential challenges. We will address these challenges through placebo and robustness checks as well as an instrumental variable strategy after having presented the main results.

4.1 Empirical Model

To exploit variation in the concentration of PM10 within counties across election dates, we estimate a two-way fixed effect regression,

$$y_{it} = \alpha + \beta PM10_{it} + \boldsymbol{X'_{it}}\gamma + \delta_i + \tau_t + \varepsilon_{it}, \tag{1}$$

whereby the outcome variable y_{it} denotes an election outcome in county i at election date t. The regressor of interest is $PM10_{it}$, the air concentration of PM10 (in tens of $\mu g/m^3$) measured on the day of the election, which is a proxy for the overall level of air pollution on the day. The vector X_{it} controls for two types of time-varying confounders, namely weather (temperature, relative humidity, wind speed, precipitation and ozone levels) and demographic variables (total population, GDP per capita and the employment rate). The county and election date fixed effects, δ_i and τ_t, absorb all confounding factors that are constant within a county over time as well as those that are common to all counties during the same election.

The error term ε_{it} summarizes all determinants of election outcomes that are not absorbed by the controls and fixed effects. To account for serial correlation within counties, we cluster the standard errors at the county level.

4.2 Identification

Our parameter of interest, β, measures the contemporaneous effect of a change in air pollution on election outcomes within the same county. A causal interpretation of β requires that pollution be uncorrelated with any determinants of election outcomes conditional on controls and fixed effects, i.e.

$$E(\varepsilon_{it}|PM10_{it}, \boldsymbol{X_{it}}, \delta_i, \tau_t) = 0. \tag{2}$$

Given the two-way fixed effects, β is causally identified if the fluctuation in pollution levels *within a given county* is uncorrelated with time-varying determinants of voting in the same county. Our controls account for several common challenges to identification. Weather conditions may affect who votes as well as for what party – for example, by affecting turnout or people's mood on election day – while being potentially correlated with air pollution. To address this challenge, we control for a set of potential confounders, namely temperature, relative humidity, wind speed and precipitation. When the outcome is a vote share, we also control for voter turnout. This helps with the interpretation of the effect: conditional on turnout, β represents the effect on pollution on vote shares rather than the number of votes.

We address several identification challenges in robustness checks. One challenge could be local economic shocks or public policies that may simultaneously affect pollution and voting. For example, the closure of a nearby factory or changes in local environmental regulations may reduce pollution levels while leading to a response among voters. We address this challenge in three ways. First, we perform balancing tests whereby we regress economic outcomes on pollution and condition on fixed effects and controls. Insignificant coefficients suggest that the fluctuations in pollution used for identification are unrelated with fluctuations in economic variables. Second, we show regressions with placebo election dates before and after the actual date. The idea is that profound local shocks or policy changes should affect pollution levels both before and after the actual election. However, if we do not observe significant effects after the election date, this indicates that our results are not confounded by local shocks. As a third robustness check, we follow Deryugina et al. (2019) and instrument for air pollution with changes in local wind directions, which are plausibly orthogonal to local economic shocks.

A further challenge is voting by mail, whose share among all eligible votes in the sample period stands between 13% and 28% (Bundeswahlleiter, 2017). Because we neither observe the time at which mail voters send their ballot papers nor the place in which they cast their vote, we likely assign the incorrect level of air pollution to mail voters. We assign the concentration of particulate matter on the election day despite the fact that they have cast their vote up to one month before the election, and potentially in a different place. In Appendix B, we show that the absence of detailed data on mail voting is akin to a measurement error problem, which – under reasonable assumptions – leads to attenuation bias. A back-of-the-envelope calculation shows that the estimates are attenuated by around 15–20%.

5 Results

5.1 Main Results

Table 2 displays our estimates for the effect of air pollution on voting for incumbent parties. PM10 is measured in $10\mu g/m^3$, whereas the outcomes are shares that are bounded between zero and one. A coefficient of 0.01 means that an increase in PM10 by $10\mu g/m^3$ increases the respective outcome by one percentage point. An increase in PM10 by $10\mu g/m^3$ in turn is equivalent to an increase by two within-county standard deviations in the concentration of PM10.[14] In Columns (1) and (3), we condition on county and election date fixed effects, whereas in Columns (2) and (4), we additionally control for weather variables, demographics, and election type fixed effects, which absorb systematic

[14]As shown in Table 1, the within-standard deviation of PM10 measured in $10\mu g/m^3$ is $sd = 0.47$.

differences between state- and federal-level elections. Since pollution may also affect turnout, we control for turnout in Column (2).

Table 2: Main Results – Air Pollution and Voting

Outcome:	Vote Share of Incumbent Parties		Turnout	
	(1)	(2)	(3)	(4)
PM10 ($10\mu g/m^3$)	-0.0198***	-0.0205***	0.0012	0.0010
	(0.003)	(0.003)	(0.001)	(0.001)
Mean dep. var.	0.48	0.48	0.69	0.69
R^2	0.576	0.604	0.961	0.961
N	2,770	2,770	2,770	2,770
Controls				
County FE	✓	✓	✓	✓
El. Date FE	✓	✓	✓	✓
Weather		✓		✓
Ozone		✓		✓
Demographics		✓		✓
El. Type FE		✓		✓
Turnout		✓		

Notes: This table displays the results of OLS regressions of the outcomes listed at the top on the air concentration of PM10 (in $10\mu g/m^3$) and the controls listed at the bottom of each panel. Standard errors clustered at the county level are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

In Columns (1)-(2), we find strong and statistically significant effects, indicating that an increase in pollution shifts votes away from the incumbent parties. For an increase in PM10 by $10\mu g/m^3$, the vote share of the incumbent parties drops by roughly two percentage points, which is more than 4% of the mean. The results in both columns are very similar, suggesting that the fluctuation in air pollution across election days is uncorrelated with more salient fluctuations in the weather or changes in demographics. By contrast, in Columns (3) and (4) we find no effect of pollution on voter turnout. The coefficients are small in magnitude and insignificant, which suggests that air pollution does not affect people's decision on whether to vote or not. This result is important for the interpretation of the effects on voting outcomes, which reflect changes in voting behavior rather than changes in turnout.

Non-linear dose-response relationship. In Figure 3, we explore the dose-response relationship between air pollution and voting outcomes. For this purpose, we replace the regressor $PM10_{it}$ in Equation (1) with indicators for ten different levels of concentration (5-10$\mu g/m^3$, 10-15$\mu g/m^3$, 15-20$\mu g/m^3$, 20-25$\mu g/m^3$, 25-30$\mu g/m^3$, 30-35$\mu g/m^3$, 35-40$\mu g/m^3$, 40-45$\mu g/m^3$, 45-50$\mu g/m^3$, >50$\mu g/m^3$). The coefficients of these indicators are to be interpreted as the difference in voting results between a given level of pollution and the base level of less than or equal to 5$\mu g/m^3$. The results indicate that the effect of pollution on most outcomes is approximately linear for levels of air pollution below

$40\mu g/m^3$ and levels off thereafter.

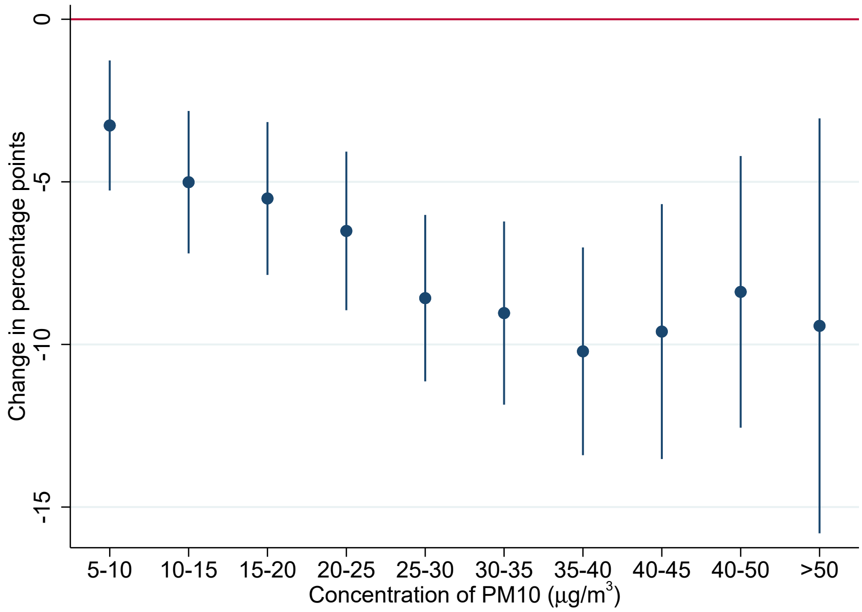


Figure 3: Dose-Response Relationship: Air Pollution and Vote Share of Incumbent Parties

Notes: This figure displays the coefficient and the relative standard errors at 95% of the OLS regression as in column (2) of Table 2, where PM10 has been divided into ten binary indicators corresponding to different levels concentration (5-10$\mu g/m^3$, 10-15$\mu g/m^3$, 15-20$\mu g/m^3$, 20-25$\mu g/m^3$, 25-30$\mu g/m^3$, 30-35$\mu g/m^3$, 35-40$\mu g/m^3$, 40-45$\mu g/m^3$, 45-50$\mu g/m^3$, >50$\mu g/m^3$). A PM10 concentration smaller than or equal to $5\mu g/m^3$ is used as the reference category. Standard errors clustered at the county level.

How strong are these effects? While the magnitude of our estimates does not imply landslide shifts in election results, it shows that pollution plays a role in affecting voting behavior. To understand the magnitude of the effect, consider first an increase in the concentration of PM10 by one within-standard deviation, which is equivalent to an increase in the concentration of PM10 in the same county by around $5\mu g/m^3$ relative to its normal level. Our estimates suggests that an increase in the level of PM10 by $5\mu g/m^3$ reduces the vote share of the incumbent government by one percentage point. Now compare this one-percent decrease in voting for the incumbent to the overall drop in votes for the incumbent in a federal election. For example, in 2005, when Angela Merkel came to power, the incumbent government's vote share had dropped by 4.8 percentage points (see Figure 2). An increase in pollution levels by one within-county standard deviation – i.e. an increase that frequently happens – leads to a drop in the incumbent vote share that was 20% of the overall decrease in 2005. By no means do we claim that air pollution brought Merkel into power, but this exercise shows that the effects of air pollution are socially significant.

5.2 Robustness Checks

Estimation with placebo election dates. To assess the plausibility of our identification strategy, we run regressions with placebo election dates. We re-estimate our main specification from Column (2) in Table 2 but construct the regressor based on the measurements on different days. For example, instead of using the concentration of PM10 on the election day, we use the level of PM10 on a day before or after the election. Ideally, we should not find significant effects of PM10 *after* the election, as pollution in the future cannot affect voting outcomes today. By contrast, significant effects before the election day are possible, as voters may make their voting decision several days in advance and/or cast their vote by mail.

The results in Figure 4 corroborate our identification strategy. Each displayed coefficient is the result of a separate regression of the incumbent share on the concentration of PM10 on a given day as well as controls and fixed effects. In the run-up to the election, we see results that are significantly different from zero and have the same sign as the estimated effect based on pollution on the election day. Reassuringly, we only find very small and mostly insignificant effects of air pollution on days immediately *after* the election. The pattern of the estimates before the election – which become larger the closer to the election date – is consistent with the literature on political campaigns, which shows that events closer to an election have a stronger effect than events further in the past (Gerber et al., 2011). Moreover, we find insignificant effects on the Sunday before ($T-7$) and the Sunday after the election ($T+7$), which rules out that the placebo results are driven by day-of-the-week effects.

These tests suggest that our results represent real effects rather than a noise pattern that emerges by chance. If the main result was the result of noise – a false positive – a pattern like the one in Figure 4 would be unlikely to emerge. Instead, we would expect to see similar estimates before and after the election, or estimates that significantly fluctuate. The placebo tests also suggest that our results are not contaminated by omitted variable bias. An omitted variable – for example, the closure of a local factory – would affect pollution and voting in the same way regardless of whether pollution is measured before or after the election. The same holds for diverging regional trends. If the results were driven by diverging trends in pollution and voting, we would expect to see similar estimates before and after the election. The fact that we see insignificant results immediately after the election suggests that the estimates are not confounded by omitted variables or time trends.

Balancing and permutation tests. In Appendices C.4 and C.5, we perform balancing and permutation tests that corroborate our identification strategy. One concern is that fluctuations in pollution are systematically related to fluctuations in economic variables. To address this concern, we regress three economic variables – population, GDP per capita, and the employment rate – on the level of PM10 on election day, conditioning on two-way fixed effects and weather controls. We do not find any significant relationship between the level of PM10 and the economic variables. We view this result as one piece of evidence in favour of our identification assumption.

Another concern is that our estimates are the result of fitting noise rather than extracting a signal. In Appendix C.5, we address this concern through permutation tests. Within each county, we randomly re-shuffle the level of pollution across election dates and otherwise run the same regressions as in Table 2. In none of 1000 permutations do we find a placebo estimate that is more extreme – that is, larger in absolute value – than our estimates based on the true level of pollution. Our estimate is far away from the distribution of placebo estimates. We view this finding as evidence that our results pick up signal rather than noise.

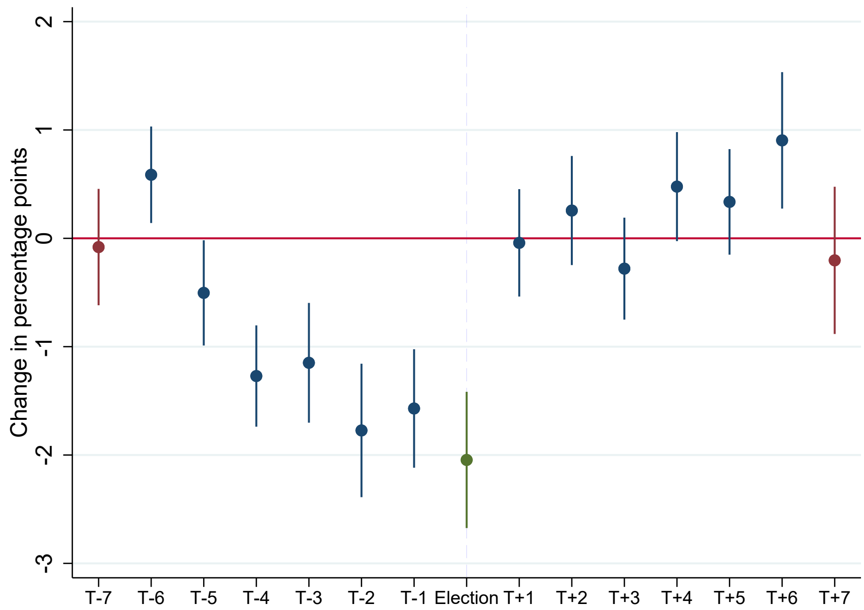


Figure 4: Effect of Pollution on Voting with Placebo Election Dates

Notes: This graph displays the point estimates and 95% confidence intervals for OLS regressions of the outcomes listed at the top on the air concentration of PM10 (in $10\mu g/m^3$) on a given day. The lead terms ($T-1, T-2, \ldots$) refer to days before the election, the lag terms ($T+1, T+2, \ldots$) to days after. For example, in $T-2$, the regressor is the air concentration of PM10 two days before the election. In all regressions, we condition on the election date, county and election type fixed effects and control for ozone, weather, demographic and economic variables measured on the same day as those used in the main analysis in Table 2. Standard errors clustered at the county level.

IV estimation exploiting exogenous variation in wind directions. In addition to the placebo tests, we also perform an instrumental variable estimation that leverages plausibly exogenous variation in wind directions on the day of the election. An instrument that is both valid and sufficiently strong can help us to overcome two potential challenges, namely omitted variable bias and measurement error. Omitted variable bias could be present when local shocks such as weather shocks or economic shocks simultaneously affect air pollution and voting. Although our set of controls comprises many potential confounders, we cannot be certain that it comprises all of them.

A second – and perhaps more important – challenge is measurement error in the regressor PM10. We match county-level voting results to local levels of pollution via the county centroid. The matching introduces two types of measurement error. One stems from the geographic interpolation of PM10, as the location of the county centroid and the measuring stations rarely coincide. Instead, we interpolate the measure of PM10 at the centroid as a weighted average of measures taken within a 30km radius. A second type of measurement error is present because pollution exposure is likely not uniform within a county. The pollution level where most voters live may be different from the pollution level at the centroid.

To overcome both challenges, we follow the work of Deryugina et al. (2019) and employ an instrumental variable strategy that leverages exogenous variation in wind directions. The idea behind this instrument is that the wind direction affects the level of air pollution in a given location due to its physical and economic geography. For example, a county to the west of an industrial center has higher air pollution levels on days with east wind than on days with west wind. At the same time, the wind direction on a particular day can be considered exogenous to local conditions as well as measurement error in pollution, which makes it a suitable candidate for a valid instrument.

The first-stage regression predicts the level of PM10 in a given county on a given day based on the wind direction in the county on the same day:

$$PM10_{it} = \sum_{s \in S} \sum_{b=0}^{2} \theta_b \times \mathbb{1}[i \in s] \times WINDDIR_{it}^{90b} + \boldsymbol{X'_{it}\lambda} + \kappa_i + \kappa_t + \eta_{it}. \tag{3}$$

Following Deryugina et al. (2019), we allow the first stage impact of county-day variation in wind directions to vary by state to reduce the computational burden of the IV estimation and increase statistical power. Hence, equation (3) comprises 36 instruments: for each of twelve states s, we have three indicators for wind directions b.[15] Each instrument is the interaction of a state indicator – one if county i lies within state s – and indicators for wind direction which equal one if the wind direction in county i on day t lies within one of the intervals [0,90) degrees, [90,180) degrees or [180, 270) degrees. Wind directions falling into the interval [270,360) degrees are the reference category. Data on daily variation in wind directions comes from the German Meteriological Service (*Deutscher Wetterdienst*).

The IV estimates are shown in Columns (1) of Table 3. The first stage is sufficiently strong, with a Kleibergen-Paap F-statistic of 11.53. The point estimate is considerably larger in absolute value compared to the main results in Table 2, it is more than three times the size of its OLS counterpart. We view the difference between the OLS and IV estimates primarily as evidence of bias from measurement error. The results are consistent with attenuation bias, similar to what Deryugina et al. (2019) find in their study on air pollution and mortality in the US.

Further robustness checks. We present some additional analyses and further robustness checks in Table 3. First, in Column (2) we find that our main results are robust to controlling for temperature in a non-linear way by including binary indicators for temperature bins. In Column (3), we show that the results are robust to controlling for nitrogen dioxide (NO2), an air pollutant mainly stemming from traffic emissions that Germany tracks closely. This is to rule out that our findings are mainly driven by traffic emissions. Second, in addition to our main outcome, the vote share going to the incumbent government parties, we apply the main specification to the alternative outcomes of the vote shares for the established opposition as well as other parties. We find that the established opposition parties benefit from increased levels of air pollution on election day, while there is a significant but small effect on the vote share other parties (see Columns (4)-(5) of Table 3).

[15] For this purpose, we merged the three city-states of Berlin, Hamburg and Bremen as well as the small state of Saarland with their larger neighboring states – Berlin with Brandenburg, Hamburg and Bremen with Lower Saxony, and Saarland with Rhineland-Palatinate – yielding twelve states in total.

Table 3: Air Pollution and Voting: Robustness Checks and Additional Results

Outcome:	Vote Share of Incumbent Parties (IV) (1)	Vote Share of Incumbent Parties (OLS) (2)	Vote Share of Incumbent Parties (OLS) (3)	Vote Share of Established Opposition Parties (OLS) (4)	Vote Share of Other Opposition Parties (OLS) (5)
PM10 ($10\mu g/m^3$)	-0.0575***	-0.0185***	-0.0187***	0.0291***	-0.0087***
	(0.011)	(0.003)	(0.003)	(0.004)	(0.002)
Mean dep. var.	0.48	0.48	0.48	0.42	0.10
R^2	0.021	0.601	0.605	0.705	0.902
N	2770	2770	2762	2770	2770
Cragg-Donald F	13.17				
Kleibergen-Paap F	11.53				
Kleibergen-Paap LM	74.45				
Controls					
County FE	✓	✓	✓	✓	✓
El. Date FE	✓	✓	✓	✓	✓
Weather	✓	✓	✓	✓	✓
Temperature	linear	dummies	linear	linear	linear
Ozone	✓	✓	✓	✓	✓
NO2			✓		
Demographics	✓	✓	✓	✓	✓
El. Type FE	✓	✓	✓	✓	✓
Turnout	✓	✓	✓	✓	✓

Notes: Column (1) reports the results of second-stage regressions where PM10 (in $10\mu g/m^3$) has been instrumented with wind directions following Deryugina et al. (2019). Columns (2)-(3) report the results of the same OLS regression presented in Table 2 additionally controlling for temperature dummies and NO2 respectively. Columns (4)-(5) report the results of OLS regressions of the vote share for established opposition and other parties on the air concentration of PM10 (in $10\mu g/m^3$) and the controls listed at the bottom. Standard errors clustered at the county level are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

6 Mechanisms and Additional Results

In the previous section, we have documented that ambient air pollution reduces the electoral support for the incumbent coalition parties in favor of the established opposition. In this section, we use data from surveys and opinion polls to generalize our findings and shed light on the underlying mechanisms. The main mechanisms highlighted in the literature are impaired cognitive functioning and mood effects, which may operate through greater anxiety and lower levels of happiness. With the data at hand, we can shed light on the importance of mood effects by looking at measures of affective well-being. In addition, we use data on perceptions of the economy as well as political interest to investigate whether the effect of pollution on voting represents a conscious or unconscious choice. For example, if higher pollution leads to a stronger interest in politics or changes perceptions about the economy, this may be seen as evidence for a conscious choice: pollution changes how people see the world, which also changes how they vote. The absence of such effects would suggest that the effect is more likely to operate through unconscious choices. Pollution may affect people's emotions, which in turn changes how they make decisions, although the observed change in decisions is not a conscious choice.

6.1 Data

Monthly opinion poll data. We use data from the *Politbarometer*, a monthly opinion poll that has been run and presented by a national TV station (*Zweites Deutsches Fernsehen*, ZDF) since the 1970s. The poll focuses on opinions and attitudes of the electorate in Germany. In addition to surveying opinions on current political topics and individual politicians, the questionnaire comprises a number of questions that have been surveyed over a long period of time, including the assessment of the current (federal) government and opposition. We use the *Politbarometer* microdata from Forschungsgruppe Wahlen (2020) over the period from 2003 to 2019, which are repeated cross-sections of 1,500–2,000 respondents per month. The data only indicate the week of the interview and the respondent's state of residence, and is thus, less precise than the election data in terms of location and time. We merge average levels of pollution by state and week to the opinion poll and use a binary indicator for state-by-week PM10 concentrations exceeding $20\mu g/m^3$ (roughly the median) as a proxy for elevated pollution exposure.

Panel survey data. We also use data from the Socio-Economic Panel (SOEP), a long-running representative panel survey since 1984, covering individuals living in private households in Germany (SOEP, 2019). The questionnaire has included questions on individuals' political attitudes since the mid-1980s as well as their affective well-being since 2007. To be consistent with the analysis of the *Politbarometer* data, we merge average levels of pollution by county of residence over the seven days preceding the interview date and use a binary indicator for county-level PM10 concentrations exceeding $20\mu g/m^3$ as a proxy for elevated pollution exposure.

6.2 Results from Opinion Polls

Figure 5 shows the results for voting intention for the parties forming the federal coalition government at the time of the interview as well as voting intentions for the opposition and other parties. Respondents are asked about their voting intention: if the federal election were to take place the following Sunday (*Sonntagsfrage*), would they vote, and – if so – for which party. We group parties into incumbent, opposition and other parties using the same classification as in Section 3.1. Each coefficient is the result of a separate regression of the outcomes listed on the left on an indicator for elevated levels of PM10 and controls for individual characteristics of respondents (gender, age, education, urban area, marital status, employment status, occupational status), weather controls (temperature, wind speed, precipitation) as well as year-by-week and state-by-month fixed effects.

The results in Figure 5 confirm our main findings in Section 5, namely that exposure to higher levels of air pollution reduces support for the current government and increases support for the opposition. A higher concentration of PM10 is associated with lower voting intentions for the incumbent parties and higher voting intentions for the opposition. People exposed to elevated levels of PM10 report a 1.2 percentage point higher likelihood of voting for the established opposition and an equivalently lower likelihood of voting for the current government. This result amounts to 2.3% of the mean vote share of the government (52%) and 2.9% of the mean vote share of the opposition (42%). We do not observe any changes for other parties.

Figure 5 shows that the results for voting intentions are concurrent with changes in voters' approval of the government. Respondents can state their approval on an eleven-point scale from -5 (very dissatisfied) to 5 (very satisfied). We construct binary indicators for a positive approval (approval > 0), a negative approval (approval < 0), and a neutral approval (approval $= 0$). Individuals exposed to higher levels of PM10 are 1.2 percentage point more likely to express negative approval for the government and 1.2 percentage point less likely to express positive approval, relative to a mean of 36% (negative approval rating) and 51% (positive approval rating) respectively. By contrast, we find no difference in respondents' approval of the opposition. At the same time, we observe a large negative and statistically significant effect on the approval of elites in general.[16] The effect is sizable with a reduction of elite approval by about 3.1 percentage points relative to a mean of 27.7%. These results suggest that the observed effects on voting – fewer votes for the current government, more for the opposition – are driven by voters' dissatisfaction with the government and the elites rather than a change in people's views about the opposition.

In Figure 6, we investigate the role of people's perceptions of the economy and their interest in politics in general. The survey asks about respondents' assessment of the state of the German economy and their own economic situation on a five-point scale from 1 (very good) to 5 (very bad). The outcomes *State of economy bad*/*Own economic situation bad* are binary indicators for responses *bad/very bad*, while *State of economy good*/*Own economic situation good* indicate responses *good/very good*. We find no evidence that high levels of air pollution affect people's perception of the state of the economy or their own economic situation. There is also no evidence that it affects people's interest in politics. Respondents are further asked about their extent of interest in politics on a five-point scale

[16] The survey asks whether respondents believe that currently in Germany, by and large, the right people are in leading positions or not. The outcome *Approval of elites* is a binary indicator for responding "yes".

from 1 (very strong) to 5 (none). *High political interest* is a binary indicator for responses *strong/very strong*, whereas *Low political interest* indicates responses *none/little*. The stated interest in politics is no different between people exposed to a high versus low concentration of PM10.

Overall, these findings suggest that pollution affects people's voting intentions and behavior through their dissatisfaction with the current government rather than their dissatisfaction with the opposition or their own economic situation. Moreover, the fact that we do not see an effect on political interest supports the notion that the overall effect of air pollution on voting operates through subconscious channels.

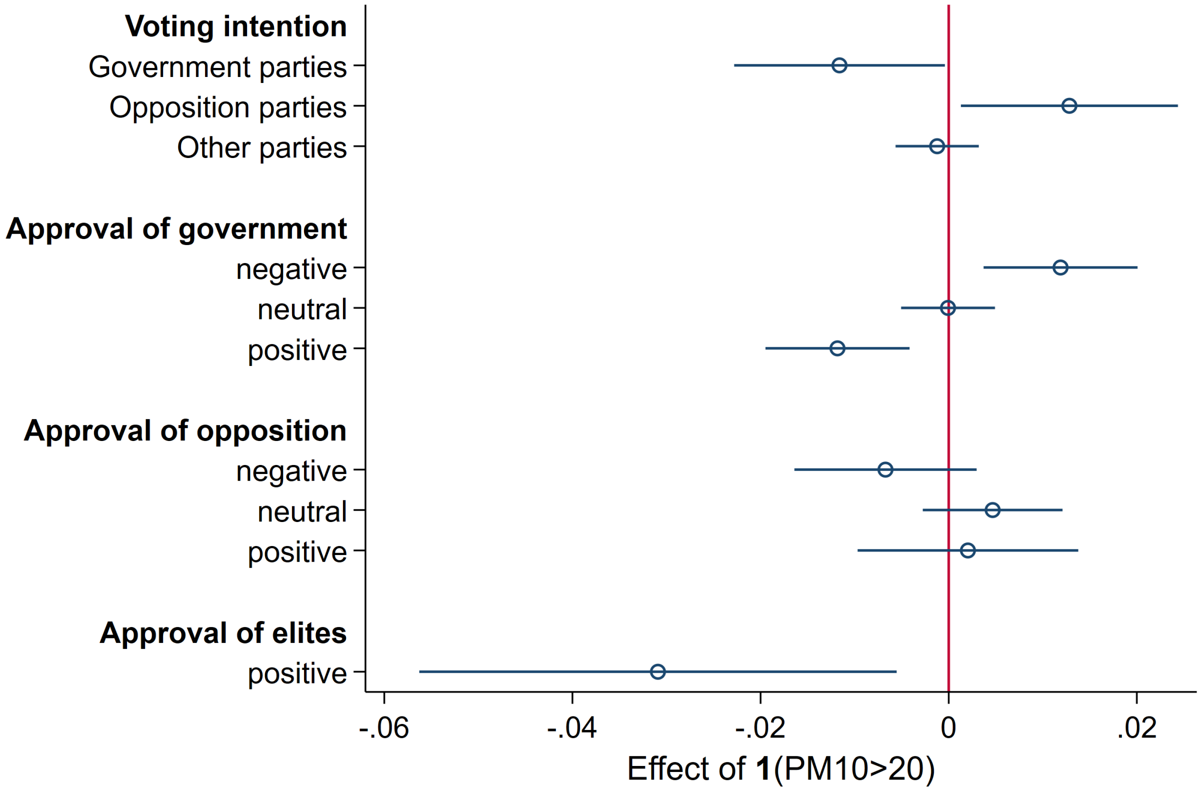


Figure 5: Effect of Air Pollution on Voting Intentions and Government Approval

Notes: This graph displays the point estimates and 95% confidence intervals for OLS regressions of survey questions from a weekly opinion poll (*Politbarometer*) on a binary indicator for the PM10 concentration being above $20\mu g/m^3$ in a respondent's state in the week of the interview. The construction of the binary indicators is described in the text of Section 6.2. The regressions control for individual characteristics of respondents (gender, age, education, urban area, marital status, employment status, occupational status), weather controls (temperature, wind speed, precipitation) as well as year-by-week and state-by-month fixed effects. Standard errors clustered at the state-by-year level.

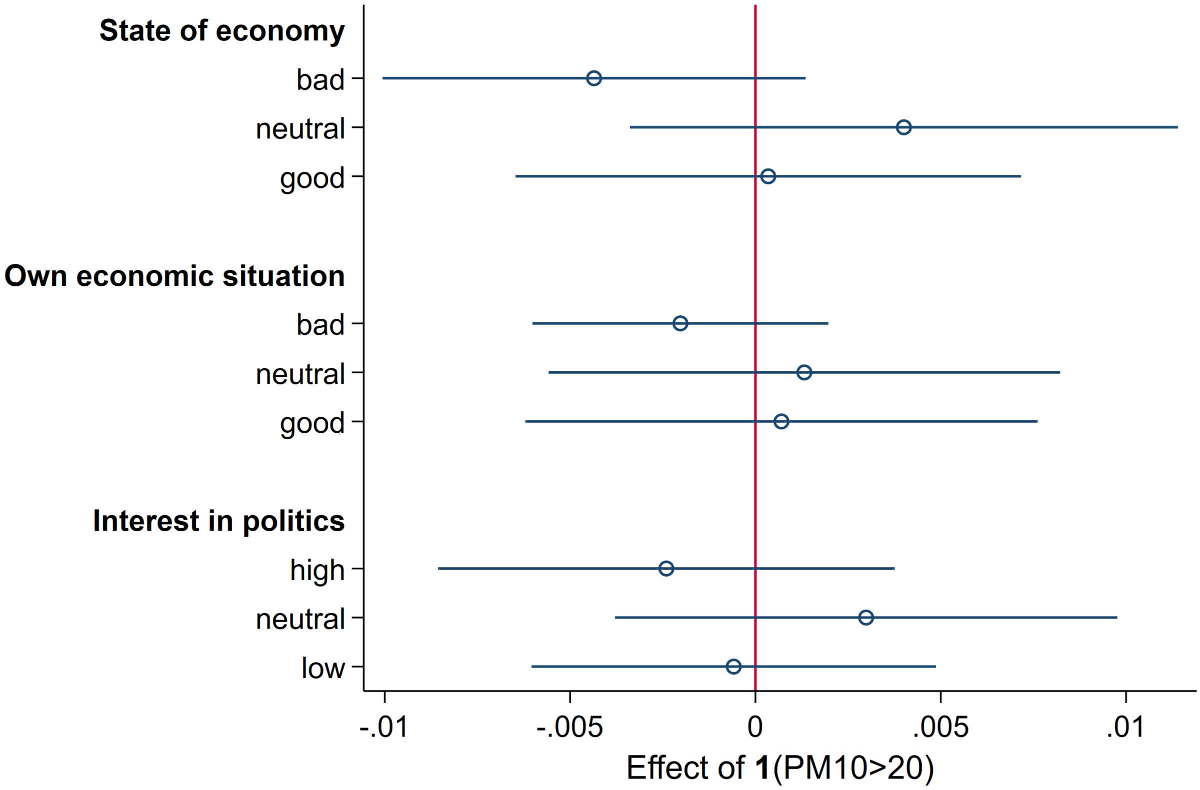


Figure 6: Effect of Air Pollution on Interest in Politics and Perceptions of the Economy

Notes: This graph displays the point estimates and 95% confidence intervals for OLS regressions of survey questions from a weekly opinion poll (*Politbarometer*) on a binary indicator for the PM10 concentration being above $20\mu g/m^3$ in a respondent's state in the week of the interview. The construction of the binary indicators is described in the text of Section 6.2. The regressions control for individual characteristics of respondents (gender, age, education, urban area, marital status, employment status, occupational status), weather controls (temperature, wind speed, precipitation) as well as year-by-week and state-by-month fixed effects. Standard errors clustered at the state-by-year level.

6.3 Results from the Socio-Economic Panel

We complement the results from the opinion poll with data from the SOEP. The main advantage of the SOEP is its panel structure. Respondents are repeatedly asked the same questions, including questions about affective well-being and political preferences. This allows us to run regressions with individual fixed effects and compare the answers of the *same* person who was exposed to different levels of air pollution on different interview dates.

We use the SOEP to generalize our main findings, as well as to illuminate the role of emotions and risk preferences in explaining the overall effect. Our main outcomes are party identification, affective well-being and risk attitudes. To measure support for the incumbent government and the opposition, we use survey questions on party identification. Survey respondents are asked whether they lean towards a specific party in the long run and – if so – to which party they lean. Based on the responses, we construct binary indicators for *Party identification government/opposition* depending on which coalition was in power at the time of the interview date. To measure affective well-being, we use survey questions asking respondents how often they felt angry, worried, happy, or sad in the last four weeks. Based on the responses – ranging from 1 (*very rarely*) to 5 (*very often*) – we construct binary indicators that equal one if a respondent answers *often* or *very often*. As these four dimensions of affective well-being are strongly correlated, we further combine them into one dimension which we call "Negative emotions" using principal component analysis (PCA). Specifically, we run a PCA on the four binary indicators of affective well-being and use the first principal component as a summary outcome of affective well-being.

As discussed in Section 2, risk attitudes may also play an important role in voters' decision-making. In light of recent evidence that variation in people's emotions over time predict changes in risk attitudes (Meier, 2021), we additionally use information on self-reported risk attitudes from the SOEP. Respondents are asked whether they are generally willing to take risks on a scale from 0 (not at all willing to take risks) to 10 (very willing to take risks). This question about risk taking in general has been shown to be very predictive of risky behavior (Dohmen et al., 2011). Based on this survey question, we create two binary variables for risk attitudes. The indicator "Risk averse" takes on a value of one if individuals report values between 0 and 4 and zero otherwise, while the binary indicator "Risk loving" is one for responses between 6 and 10 and zero otherwise.

Figure 7 displays the results from individual fixed effects regressions for the 2000-2019 period. The coefficients are based on separate regressions of the binary indicators listed on the left on a binary indicator that equals one if the the average concentration of PM10 in a respondent's county of residence was above $20\mu g/m^3$ on the seven days preceding the interview. The regressions control for individual characteristics (age, marital status, number of children, education, net household income), weather controls (temperature, wind speed, precipitation) as well as year, quarter and state fixed effects. The results confirm the pattern found in voting data in Section 5. On days with higher air pollution, the same person shows less support for the government and more support for the opposition compared to days with low levels of air pollution.

The data on affective well-being allow us to test whether emotions are an important mechanism explaining the effect of air pollution on voting. As laid out in Section 2, anger, anxiety and (un-) happiness may affect electoral decision-making by changing people's conscious or unconscious perception of the status quo. Negative emotions, such as anger and unhappiness, have been shown to reduce the bias for the status quo, lead to greater willingness to change and reduce reliance on heuristics in decision-making. The results in Figure 7 are consistent with this mechanism. We find that higher levels of PM10 increase the likelihood of the negative emotions such as anger, worry and sadness and at the same time reduce happiness. Effect sizes imply changes around 0.3 to 0.4 percentage points relative to means of 22% for being angry often or very often, 7% for being worried, 59% for feeling happy and 12% for feeling sad. Although these effect sizes are small relative to their respective means, they indicate that higher air pollution can change people's emotions. To gain statistical power, we construct an index of affective well-being by taking the first principal component of the four dimensions of well-being, namely anger, worry, happiness, and sadness. The results show that air pollution has a significant effect on emotions: the positive coefficient means that a high level of air pollution is associated with more negative emotions. Finally, we do not find any evidence that exposure to poor air quality shifts individuals' self-reported risk attitudes. Both binary indicators for being rather risk averse and risk loving respectively are small and statistically insignificant. This means that the channel via which negative emotions affect voting outcomes is unlikely to be risk attitudes. Overall, these findings are consistent with a psychological mechanism linking exposure to poor air quality with voting decisions. People who are exposed to elevated levels of particulate air pollution feel angry and unhappy more often, which may translate to a reduction in the status quo bias and therefore a reduction in the political support for the incumbent government in favor of the opposition.

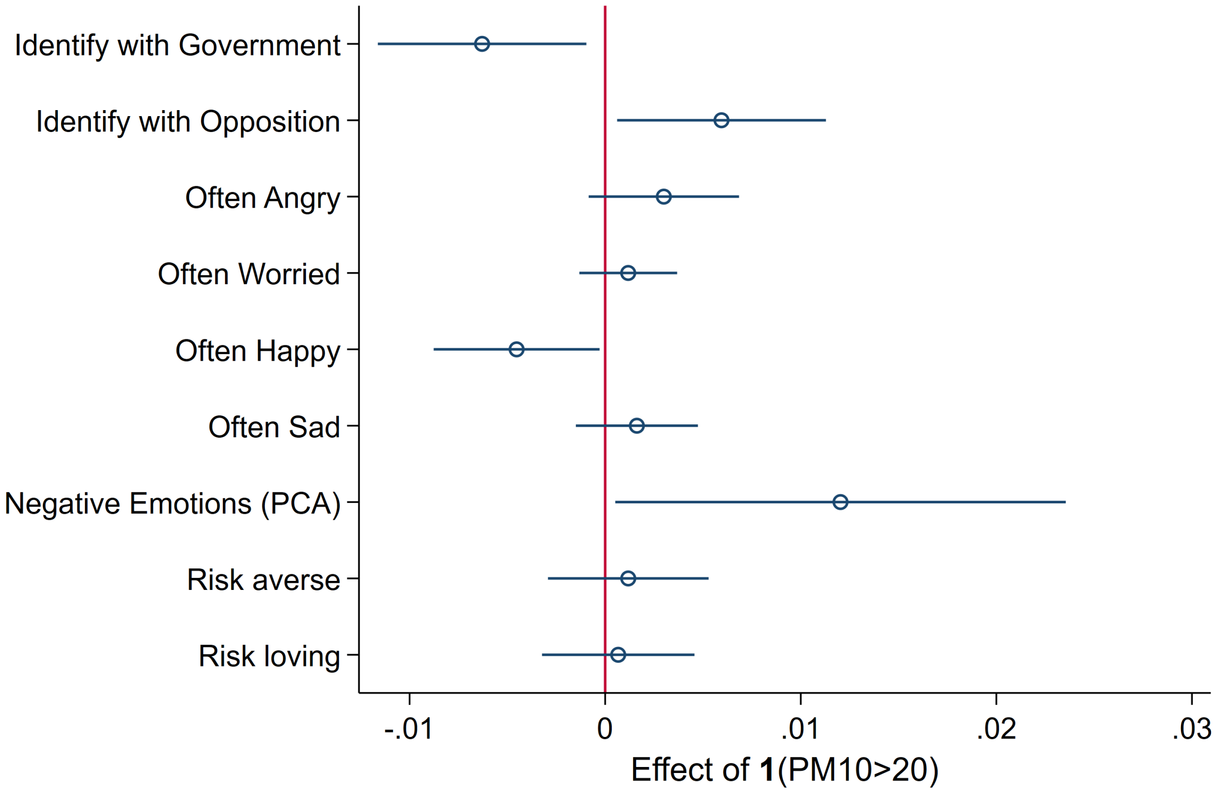


Figure 7: Effect of Air Pollution on Political Preferences and Affective Well-being

Notes: This graph displays the point estimates and 95% confidence intervals for OLS regressions of binary indicators of party identification, affective well-being, the first principal component of the four indicators of affective well-being as well as binary indicators for risk attitudes on a binary indicator for average PM10 concentrations being above $20\mu g/m^3$ over the seven days preceding the interview date. The results are based on survey responses from the SOEP over the period from 2000 to 2019. The regressions control for individual fixed effects as well as further characteristics of respondents (age, marital status, number of children, education, net household income), weather controls (temperature, wind speed, precipitation) as well as year, quarter and state fixed effects. The variable *Negative Emotions (PCA)* is the first principal component of four dimensions of affective well-being, namely anger, worry, happiness, and sadness. A larger value of this index indicates more negative emotions.

7 Conclusion

In this paper, we have used parliamentary elections as a real-world laboratory to show that ambient air pollution affects voting decisions. Using county-level voting outcomes from federal and state elections in Germany over a nineteen-year period as well as data on ambient concentrations of particulate matter and weather conditions on the election day, we find that higher concentrations of particulate matter reduce the electoral support of the incumbent government coalition's parties and increases the vote share of the opposition. We find similar results based on a weekly opinion poll and a large panel survey.

Our empirical setup as well as additional evidence from a survey suggest that our findings represent a behavioral bias rather than a voter's conscious decision. Our identification strategy exploits deviations in air pollution on election day from the usual level of pollution in a given county. Unlike changes in rainfall or temperature, such fluctuations in air pollution are not noticeable for voters. It is thus unlikely that our results reflect a deliberate choice, such as voters punishing the government for poor air quality. Our results are more likely to represent a subconscious change in behavior. Pollution can affect emotions and cognitive functioning, which in turn can lead to unintended changes in voting behavior. Based on survey data, we find that a plausible psychological mechanism is the impact of air pollution on people's emotions such as anger and unhappiness, which may reduce the support for the political status quo.

Our findings show that air pollution can have important effects on society. Parliamentary elections determine government formation as well as policy setting, which has a substantial impact on individual voters and society at large. Our results that air pollution affects the decision-making of the population at large in a high-stakes real-world setting, where people are faced with a decision concerning whether to retain or abandon the political status quo.

This finding opens up several avenues for future research. First, it would be welcome to enhance our understanding of the mechanisms through which air pollution affects decision making. Although we are able to shed some light on potential mechanisms, our survey data do not allow us to illuminate the neurological and psychological responses to air pollution that affect decision making. In particular, future studies should focus on the role of the decision-making environment and the individual returns associated with these decisions. Existing research suggests that people appear to be less willing to take risks when exposed to elevated levels of air pollution in specific settings (investment decisions), while they show more impulsive and aggressive behavior in other situations (violent criminal behavior). It would be important to understand why air pollution triggers different responses in different contexts. A second avenue for future research is to understand the effect of long-run changes in air pollution on voting. Our research identifies the effect of short-run fluctuations in air pollution, which points to subconscious changes in voting behavior. However, it would be equally important to know whether long-run changes in air pollution – namely changes that people actually notice – lead to deliberate changes in people's voting behavior.

References

Achen, C. H. and Bartels, L. (2017). *Democracy for Realists*. Princeton University Press.

Aguilar-Gomez, S., Dwyer, H., Graff Zivin, J. S. and Neidell, M. J. (2022). This is Air: The "Non-Health" Effects of Air Pollution. Working Paper 29848, National Bureau of Economic Research.

Alesina, A. and Passarelli, F. (2019). Loss Aversion in Politics. *American Journal of Political Science* 63: 936–947, doi:10.1111/ajps.12440.

Angie, A. D., Connelly, S., Waples, E. P. and Kligyte, V. (2011). The influence of discrete emotions on judgement and decision-making: A meta-analytic review. *Cognition and Emotion* 25: 1393–1422, doi:10.1080/02699931.2010.550751, pMID: 21500048.

Aragón, F. M., Miranda, J. J. and Oliva, P. (2017). Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management* 86: 295–309, doi:https://doi.org/10.1016/j.jeem.2017.02.008, special issue on environmental economics in developing countries.

Archsmith, J., Heyes, A. and Saberian, S. (2018). Air Quality and Error Quantity: Pollution and Performance in a High-Skilled, Quality-Focused Occupation. *Journal of the Association of Environmental and Resource Economists* 5: 827–863, doi:10.1086/698728.

Arnold, F. and Freier, R. (2016). Only conservatives are voting in the rain: Evidence from German local and state elections. *Electoral Studies* 41: 216–221, doi:https://doi.org/10.1016/j.electstud.2015.11.005.

Attanasi, G., Corazzini, L. and Passarelli, F. (2017). Voting as a lottery. *Journal of Public Economics* 146: 129–137, doi:10.1016/j.jpubeco.2016.11.

Balakrishnan, U. and Tsaneva, M. (2021). Air pollution and academic performance: Evidence from India. *World Development* 146: 105553, doi:https://doi.org/10.1016/j.worlddev.2021.105553.

Barwick, P. J., Li, S., Lin, L. and Zou, E. (2019). From Fog to Smog: the Value of Pollution Information. Working Paper 26541, National Bureau of Economic Research, doi:10.3386/w26541.

Bedi, A. S., Nakaguma, M. Y., Restrepo, B. J. and Rieger, M. (2021). Particle Pollution and Cognition: Evidence from Sensitive Cognitive Tests in Brazil. *Journal of the Association of Environmental and Resource Economists* 8: 443–474, doi:10.1086/711592.

Bell, M. L., Zanobetti, A. and Dominici, F. (2013). Evidence on Vulnerability and Susceptibility to Health Risks Associated With Short-Term Exposure to Particulate Matter: A Systematic Review and Meta-Analysis. *American Journal of Epidemiology* 178: 865–876, doi:10.1093/aje/kwt090.

Bondy, M., Roth, S. and Sager, L. (2020). Crime Is in the Air: The Contemporaneous Relationship between Air Pollution and Crime. *Journal of the Association of Environmental and Resource Economists* 7: 555–585, doi:10.1086/707127.

Bruyneel, S. D., Dewitte, S., Franses, P. H. and Dekimpe, M. G. (2009). I felt low and my purse feels light: depleting mood regulation attempts affect risk decision making. *Journal of Behavioral Decision Making* 22: 153–170, doi:10.1002/bdm.619.

Bundeswahlleiter (2017). Anteil der Briefwählerinnen und Briefwähler bei den Bundestagswahlen 1994 bis 2017.

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J. D., O'Dell, K., Ford, B., Fischer, E. V. and Pierce, J. R. (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management* 98: 102267, doi:https://doi.org/10.1016/j.jeem.2019.102267.

Chang, T., Graff Zivin, J., Gross, T. and Neidell, M. (2016). Particulate Pollution and the Productivity of Pear Packers. *American Economic Journal: Economic Policy* 8: 141–169.

Chang, T., Graff Zivin, J., Gross, T. and Neidell, M. (2019). The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China. *American Economic Journal: Applied Economics* 11: 151–172.

Chang, T. Y., Huang, W. and Wang, Y. (2018). Something in the Air: Pollution and the Demand for Health Insurance. *The Review of Economic Studies* 85: 1609–1634, doi:10.1093/restud/rdy016.

Chen, S., Guo, C. and Huang, X. (2018). Air Pollution, Student Health, and School Absences: Evidence from China. *Journal of Environmental Economics and Management* 92: 465–497, doi:https://doi.org/10.1016/j.jeem.2018.10.002.

Chen, X. (2019). Smog, Cognition and Real-World Decision Making. *International Journal of Health Policy and Management* 8: 76–80.

Clifford, A., Lang, L., Chen, R., Anstey, K. J. and Seaton, A. (2016). Exposure to air pollution and cognitive functioning across the life course–a systematic literature review. *Environmental Research* 147: 383–398, doi:10.1016/j.envres.2016.01.018.

Currie, J., Hanushek, E. A., Kahn, E. M., Neidell, M. and Rivkin, S. G. (2009). Does Pollution Increase School Absences? *The Review of Economics and Statistics* 91: 682–694.

Danziger, S., Levav, J. and Avnaim-Pesso, L. (2011). Extraneous factors in judicial decisions. *Proceedings of the National Academy of Sciences* 108: 6889–6892, doi:10.1073/pnas.1018033108.

DellaVigna, S. (2009). Psychology and Economics: Evidence from the Field. *Journal of Economic Literature* 47: 315–72, doi:10.1257/jel.47.2.315.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D. and Reif, J. (2019). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *American Economic Review* 109: 4178–4219, doi:10.1257/aer.20180279.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of theEuropean Economic Association* 9: 522–550.

Dong, R., Fisman, R., Wang, Y. and Xu, N. (2021). Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics* 139: 971–984, doi:https://doi.org/10.1016/j.jfineco.2019.12.004.

Ebenstein, A., Lavy, V. and Roth, S. (2016). The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution. *American Economic Journal: Applied Economics* 8: 36–65, doi:10.1257/app.20150213.

Eckles, D. and Schaffner, B. (2011). Risk Tolerance and Support for Potential Military Interventions. *The Public Opinion Quarterly* 75, doi:10.2307/41288400.

Eckles, D. L., Kam, C. D., Maestas, C. D. and Schaffner, B. F. (2014). Risk Attitudes and the Incumbency Advantage. *Political Behavior* 36: 731–749, doi:10.1007/s11109-013-9258-9.

Edmans, A., García, D. and Norli, Ø. (2007). Sports Sentiment and Stock Returns. *The Journal of Finance* 62: 1967–1998, doi:https://doi.org/10.1111/j.1540-6261.2007.01262.x.

Ehrlich, S. and Maestas, C. (2010). Risk Orientation, Risk Exposure, and Policy Opinions: The Case of Free Trade. *Political Psychology* 31: 657–684, doi:10.1111/j.1467-9221.2010.00774.x.

Eisinga, R., Te Grotenhuis, M. and Pelzer, B. (2012a). Weather conditions and political party vote share in Dutch national parliament elections, 1971–2010. *International Journal of Biometeorology* 56: 1161–1165, doi:10.1007/s00484-011-0504-8.

Eisinga, R., Te Grotenhuis, M. and Pelzer, B. (2012b). Weather conditions and voter turnout in Dutch national parliament elections, 1971–2010. *International Journal of Biometeorology* 56: 783–786, doi:10.1007/s00484-011-0477-7.

Eren, O. and Mocan, N. (2018). Emotional Judges and Unlucky Juveniles. *American Economic Journal: Applied Economics* 10: 171–205, doi:10.1257/app.20160390.

Eriksson, L. M. (2016). Winds of change: voter blame and Storm Gudrun in the 2006 Swedish parliamentay elections. *Elecoral Studies* 41: 129–142, doi:https://doi.org/10.1016/j.electstud.2015.12.003.

European Environment Agency (2016). Air quality standards under the Air Quality Directive, and WHO air quality guidelines.

Forschungsgruppe Wahlen (2020). Politbarometer 1977–2019 (Partielle Kumulation). GESIS Datenarchiv, Köln. ZA2391 Datenfile Version 12.0.0, https://doi.org/10.4232/1.13631, doi:10.4232/1.13631.

Fowler, A. and Hall, A. B. (2018). Do Shark Attacks Influence Presidential Elections? Reassessing a Prominent Finding on Voter Competence. *The Journal of Politics* 80: 1423–1437, doi:10.1086/699244.

Fowler, A. and Montagnes, B. P. (2015). College football, elections, and false-positive results in observational research. *Proceedings of the National Academy of Sciences* 112: 13800–13804, doi: 10.1073/pnas.1502615112.

Gerber, A. S., Gimpel, J. G., Green, D. P. and Shaw, D. R. (2011). How Large and Long-lasting Are the Persuasive Effects of Televised Campaign Ads? Results from a Randomized Field Experiment. *American Political Science Review* 105: 135–150, doi:10.1017/S000305541000047X.

Gomez, B. T., Hansford, T. G. and Krause, G. A. (2007). The Republicans Should Pray for Rain: Weather, Turnout, and Voting in U.S. Presidential Elections. *Journal of Politics* 69: 649–663, doi: https://doi.org/10.1111/j.1468-2508.2007.00565.x.

Grable, J. E. and Roszkowski, M. J. (2008). The influence of mood on the willingness to take financial risks. *Journal of Risk Research* 11: 905–923.

Graff Zivin, J., Liu, T., Song, Y., Tang, Q. and Zhang, P. (2020). The unintended impacts of agricultural fires: Human capital in China. *Journal of Development Economics* 147: 102560, doi:https://doi.org/10.1016/j.jdeveco.2020.102560.

Graff Zivin, J. and Neidell, M. (2012). The Impact of Pollution on Worker Productivity. *American Economic Review* 102: 3652–73, doi:10.1257/aer.102.7.3652.

Graff Zivin, J. and Neidell, M. (2013). Environment, Health, and Human Capital. *Journal of Economic Literature* 51: 689–730, doi:10.1257/jel.51.3.689.

Hanna, R. and Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics* 122: 68–79, doi:https://doi.org/10.1016/j.jpubeco.2014.10.004.

Hansford, T. G. and Gomez, B. T. (2010). Estimating the electoral effects of voter turnout. *The American Political Science Review* 104: 268–288.

He, J., Liu, H. and Salvo, A. (2019). Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China. *American Economic Journal: Applied Economics* 11: 173–201, doi:10.1257/app.20170286.

Healy, A. and Malhotra, N. (2010). Random Events, Economic Losses, and Retrospective Voting: Implications for Democratic Competence. *Quarterly Journal of Political Science* 5: 193–208, doi: 10.1561/100.00009057.

Healy, A. J., Malhotra, N. and Mo, C. H. (2010). Irrelevant events affect voters' evaluations of government performance. *Proceedings of the National Academy of Sciences* 107: 12804–12809, doi: 10.1073/pnas.1007420107.

Heissel, J., Persico, C. and Simon, D. (2021). The Impact of Accumulated and Acute Exposure to Traffic Pollution on Child Academic Outcomes. *Journal of Human Resources* 56: 406–445.

Herrnstadt, E., Heyes, A., Muehlegger, E. and Saberian, S. (2021). Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago. *American Economic Journal: Applied Economics* 13: 70–100.

Heyes, A., Neidell, M. and Saberian, S. (2016). The Effect of Air Pollution on Investor Behavior: Evidence from the S&P 500. Working Paper 22753, National Bureau of Economic Research, doi: 10.3386/w22753.

Heyes, A., Rivers, N. and Schaufele, B. (2019). Pollution and Politician Productivity: The Effect of PM on MPs. *Land Economics* 95: 157–173.

Heyes, A. and Saberian, S. (2019). Temperature and decisions: Evidence from 207,000 court cases. *American Economic Journal: Applied Economics* 11: 238–65, doi:10.1257/app.20170223.

Heyes, A. and Zhu, M. (2019). Air pollution as a cause of sleeplessness: Social media evidence from a panel of Chinese cities. *Journal of Environmental Economics and Management* 98: 102247, doi:https://doi.org/10.1016/j.jeem.2019.07.002.

Hirshleifer, D. and Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance* 58: 1009–1032.

Hockey, G. R. J., John Maule, A., Clough, P. J. and Bdzola, L. (2000). Effects of negative mood states on risk in everyday decision making. *Cognition & Emotion* 14: 823–855.

Huang, J., Xu, N. and Yu, H. (2020). Pollution and Performance: Do Investors Make Worse Trades on Hazy Days? *Management Science* 66: 4455–4476, doi:10.2139/ssrn.2846165.

Jans, J., Johansson, P. and Nilsson, J. P. (2018). Economic status, air quality, and child health: Evidence from inversion episodes. *Journal of Health Economics* 61: 220–232, doi:https://doi.org/10.1016/j.jhealeco.2018.08.002.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica* 47: 263–291.

Kam, C. and Simas, E. (2012). Risk attitudes, candidate characteristics, and vote choice. *The Public Opinion Quarterly* 76: 747–760, doi:10.2307/41684598.

Kampa, M. and Castanas, E. (2008). Human health effects of air pollution. *Environmental Pollution* 151: 362 – 367, doi:https://doi.org/10.1016/j.envpol.2007.06.012.

Kamstra, M. J., Kramer, L. A. and Levi, M. D. (2003). Winter blues: A sad stock market cycle. *American Economic Review* 93: 324–343, doi:10.1257/000282803321455322.

Kliger, D. and Levy, O. (2003). Mood-induced variation in risk preferences. *Journal of Economic Behavior & Organization* 52: 573 – 584, doi:https://doi.org/10.1016/S0167-2681(03)00069-6.

Klingen, J. and van Ommeren, J. N. (2022). Risk-Taking and Air Pollution: Evidence From Chess. *Environmental and Resource Economics* 81: 73–93, doi:http://dx.doi.org/10.1007/s10640-021-00618-1.

Koecher, R. (2021). Gespannt und ratlos. *Frankfurter Allgemeine Zeitung*, 15 September 2021.

Künn, S., Palacios, J. and Pestel, N. (2021). Indoor air quality and strategic decision making. Working Paper (earlier version available as IZA Discussion Paper No. 12632).

Lepori, G. M. (2015). Positive mood and investment decisions: Evidence from comedy movie attendance in the U.S. *Research in International Business and Finance* 34: 142 – 163, doi:https://doi.org/10.1016/j.ribaf.2015.02.001.

Lerner, J. S. and Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology* 81: 146–159, doi:10.1037/0022-3514.81.1.146.

Lerner, J. S., Li, Y., Valdesolo, P. and Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology* 66: 799–823, doi:10.1146/annurev-psych-010213-115043, pMID: 25251484.

Lerner, J. S., Li, Y. and Weber, E. U. (2013). The financial costs of sadness. *Psychological Science* 24: 72–79, doi:10.1177/0956797612450302, pMID: 23150274.

Lerner, J. S., Small, D. A. and Loewenstein, G. (2004). Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychological Science* 15: 337–341, doi:10.1111/j.0956-7976.2004.00679.x, pMID: 15102144.

Levinson, A. (2012). Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics* 96: 869–880, doi:https://doi.org/10.1016/j.jpubeco.2012.06.007.

Levy, T. and Yagil, J. (2011). Air pollution and stock returns in the US. *Journal of Economic Psychology* 32: 374–383.

Li, Z., Folmer, H. and Xue, J. (2014). To what extent does air pollution affect happiness? the case of the jinchuan mining area, china. *Ecological Economics* 99: 88–99, doi:https://doi.org/10.1016/j.ecolecon.2013.12.014.

Liberini, F., Redoano, M. and Proto, E. (2017). Happy voters. *Journal of Public Economics* 146: 41–57.

Lichter, A., Pestel, N. and Sommer, E. (2017). Productivity effects of air pollution: Evidence from professional soccer. *Labour Economics* 48: 54–66.

Lim, Y.-H., Kim, H., Kim, J. H., Bae, S., Park, H. Y. and Hong, Y.-C. (2012). Air pollution and symptoms of depression in elderly adults. *Environmental Health Perspectives* 120: 1023–1028, doi:10.1289/ehp.1104100.

Liñeira, R. and Henderson, A. (2019). Risk attitudes and independence vote choice. *Political Behavior* doi:10.1007/s11109-019-09560-x.

Lodovici, M. and Bigagli, E. (2011). Oxidative stress and air pollution exposure. *Journal of toxicology* 2011: 487074–487074, doi:10.1155/2011/487074.

Loewenstein, G., O'Donoghue, T. and Rabin, M. (2003). Projection bias in predicting future utility. *The Quarterly Journal of Economics* 118: 1209–1248.

Lu, J. G. (2020). Air pollution: A systematic review of its psychological, economic, and social effects. *Current Opinion in Psychology* 32: 52–65.

Luechinger, S. (2009). Valuing Air Quality Using the Life Satisfaction Approach. *The Economic Journal* 119: 482–515, doi:https://doi.org/10.1111/j.1468-0297.2008.02241.x.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A. and Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: A review. *Frontiers in Public Health* 8: 14, doi:10.3389/fpubh.2020.00014.

Marcus, G., Neuman, W. R. and MacKuen, M. (2000). *Affective Intelligence and Political Judgment*. Chicago: The University of Chicago Press.

Marcus, G., Neuman, W. R. and MacKuen, M. (eds) (2007). *The Affect Effect: Dynamics of Emotion in Political Thinking and Behavior*. Chicago: The University of Chicago Press.

Meier, A. N. (2021). Emotions and Risk Attitudes. *American Economic Journal: Applied Economics, forthcoming* .

Meier, A. N., Schmid, L. and Stutzer, A. (2019). Rain, emotions and voting for the status quo. *European Economic Review* 119: 434–451, doi:https://doi.org/10.1016/j.euroecorev.2019.07.014.

Meyer, S. and Pagel, M. (2017). Fresh Air Eases Work–The Effect of Air Quality on Individual Investor Activity. Working Paper 24048, National Bureau of Economic Research, doi:10.3386/w24048.

Morgenstern, S. and Zechmeister, E. (2003). Better the Devil You Know than the Saint You Don't? Risk Propensity and Vote Choice in Mexico. *Journal of Politics* 63: 93 – 119, doi:10.1111/0022-3816.00060.

Morisi, D. (2018). Choosing the Risky Option: Information and Risk Propensity in Referendum Campaigns. *Public Opinion Quarterly* 82: 447–469, doi:10.1093/poq/nfy033.

Nowakowski, A. (2021). Do unhappy citizens vote for populism? *European Journal of Political Economy* 68: 101985, doi:https://doi.org/10.1016/j.ejpoleco.2020.101985.

Otto, A. R. and Eichstaedt, J. C. (2018). Real-world unexpected outcomes predict city-level mood states and risk-taking behavior. *PloS one* 13: e0206923.

Powdthavee, N. and Oswald, A. J. (2020). Is there a link between air pollution and impaired memory? Evidence on 34,000 English citizens. *Ecological Economics* 169: 106485, doi:https://doi.org/10.1016/j.ecolecon.2019.106485.

Qin, Y., Wu, J. and Yan, J. (2019). Negotiating housing deal on a polluted day: Consequences and possible explanations. *Journal of Environmental Economics and Management* 94: 161–187, doi:10.1016/j.jeem.2019.02.00.

Roth, S. J. (2021). The Contemporaneous Effect of Indoor Air Pollution on Cognitive Performance: Evidence from the UK.

Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management* 98: 102250, doi:https://doi.org/10.1016/j.jeem.2019.102250.

Salvi, A. and Salim, S. (2019). Neurobehavioral consequences of traffic-related air pollution. *Frontiers in neuroscience* 13: 1232–1232, doi:10.3389/fnins.2019.01232.

Sanders, J. G. and Jenkins, R. (2016). Weekly fluctuations in risk tolerance and voting behaviour. *PLOS ONE* 11: 1–12, doi:10.1371/journal.pone.0159017.

Sforza, A. (2014). The Weather Effect: estimating the effect of voter turnout on electoral outcomes in Italy. *Banco de Portugal Working Paper* 5.

Shepsle, K. A. (1972). The Strategy of Ambiguity: Uncertainty and Electoral Competition. *American Political Science Review* 66: 555–568.

Simonsohn, U. (2010). Weather to go to college. *The Economic Journal* 120: 270–280, doi:https://doi.org/10.1111/j.1468-0297.2009.02296.x.

SOEP (2019). Socio-Economic Panel (SOEP), data for years 1984-2018, version 35. doi:10.5684/soep.v35.

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management* 70: 34–50, doi:https://doi.org/10.1016/j.jeem.2014.11.002.

Sun, X., Zhao, T., Liu, D., Gong, S., Xu, J. and Ma, X. (2020). Quantifying the Influences of PM2.5 and Relative Humidity on Change of Atmospheric Visibility over Recent Winters in an Urban Area of East China. *Atmosphere* 11, doi:10.3390/atmos11050461.

Trushna, T., Dhiman, V., Raj, D. and Tiwari, R. R. (2020). Effects of ambient air pollution on psychological stress and anxiety disorder: a systematic review and meta-analysis of epidemiological evidence. *Reviews on Environmental Health* doi:doi:10.1515/reveh-2020-0125.

Valentino, N. A., Hutchings, V. L., Banks, A. J. and Davis, A. K. (2008). Is a Worried Citizen a Good Citizen? Emotions, Political Information Seeking, and Learning via the Internet. *Political Psychology* 29: 247–273.

Ward, G. (2015). Is Happiness a Predictor of Election Results? CEP Discussion Papers, Centre for Economic Performance, LSE.

Ward, G., Neve, J. D., Ungar, L. and Eichstaedt, J. (2020). (Un)happiness and voting in U.S. presidential elections. *Journal of Personality and Social Psychology* 120: 370–383.

Weuve, J., Puett, R. C., Schwartz, J., Yanosky, J. D., Laden, F. and Grodstein, F. (2012). Exposure to Particulate Air Pollution and Cognitive Decline in Older Women. *Archives of Internal Medicine* 172: 219–227, doi:10.1001/archinternmed.2011.683.

World Health Organization (2005). Air Quality Guidelines. Global Update 2005.

Zhang, X., Chen, X. and Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences* 115: 9193–9197, doi:10.1073/pnas.1809474115.

Zhang, X., Zhang, X. and Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management* 85: 81–94, doi:10.1016/j.jeem.2017.04.00.

Zheng, S., Wang, J., Sun, C., Zhang, X. and Kahn, M. E. (2019). Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behaviour* 3: 237–243, doi:10.1038/s41562-018-0521-2.

A Election Data

A.1 Party Classifications

Our dataset contains information on the number of valid votes cast for the six main political parties in Germany — namely CDU/CSU, SPD, Greens, FDP, Die Linke and AfD — as well as the total of votes cast for the other minor parties. As mentioned in Section 3.1, our analysis primarily focuses on the vote share of incumbent parties. For completeness, we also investigate the effect on and established opposition and other, non-established parties. Below is a description of the parties' classifications that have been used.

Table A1: Classification of Parties

Category	Explanation
Established parties	These are the five main actors on the German political scene: the Social Democratic Party of Germany (SPD), the Christian Democratic Union of Germany (CDU/CSU), the Free Democratic Party (FDP), the Green Party, the Left Party (Die Linke).
Other parties	These are smaller opposition parties, many of which are not frequently represented in the federal or state parliaments. This category includes the far-right party Alternative for Germany (AfD): despite it entering the Bundestag in 2017, it was not regularly represented in parliaments over the sample period, which is why it is not classified as an established party in our analysis.
Incumbent parties	The party or coalition that was in power before a specific election. In each case, we compute the incumbent by taking the sum of the vote shares of the parties forming the coalition. For national elections, these coalitions are: SPD-Greens from 1998 to 2005; CDU-SPD from 2005 to 2009; CDU-FDP from 2009 to 2013; CDU-SPD from 2013 to 2017. For state elections, each state elects its own government and therefore the incumbent varies from state to state. *Baden-Württemberg:* CDU-FDP from 1996 to 2011; SPD-Greens from 2011 to 2016. *Bavaria:* CDU from 1998 to 2008 and then from 2013 to 2018/date; CDU-FDP from 2008 to 2013. *Berlin:* CDU-SPD from 1999 to 2001 and from 2011 to 2016/date; SPD-Die Linke from 2001 to 2011. *Brandenburg:* SPD-CDU from 1999 to 2009; SPD-Die Linke from 2009 to 2018. *Bremen:* SPD-CDU from 1999 to 2007; SPD-Greens from 2007 to 2018. *Hamburg:* SPD-Greens from 1997 to 2001; CDU-FDP-Schill Partei from 2001 to 2004; CDU from 2004 to 2008; CDU-Greens from 2008 to 2011; SPD from 2011 to 2015. *Hesse:* CDU-FDP from 1999 to 2003 and from 2008 to 2013; CDU from 2003 to 2008; CDU-Greens from 2013 to 2018. *Mecklenburg-Vorpommern:* SPD-Die Linke from 1998 to 2006; SPD-CDU from 2006 to 2016. *Lower Saxony:* SPD from 1998 to 2003; CDU-FDP from 2003 to 2013; SPD-Greens from 2013 to 2017.

continued

Table A1 continued

Category	Explanation
	Northrhine-Westphalia: SPD-Greens from 1995 to 2005 and from 2010 to 2017; CDU-FDP from 2005 to 2010 and from 2017 to date. *Rhineland-Palatinate:* SPD-FDP from 1996 to 2006; SPD from 2006 to 2011; SPD-Greens from 2011 to 2016. *Saarland:* CDU from 1999 to 2009; CDU-FDP-Greens from 2009 to 2012; CDU-SPD from 2012 to 2017. *Saxony:* CDU from 1999 to 2004; CDU-SPD from 2004 to 2009; CDU-FDP from 2009 to 2014. *Saxony-Anhalt:* SPD from 1998 to 2002; CDU-FDP from 2002 to 2011; CDU-SPD-Greens from 2011 to 2016. *Schleswig-Holstein:* SPD-Greens from 1996 to 2005; CDU-SPD from 2005 to 2009; CDU-FDP from 2009 to 2012; SPD-Greens from 2012 to 2017. *Thuringia:* CDU from 1999 to 2004; CDU-SPD from 2004 to 2014; SPD-Greens-Die Linke for 2014 to 2018.
Established Opposition	The established parties that were not in power (were at the opposition) before a specific election. In each case, we compute the established opposition by taking the sum of the vote shares of all the parties. For national elections, the established opposition is represented by: CDU-FDP-Die Linke from 1998 to 2005; FDP-Greens-Die Linke from 2005 to 2009; SPD-Greens-Die Linke from 2009 to 2013; FDP-Greens-Die Linke from 2013 to date. For federal elections, each state elects its own government, so established opposition parties vary from state to state. *Baden-Württemberg:* SPD-Greens-Die Linke from 1996 to 2011; CDU-FDP-Die Linke from 2011 to 2016. *Bavaria:* SPD-FDP-Greens-Die Linke from 1998 to 2008 and from 2013 to 2018; SPD-Greens-Die Linke from 2008 to 2013. *Berlin:* FDP-Greens-Die Linke from 1999 to 2001; CDU-FDP-Greens from 2001 to 2011; FDP-Greens-Die Linke from 2016 to date. *Brandenburg:* FDP-Greens-Die Linke from 1999 to 2009; CDU-FDP-Greens from 2009 to 2018. *Bremen:* FDP-Greens-Die Linke from 1999 to 2007; CDU-FDP-Die Linke from 2007 to 2018. *Hamburg:* CDU-FDP-Die Linke from 1997 to 2001; SPD-Greens-Die Linke from 2001 to 2004; SPD-FDP-Greens-Die Linke from 2004 to 2008; SPD-FDP-Die Linke from 2008 to 2011; CDU-FDP-Greens-Die Linke from 2011 to 2015. *Hesse:* SPD-Greens-Die Linke from 1999 to 2003 and from 2008 to 2013; SPD-FDP-Greens-Die Linke from 2003 to 2008; SPD-FDP-Die Linke from 2013 to 2018. *Mecklenburg-Vorpommern:* CDU-FDP-Greens from 1998 to 2006; FDP-Greens-Die Linke from 2006 to 2016. *Lower Saxony:* CDU-FDP-Greens-Die Linke from 1998 to 2003; SPD-Greens-Die Linke from 2003 to 2013; CDU-FDP-Die Linke from 2013 to 2017. *Northrhine-Westphalia:* CDU-FDP-Die Linke from 1995 to 2005 and from 2010 to 2017; SPD-Greens-Die Linke from 2005 to 2010 and from 2017 to date. *Rhineland-Palatinate:* CDU-Greens-Die Linke from 1996 to 2006 and from 2011 to 2016; CDU-FDP-Greens-Die Linke from 2006 to 2011.

continued

Table A1 continued

Category	Explanation
	Saarland: SPD-FDP-Greens-Die Linke from 1999 to 2009; SPD-Die Linke from 2009 to 2012; FDP-Greens-Die Linke from 2012 to 2017. *Saxony:*: SPD-FDP-Greens-Die Linke from 1999 to 2004; FDP-Greens-Die Linke from 2004 to 2009; SPD-Greens-Die Linke from 2009 to 2014. *Saxony-Anhalt:* CDU-FDP-Greens-Die Linke from 1998 to 2002; SPD-Greens-Die Linke from 2002 to 2011; FDP-Die Linke from 2011 to 2016. *Schleswig-Holstein:* CDU-FDP-Die Linke from 1996 to 2005; FDP-Greens-Die Linke from 2005 to 2009; SPD-Greens-Die Linke from 2009 to 2012; CDU-FDP-Die Linke from 2012 to 2017. *Thuringia:* SPD-FDP-Greens-Die Linke from 1999 to 2004; FDP-Greens-Die Linke from 2004 to 2014; CDU-FDP from 2014 to 2018.

Figure A1 offers a graphical representation of Table A1, showing the frenquency with which each of the main established parties was the incumbent or the opposition in our sample period of 2000-2018, distinguishing between federal (BW) and state (LW) elections.

A.2 Election Dates

We investigate outcomes from 82 election, five national (*Bundestagswahl*, BW) and 67 state (*Landtagswahl*, LW), in 2000-2018 the period. The national parliament (*Bundestag*) is elected for a four-year term, while the federal ones (*Landtag*) remain in power for four or five years depending on the state. Below the election dates for both bodies are listed.

Table A2: Date and Type of Elections

Date	Type
National Elections (*Bundestag*) - All States	
September 22, 2002	National (*Bundestag*)
September 18, 2005	National (*Bundestag*). Early election.
September 27, 2009	National (*Bundestag*)
September 22, 2013	National (*Bundestag*)
September 24, 2017	National (*Bundestag*)
Baden-Württemberg	
March 25, 2001	State (*Landtag*)
March 26, 2006	State (*Landtag*)
March 27, 2011	State (*Landtag*)
March 13, 2016	State (*Landtag*)
Bavaria	
September 21, 2003	State (*Landtag*)
September 28, 2008	State (*Landtag*)
September 15, 2013	State (*Landtag*)
October 14, 2018	State (*Landtag*)
Berlin	
October 21, 2001	State (*Landtag*)
September 17, 2006	State (*Landtag*)

continued

Table A2 continued

Date	Type
September 18, 2011	State (*Landtag*)
September 18, 2016	State (*Landtag*)
Brandenburg	
September 19, 2004	State (*Landtag*)
September 27, 2009	State (*Landtag*)
September 14, 2014	State (*Landtag*)
Bremen	
May 25, 2003	State (*Landtag*)
May 13, 2007	State (*Landtag*)
May 22, 2011	State (*Landtag*)
May 10, 2015	State (*Landtag*)
Hamburg	
September 23, 2001	State (*Landtag*)
February 29, 2004	State (*Landtag*). Early election.
February 27, 2008	State (*Landtag*)
February 20, 2011	State (*Landtag*)
February 15, 2015	State (*Landtag*)
Hesse	
February 2, 2003	State (*Landtag*)
January 27, 2008	State (*Landtag*)
September 22, 2013	State (*Landtag*)
October 28, 2018	State (*Landtag*)
Mecklenburg-Vorpommern	
September 22, 2002	State (*Landtag*)
September 17, 2006	State (*Landtag*)
September 4, 2011	State (*Landtag*)
September 4, 2016	State (*Landtag*)
Lower Saxony	
February 2, 2003	State (*Landtag*)
January 27, 2008	State (*Landtag*)
January 20, 2013	State (*Landtag*)
October 15, 2017	State (*Landtag*)
Northrhine-Westphalia	
May 14, 2000	State (*Landtag*)
May 22, 2005	State (*Landtag*)
May 09, 2010	State (*Landtag*)
May 13, 2012	State (*Landtag*). Early election.
May 14, 2017	State (*Landtag*)
Rhineland-Palatinate	
March 25, 2001	State (*Landtag*)
March 26, 2006	State (*Landtag*)
March 27, 2011	State (*Landtag*)
March 13, 2016	State (*Landtag*)
Saarland	
September 5, 2004	State (*Landtag*)
August 30, 2009	State (*Landtag*)
March 25, 2012	State (*Landtag*). Early election.

continued

Table A2 continued

Date	Type
March 26, 2017	State (*Landtag*)
Saxony	
September 19, 2004	State (*Landtag*)
August 30, 2009	State (*Landtag*)
August 31, 2014	State (*Landtag*)
Saxony-Anhalt	
April 21, 2002	State (*Landtag*)
March 26, 2006	State (*Landtag*)
March 20, 2011	State (*Landtag*).
March 13, 2016	State (*Landtag*)
Schleswig-Holstein	
February 27, 2000	State (*Landtag*)
February 20, 2005	State (*Landtag*)
September 27, 2009	State (*Landtag*)
May 6, 2012	State (*Landtag*). Early election.
May 7, 2017.	State (*Landtag*)
Thuringia	
June 13, 2004	State (*Landtag*)
August 30, 2009	State (*Landtag*)
September 14, 2014	State (*Landtag*).

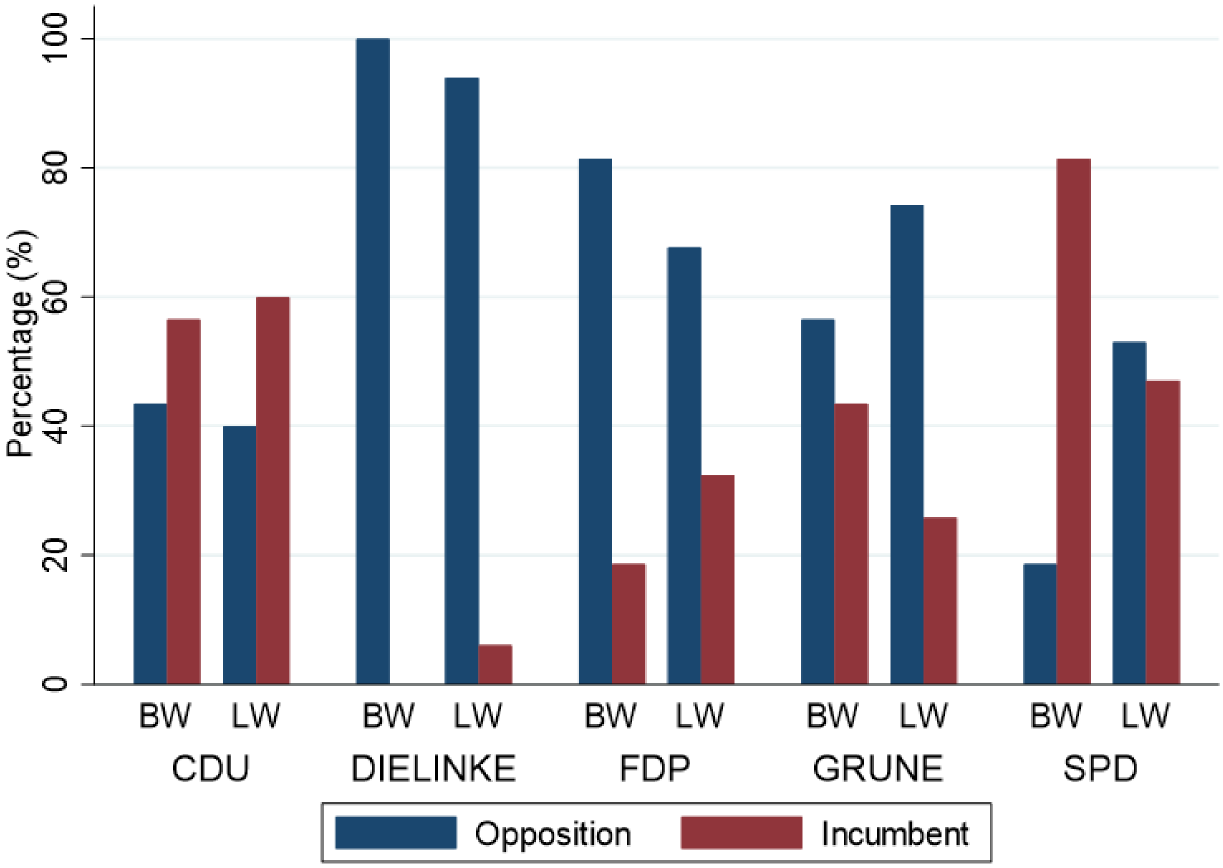


Figure A1: Frequency of Incumbency and Opposition by Party and Election Type (2000–2018)

Notes: This graph shows how frequently each of the major parties has been the incumbent or opposition party in federal elections (BW) and state elections (LW). For example, the SPD was an incumbent party in 80% of the federal elections in our sample and in around 50% of the state elections.

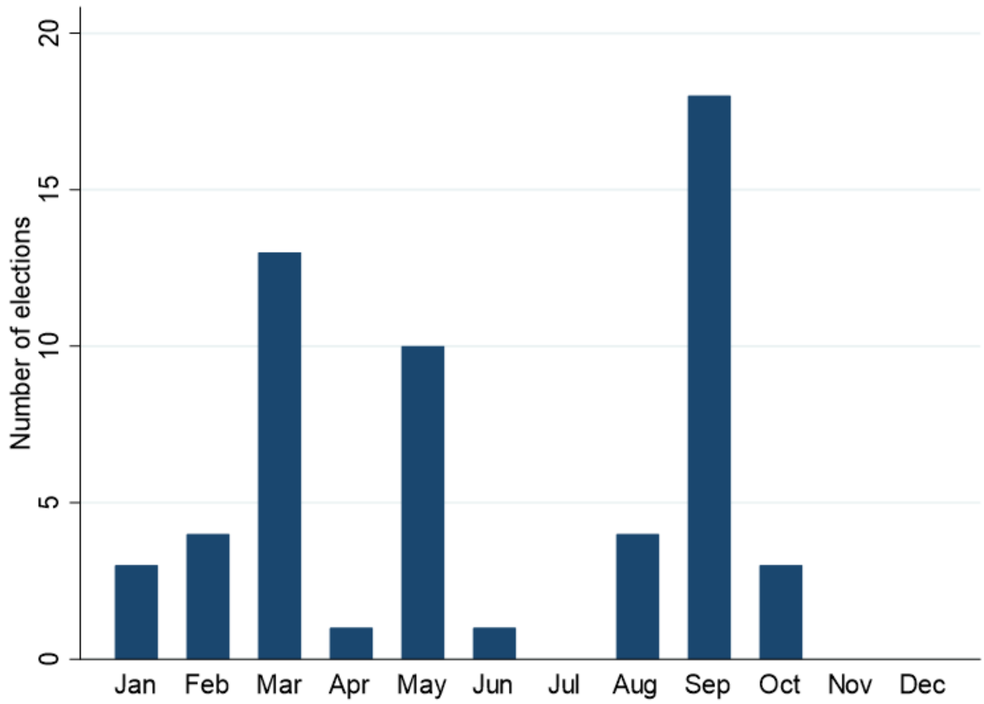


Figure A2: Distribution of elections by calendar month

B Voting by mail as a Measurement Error Problem

A challenge for our empirical analysis is that some votes are cast by mail. The share of mail voters has steadily increased over the sample period: in federal elections, it increased from 13.4% of all votes in 2002 to 28.6% in 2017 (Bundeswahlleiter, 2017). The possibility of voting by mail adds two potential problems to our estimation strategy. First, for most counties, voting data are not available separately by means of voting, at the ballot box or by mail. Therefore, the overall voting data at the county level that we use are a combination of votes cast at the ballots in the county on the election day and votes mailed by residents of that county, potentially at anytime in the month before the election day and from anywhere that they might have been at that time. Both these facts make it likely for us to assign an incorrect level of air pollution to those votes sent by mail.

The fact that we potentially assign an incorrect pollution level to a share of voters is akin to a measurement error problem, as the true exposure when making voting decisions is different from the exposure we assign, namely the level of PM10 on election day. Let the level of PM10 on election day be $PM10_{it}$ with mean μ_{PM10} and standard deviation σ_{PM10} and the share of mail voters be $\alpha \in (0, 1)$. We assume that mail voters only vote on one particular day, on which the level of PM10 is Q_{it}, with mean μ_Q and standard deviation σ_Q. $PM10$, Q and the outcome y are within-transformed, i.e. they represent the residuals after differencing out county and election date fixed effects. The indices i and t stand for county and election date, respectively. Assume that the true relationship is

$$y_{it} = \beta_0 + \beta_1((1-\alpha)PM10_{it} + \alpha Q_{it}) + \varepsilon_{it}, \tag{4}$$

and that the model is otherwise correctly specified, $cov(PM10_{it}, \varepsilon_{it}) = cov(Q_{it}, \varepsilon_{it}) = 0$. In Equation (4), the true exposure on the day when people cast their vote is a weighted average of the concentration of PM10 on the election day and the day on which the mail voters made their voting decisions. By contrast, in our analysis we assign to each voter the level of PM10 on the election day and estimate

$$y_{it} = \gamma_0 + \gamma_1 PM10_{it} + \eta_{it}. \tag{5}$$

The estimate we obtain from estimating Equation (5) is

$$\gamma_1 = \beta_1 \left[(1-\alpha) + \alpha \frac{cov(PM10_{it}, Q_{it})}{Var(PM10_{it})} \right] = \beta_1 \left[(1-\alpha) + \alpha\delta \right]. \tag{6}$$

The bias resulting from measurement error is the the term in the square brackets. The bias is a function of the share of mail votes α and the serial correlation in the level of PM10, δ. Measurement error attenuates the estimates as long as

$$\frac{\alpha - 1}{\alpha} < \delta < 1. \tag{7}$$

Whether δ lies within this range is an empirical question. Note that δ is equivalent to a coefficient of a regression of PM10 several days before the election on PM10 on election day. In Table B1, we run this regression and control for county and election date fixed effects. The results suggest that δ is positive and small: for most lags the coefficient is around 0.25 and for the lag $t-25$ the coefficient is zero. The estimates for δ being in the range $[0, 0.27]$ means that we have attenuation bias.

Table B1: Regression of Lagged PM10 on Contemporaneous PM10

Dependent variable:	$PM10_{t-5}$	$PM10_{t-10}$	$PM10_{t-15}$	$PM10_{t-20}$	$PM10_{t-25}$	$PM10_{t-30}$
PM10 ($10\mu g/m^3$)	0.2847***	0.2284***	0.2700***	0.2791***	-0.0006	0.2358***
	(0.026)	(0.032)	(0.031)	(0.025)	(0.039)	(0.029)
Mean dep. var.	2.14	2.20	2.18	1.88	2.41	2.49
R^2	0.825	0.800	0.783	0.703	0.666	0.790
N	2770	2765	2759	2758	2756	2760
Controls						
County FE	✓	✓	✓	✓	✓	✓
El. Date FE	✓	✓	✓	✓	✓	✓

Notes: This table displays the results of separate OLS regressions of the level of PM10 (in $10\mu g/m^3$) on $t-s$ days before the election on the day of election on the level of PM10 on election day. Standard errors clustered at the county level are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Based on Equation (6), we can also quantify the attenuation bias. Suppose the share of mail votes is $\alpha = 0.2$ and the regression coefficient in Table B1 is 0.25. In that case, the term in square brackets equals 0.85, which means that our estimates are 15% lower than the true effect because we assign the incorrect level of PM10 to mail votes.

The model can also be generalized to mail voting being up to S days before the election $s = 1, \ldots, S$.

Assuming that $cov(Q_{i,t-s}, PM10_{it}) = 0 \ \forall \ s$, the estimate becomes

$$\gamma_1 = \beta_1 \left[\left(1 - \sum_{s=1}^{S} \alpha_s\right) + \sum_{s=1}^{S} \alpha_s \frac{cov(PM10_{it}, Q_{i,t-s})}{Var(PM10_{it})} \right] = \beta_1 \left[\left(1 - \sum_{s=1}^{S} \alpha_s\right) + \sum_{s=1}^{S} \alpha_s \delta_s \right], \tag{8}$$

with α_s being the share of voters who vote by mail s days before the election. The results suggest that the most coefficients δ_s are around 0.25, which means that we likely have attenuation bias and our estimates represent a lower bound to the true effect.

When we instrument for PM10 on the election day with wind directions on the same day, we can eliminate one part of the attenuation bias, namely the part governed by δ. Wind directions on the election day are plausibly orthogonal to pollution levels several days or weeks before, such that $\delta = 0$. However, the IV estimation cannot fully eliminate the attenuation bias, which in large parts is governed by $(1 - \alpha)$, the share of people voting on the election day.

C Additional Checks

C.1 More on the Variation of PM10

Figures C1-C6 illustrate the variation of particulate matter within and across counties. Figure C1 shows the year-on-year variation in average levels of PM10 dividing measuring stations into three groups: stations in the bottom 25% of average levels of PM10 across years, those in the middle 50%, and those in the top 25%. In each of these groups, the level of PM10 varies from year to year, but the variation follows the same decreasing trajectory in all three groups. Figure C2 reports average levels of PM10 across election dates.

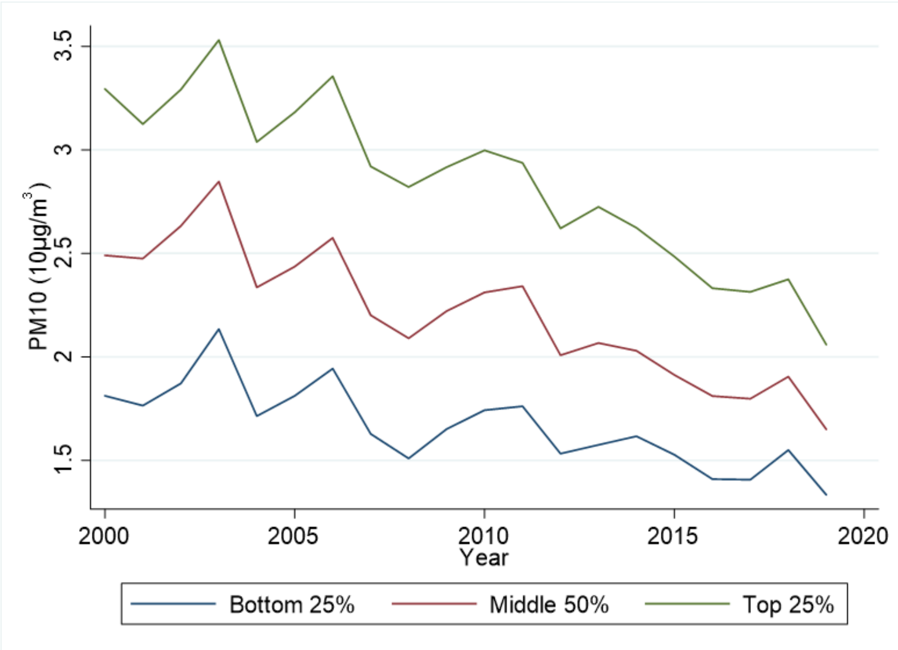


Figure C1: Average level of PM10 by year

Notes: This figure displays the yearly average level of PM10 in the period 2000-2018 dividing measuring stations into three groups: 1) stations in the lowest 25% in terms of average pollution across years, 2) stations between the 25th and 75th percentile in this distribution, and 3) stations in the top 25% of this distribution.

Figure C4 illustrates our identifying variation based on the example of Munich. Panel (a) shows the fluctuation in the level of PM10 across Sundays in a given year, in this case in 2016. The level of PM10 fluctuates considerably around an annual mean of around $18\mu g/m^3$. The fluctuations are larger in winter than in summer, although even in winter pollution levels can be low. Panel (b) illustrates the identifying variation, namely the fluctuation in PM10 within the same city across election dates. The level of PM10 fluctuates considerably across election dates. In the regressions, we condition on election date fixed effects, which absorb fluctuations that are common to all counties in Germany, not just Munich.

Figure C5 illustrates the extent of identifying variation that is left after conditioning on fixed effects and controls. Each panel displays the residuals of PM10 after conditioning on county and election date fixed effects (Panel a) and additionally conditioning on weather controls (Panel b). Both graphs show that our estimation relies on a significant degree of identifying variation, even after controlling

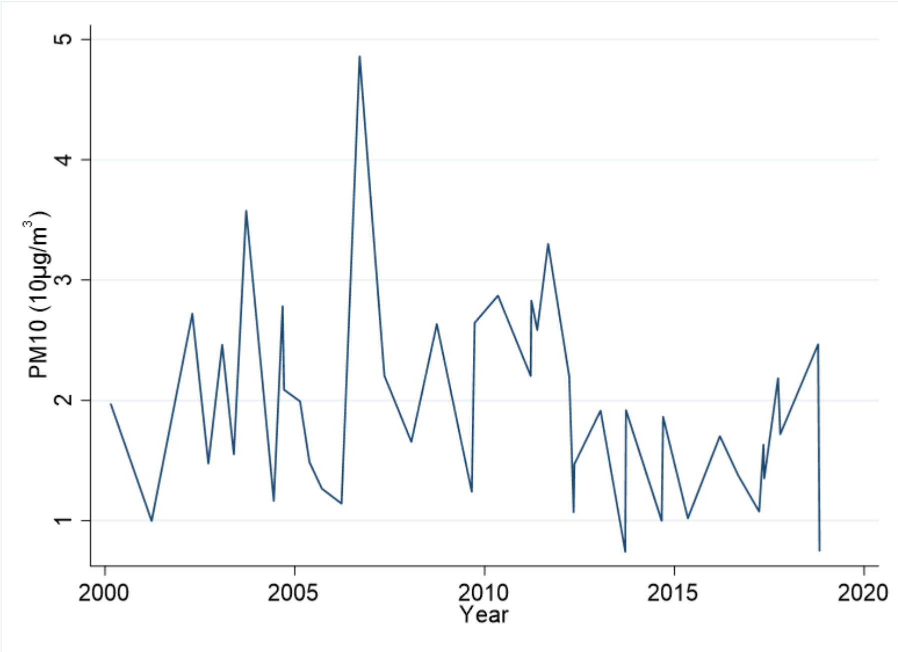


Figure C2: Average level of PM10 by election date

for weather.

Whereas Figure C5 shows the amount of identifying variation in the sample, Figure C6 shows how the identifying variation varies across counties. The figure displays the distribution of the within-county variation in PM10 after conditioning on election date fixed effects. Most counties have a within-standard deviation between 0.5 and 1, although there are some positive outliers, i.e. counties with a particularly high within-county standard deviation of PM10.

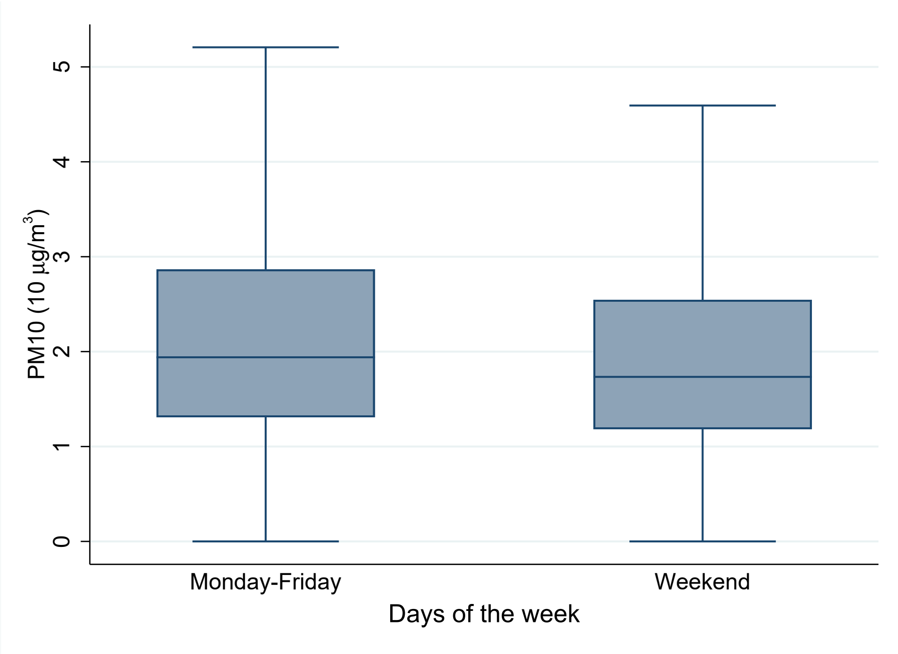
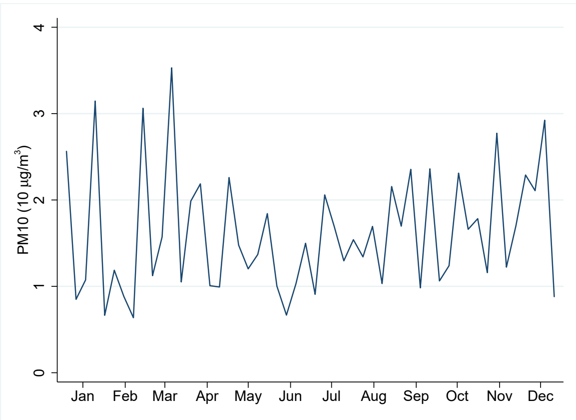
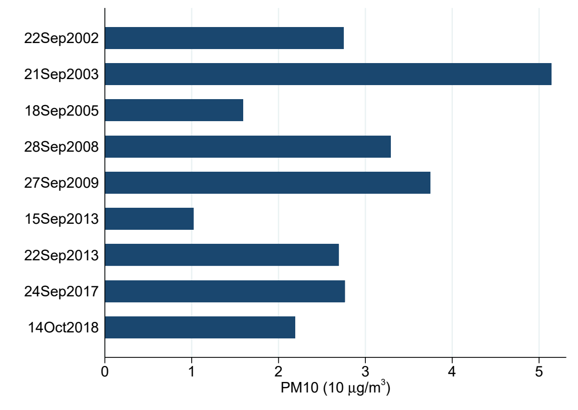


Figure C3: Concentration of PM10 across days of the week

Notes: This figure displays the distribution of the concentration of PM10 over days of the week in the period 2000-2018.



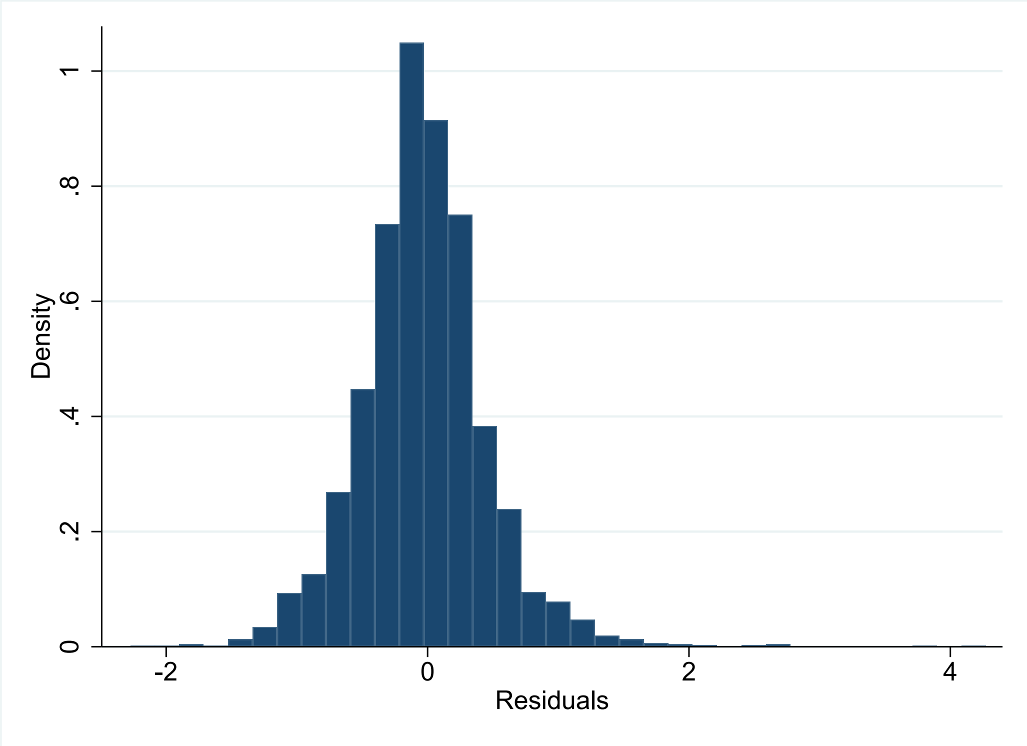
(a) Pollution in Munich on all Sundays in 2016



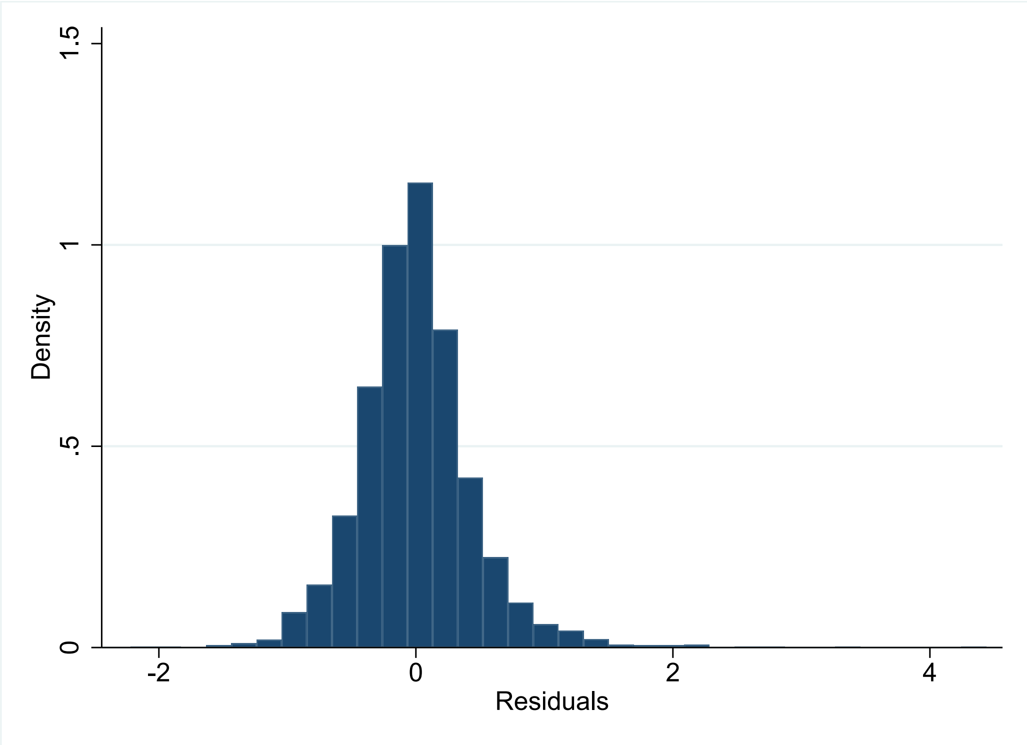
(b) Pollution in Munich across Election Dates

Figure C4: Example for Variation of Pollution within a County: Munich

Notes: This graph illustrates the variation of PM10 in Munich, a large city in the south of Germany. Panel (a) shows the level of PM10 on all Sundays in 2016. Panel (b) illustrates the identifying variation. It displays the level of PM10 on all the election dates in our sample period.



(a) Residuals of PM10 Conditional on Two-way FE



(b) Residuals of PM10 Conditional on Two-way FE and Weather Controls

Figure C5: Residuals of PM10

Notes: This graph displays the distribution of the residuals of PM10 after conditioning on two-way fixed effects (Panel a), and after conditioning on two-way fixed effects and weather controls (Panel b). One unit equals $10\mu g/m^3$.

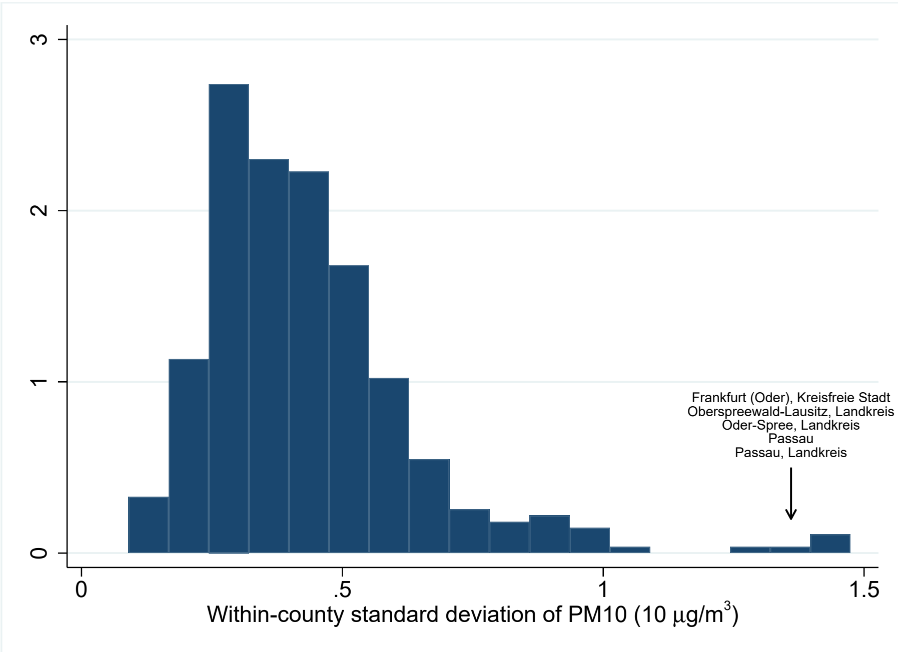


Figure C6: Histogram of within standard deviations

Notes: This graph displays the distribution of the within-county standard deviations of PM10 after conditioning on election date fixed effects.

C.2 States with Territorial Reforms

Three states underwent substantial territorial reforms during our sample period: in 2007 Saxony-Anhalt moved from 24 to 14 counties, in 2008 Saxony moved from 29 to 13 counties, and in 2011 Mecklenburg-Vorpommern moved from 18 to 8 counties. The goal of these reforms was to reduce the number of counties within a state, which was achieved by including counties into other existing ones, merging counties to form a brand new entity, or counties being dissolved with their territory being redistributed between various existing or newly formed counties.

It is practice in the literature to ”reconstruct” the new territorial entity for the entire estimation period. The challenge for our analysis is that county-level data pre- and post-election are not readily comparable. In order to build a panel dataset for counties in these states, we require information on voting results *before the reform* based on the county definition *after the reform*. We construct this data based on municipality-level voting data, which we obtained from the statistical offices of the three states along with correspondence files that link municipalities and counties.

All of the results presented in the main analysis of this paper use voting and socio-economic observations for these three states thus created. However, we also decided to conduct a robustness check employing the same specifications reported in Table 2 excluding the three states that saw counties' reforms from the estimation sample.

The results are presented in Table C1. The sample size decreases by 90 observations, but the coefficients remain quantitatively and qualitatively unaltered.

Table C1: Removing States with County Reforms

Outcome:	Vote Share of Incumbent Parties	Vote Share of Incumbent Parties	Turnout	Turnout
	(1)	(2)	(3)	(4)
A. Without controls				
PM10 ($10 \mu g/m^3$)	-0.0207***	-0.0219***	0.0014*	0.0012
	(0.003)	(0.003)	(0.001)	(0.001)
Mean dep. var.	0.48	0.48	0.69	0.69
R^2	0.575	0.605	0.962	0.963
N	2680	2680	2680	2680
Controls				
County FE	✓	✓	✓	✓
El. Date FE	✓	✓	✓	✓
Weather		✓		✓
Ozone		✓		✓
Demographics		✓		✓
El. Type FE		✓		✓
Turnout		✓		

Notes: This table displays the results of the same OLS regressions presented in Table 2, excluding those states that experienced reforms of counties in the sample period (i.e. Mecklenburg-Vorpommern, Saxony and Saxony-Anhalt). Standard errors clustered at the county level are displayed in parentheses. Significance levels: $*** : p < 0.01$, $** : p < 0.05$, $* : p < 0.1$.

C.3 Alternative radiuses

In Section 3.2, we mentioned that county-level measures of pollution and weather variables are calculated as the inverse distance-weighted average of measurements from all stations within a certain radius from the county's centroid. In the our main analysis we use a radius of 30km. However, the choice of the radius entails a trade-off between the precision of the county-level measurements and the number of counties that can be considered (hence the sample size). In order to provide a more complete representation of the impact of PM10 on voting, we replicate the analysis reported in Column (2) of Table 2 using alternative radiuses. Specifically, we all the pollution and weather variables, including PM10, are calculated using a radius of 20km, 40km and 50km respectively. The dependent variable is always the vote share for incumbent parties; the independent variable of interest is the concentration of PM10 (in $10\mu g/m^3$) on the date of election; and all models control the variables mentioned in Section 4.

Table C2 reports the results of this analysis. As expected, the sample size increases with the radius; but the relation is not linear. Remember that with a radius of 30km the sample size was 2770. Decreasing the radius by ten kilometers reduces the sample size by 1101 observations; conversely, enlarging it by ten kilometers increases the sample size by only 551 observations. This is also the reason why we do not report the results for a radius of 10km: the sample would be curtailed too much and only a handful of counties would be included. Nevertheless, the magnitude and direction of the effect of PM10 on voting behavior are comparable to those reported in Table 2, thus suggesting that the estimates are not driven by our choice of radius.

Table C2: Air Pollution and Voting - Using Alternative Radiuses

Radius:	20 km (1)	40 km (2)	50 km (3)
PM10 ($10\mu g/m^3$)	-0.0239***	-0.0219***	-0.0211***
	(0.004)	(0.003)	(0.003)
Mean dep. var.	0.48	0.48	0.48
R^2	0.606	0.595	0.595
N	1669	3321	3473
Controls			
County FE	✓	✓	✓
El. Date FE	✓	✓	✓
Weather	✓	✓	✓
Ozone	✓	✓	✓
Demographics	✓	✓	✓
El. Type FE	✓	✓	✓
Turnout	✓	✓	✓

Notes: This table displays the results of the same OLS regressions presented in Column (2) of Table 2, using different radiuses for the computation of county-level measures of pollution and weather variables. The dependent variable is the vote share for incumbent parties. Standard errors clustered at the county level are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

C.4 Balancing Tests

A potential concern with our identification strategy is that pollution levels may be driven by economic or shocks. To test whether economic factors are systematically related to changes in pollution, we regress three variables – population, GDP per capita, and the employment rate – on the level of PM10 and control for fixed effects and weather controls. The results, shown in Table C3, do not point to a systematic relationship between pollution and any of these three variables. In none of the cases do we find significant effects. Although this is no proof of the absence of omitted variables, we view these results as one piece of evidence along with the placebo tests, permutation tests, and instrumental variable strategy.

Table C3: Balancing Test: Does Pollution Predict Economic Outcomes?

Outcome:	Total Population	GDP per capita	Employment rate
A. No controls			
PM10 ($10\mu g/m^3$)	-499.423	-56.688	-0.002
	(656.322)	(137.329)	(0.001)
Mean dep. var.	214509.95	31128.08	0.76
R^2	0.998	0.955	0.986
N	2770	2770	2770
Controls			
County FE	✓	✓	✓
El. Date FE	✓	✓	✓
B. With controls			
PM10 ($10\mu g/m^3$)	-665.484	-51.529	-0.002
	(632.854)	(146.427)	(0.001)
Mean dep. var.	214509.95	31128.08	0.76
R^2	0.998	0.955	0.987
N	2770	2770	2770
Controls			
County FE	✓	✓	✓
El. Date FE	✓	✓	✓
Weather	✓	✓	✓
Ozone	✓	✓	✓

Notes: This table displays the results of an OLS regression of the outcomes listed at the top on the air concentration of PM10 (in $10\mu g/m^3$) and the controls listed at the bottom. Standard errors clustered at the county level are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

C.5 Permutation Tests

To corroborate our identification strategy – and to exclude that our estimates are the result of fitting noise – we perform permutation tests. Within each county, we randomly re-shuffle the level of PM10 across election dates. For example, instead of the pollution level in Munich on the day of the state election in 2018, the procedure assigns the pollution level of the federal election in 2005 or the level on the day of some other election. For each outcome, we perform 1000 permutations and regress the outcome on PM10, two-way fixed effects, and weather controls. Our estimate based on the true levels of pollution (Table 2) is far away from the distribution of placebo estimates. We could not find a single placebo estimate that is more extreme than our estimate. These findings clearly reject the notion that our estimates are the result of fitting noise.

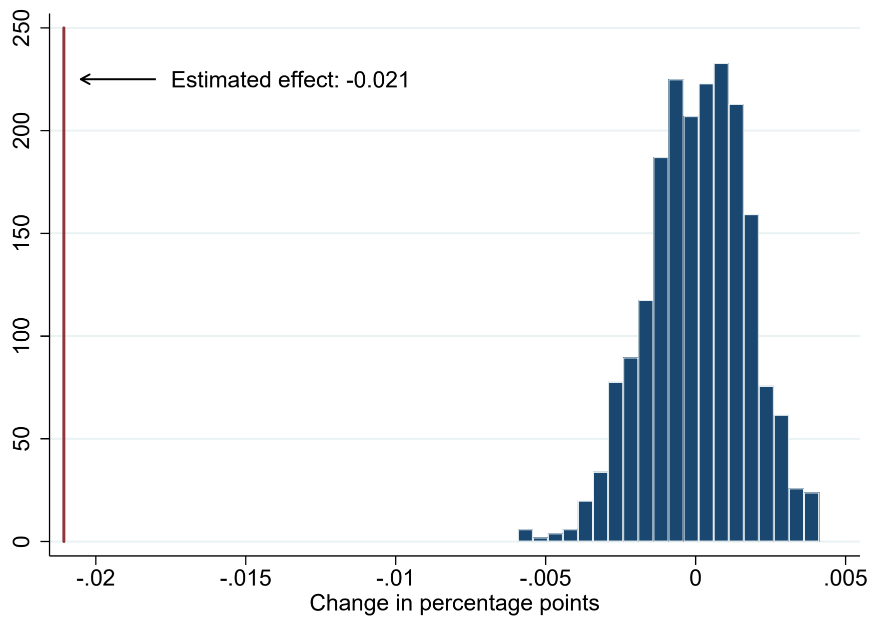


Figure C7: Permutation Tests

Notes: The figure displays the distribution of 1000 placebo estimates of a regression of the vote share for the incumbent on the level of PM10, controlling for election date and county fixed effects as well as weather controls. In each permutation, the level of PM10 was randomly re-shuffled within a county. The vertical lines indicate the estimates based on the true pollution levels, as shown in Table 2.