Empirical Essays on Local Pollution and Environmental Policies

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To Elvira

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Summary

Pollution externalities have received great attention in environmental economics and, with mitigation policies on local pollutants becoming increasingly stringent in recent years, this topic will become even more prevalent in the future. Hence, it is of crucial importance to quantify the damages incurred by individuals and firms from local pollution and to improve the general understanding of the costs and benefits of associated abatement policies. This dissertation explores these interrelated aspects: First, by assessing the effectiveness of local pollution abatement policies based on the example of German low emission zones. Second, by disentangling the direct and indirect effects of air pollution on the well-being of individuals. Third, by analyzing the impact of pollution externalities on labor market outcomes of employees, using the example of hydraulic fracturing in the US. Fourth, by quantifying the impact of groundwater nitrate pollution on the cost of drinking water supply in Germany. Each aspect is explored through micro-econometric methods based on extensive data sets on individuals and firms. Three chapters focus on recovering causal effects, where identification stems from temporal and geographical variations in pollution exposure and implementations of specific policy measures.

Keywords: Air pollution, Water pollution, Environmental Policies, Well-being, Cost functions

Zusammenfassung

Externe Effekte lokaler Umweltverschmutzung sind ein zentrales Thema der Umweltökonomie. Da die Maßnahmen zur Minderung lokaler Umweltverschmutzung in den letzten Jahren immer strenger wurden, wird dieses Thema in Zukunft an Bedeutung gewinnen. Vor diesem Hintergrund ist es von entscheidender Bedeutung, die Schäden, die Individuen und Unternehmen durch lokale Umweltverschmutzung erfahren, zu quantifizieren und das allgemeine Verständnis der Kosten und Nutzen der damit verbundenen umweltpolitischen Maßnahmen zu verbessern. Diese Dissertation untersucht diese zusammenhängenden Aspekte: Zum einen wird die Wirksamkeit von Umweltschutzmaßnahmen anhand des Beispiels von Umweltzonen in Deutschland analysiert. Zweitens, werden die direkten und indirekten Auswirkungen von Luftverschmutzung auf das Wohlbefinden von Menschen untersucht. Drittens, werden die Auswirkungen von Umweltverschmutzung auf das Arbeitsangebot von Arbeitnehmern anhand des Beispiels von Fracking in den USA analysiert. Viertens, wird der Einfluss von Nitratbelastung im Grundwasser auf die Kosten der Trinkwasserversorgung in Deutschland geschätzt. Jeder Aspekt wird durch mikroökonometrische Methoden untersucht, die auf umfangreichen Datensätzen zu Individuen und Unternehmen basieren. Die ersten drei Kapitel konzentrieren sich auf die Schätzung kausaler Effekte, welche durch zeitliche und geografische Variation in der Schadstoffbelastung und in der Umsetzung von Politikmaßnahmen identifiziert werden.

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Chapter 1

General Introduction

1.1 Motivation

This doctoral dissertation studies the economic impacts of local pollution on humans and firms, and evaluates the effectiveness of environmental policies. It aims at quantifying the effects of air and water pollution using econometric techniques that allow inference of causal relationships based on extensive micro-level data.

Reliable and causally attributable estimates of the impacts of pollution are crucial for grasping the economic costs associated with pollution exposure. Sound empirical evidence is especially relevant for policymakers who develop mitigation strategies to limit the negative impacts of pollution on society and the environment. Having reliable estimates on the pollution impacts enables them to target policies specifically at sectors where the damages and costs from pollution exposure are particularly severe. Identifying and quantifying the consequences of pollution exposure is a necessary prerequisite for designing effective environmental policies; however, it is also vital to validate whether these policies are effective in achieving their intended goals. Such empirical ex-post analyses on policies' effectiveness are essential in providing policymakers with a better understanding of the consequences accompanying future regulatory efforts.

Local pollution is often a byproduct of economic activities and affects various environmental media, like air, water, and soil.[1] Air pollution is a particular concern, as it is considered to be the greatest environmental risk to human health worldwide, with nine out of ten people breathing polluted air (WHO, 2019). A major share of air pollution stems from the combustion of fossil fuels that is

[1] Local pollutants affect only the area surrounding the emission source, in contrast to global pollutants like greenhouse gases.

omnipresent in most economic sectors, e.g., transportation, electricity generation, or the building industry. The combustion exhaust consists of a myriad of toxic air pollutants that can penetrate human lungs, enter the bloodstream, or infiltrate the brain, causing numerous diseases, disabilities, and premature deaths across the globe. Recent estimates suggest that air pollution is responsible for more than 6 million premature deaths and 93 billion days lived with illness, amounting to economic costs of more than $ 8.1 trillion, or roughly 6 percent of global GDP (World Bank, 2022). Other studies point towards even larger mortality effects, ranging up to eight million premature deaths (18 percent of annual deaths) due to air pollution from burning fossil fuels (Vohra et al., 2021). Besides causing local air pollution, fossil fuel combustion also accelerates climate change by releasing carbon dioxide. Climate change, in turn, aggravates local air pollution problems, for example, through rising temperatures that increase ground-level ozone (Meleux, Solmon and Giorgi, 2007; Murazaki and Hess, 2006).

Another central area of concern is water pollution. Water pollution originates from run-offs from agriculture and urban settlements, the drainage of untreated wastewaters, and industry discharge, contaminating ground- and surface water bodies with pathogens, nutrients, toxic substances, and other pollutants. Consuming contaminated drinking water can cause serious harm to human health, which is mirrored in the UN's Sustainable Development Goals, listing access to safe and affordable drinking water as a top priority (Griggs et al., 2013).[2] About two billion people did not have access to basic water services in 2020, primarily in the poorest countries of the world (WHO, 2021). Waterborne diseases are still a significant cause of death in these regions, especially among young children and infants, where estimates range up to half a million diarrheal deaths per year (Troeger et al., 2018). However, even high-income countries with universal access to safely managed piped drinking water incur enormous costs related to waterborne diseases. For example, recent studies from the US point towards more than 7 million waterborne illnesses occurring annually, leading to $ 3.3 billion in direct health care costs (Collier et al., 2021). Polluted surface and groundwater resources pose not only a risk to human health, they also damage ecosystems and reduce biodiversity, e.g., excessive nutrient loads from agricultural fertilizer run-offs cause eutrophication and acidification of water resources.[3] Climate change will worsen problems related

[2] Equitable access to safe and clean drinking water and sanitation are recognized as human rights by the UN (UN, 2010).

[3] Eutrophication describes the process of water bodies becoming excessively enriched with nutrients, which increases the abundance of algae and aquatic plants, decreases oxygen levels, and endangers aquatic species (Smith and Schindler, 2009).

to water quantity and quality, resulting in higher water temperatures and more floods and droughts (Schwarzenbach et al., 2010). It can also aggravate feedback loops, for example, in eutrophication when warmer temperatures foster excessive algae growth that, in turn, leads to additional releases of greenhouse gas emissions (Li et al., 2021).

This thesis contributes to a better understanding of the economic consequences of air and water pollution and related environmental mitigation policies. First, by examining the effectiveness of command-and-control policies targeting urban air pollution. Second, by exploring how air pollution affects the well-being of parents through their kids' health. Third, by studying the effect of pollution from resource extraction activities on the labor supply of neighboring individuals. Fourth, by analyzing the interdependencies between agriculture and groundwater pollution and by quantifying the impact of groundwater pollution on the cost of drinking water supply. The remainder of this chapter is structured as follows: Section 1.2 briefly introduces the underlying theory of pollution externalities, underlines the societal relevance of studying the effects of water and air pollution on individuals and firms, describes related abatement policies, and gives an overview of the existing empirical evidence. Section 1.3 describes the empirical methodology of this dissertation, and section 1.4 summarizes the contents and main conclusions of each chapter of this dissertation.

1.2 Related literature

The concept of externalities lies at the heart of environmental economics. In general, the term externality describes the uncompensated effect of an agent's (a firm or an individual) actions on other agents' utilities or production functions. Externalities might be either positive, when the acting agent does not reap all the benefits of her actions, or they might be negative, when the agent does not bear all the costs of her actions.[4] Local pollution is a classic example of a negative economic externality: Pigou (1920) lists air pollution from factory chimneys as an

[4] The concept dates back to the ideas of Marshall (1916) about external effects in the industry sector and the social benefits of infrastructure investments. It was further developed by the seminal work of Pigou (1920) introducing the concept of social cost as "divergences between marginal social net product and marginal private net product" (Pigou, 1920, chapter IX). Pigou (1920) concludes that these divergences cannot be removed through modifications in the contractual relations of agents; instead, their removal requires government intervention.

example, and numerous textbooks have illustrated the concept by means of an industrial plant dumping waste into a river and hurting downstream users.[5]

To formalize the concept of negative externalities, it is useful to think about private costs, external costs, and social costs. Private costs refer to the cost of the polluter, e.g., the cost of labor or capital inputs to produce a specific good. External costs are the costs incurred by third parties, e.g., through deteriorated health.[6] Social costs are the sum of private costs and external costs. Neo-classical economic analysis typically shows that differences between private and social costs result in inefficient allocations if the polluting agent has no incentive to internalize the external costs, resulting in welfare losses.

Economists have proposed several approaches to internalize these external costs. On the one hand, market- or incentive-based instruments regulate either the price or the quantity of pollution, e.g., environmental taxes or tradable pollution permits. On the other hand, command-and-control policies set standards or enforce the adoption of clean technologies. All of these instruments require knowledge about the responsible polluters, the affected third parties, and the external costs arising from pollution exposure.[7] Empirical estimates are necessary to quantify the external costs arising from pollution and to assess the potential benefits of these abatement policies.

The following subsections introduce the empirical literature on the external effects of air and water pollution, outline commonly applied policies targeting these local pollution issues, and lists empirical evidence on their effectiveness.

1.2.1 Water pollution

Water pollution results from various substances from anthropogenic activities being introduced to water bodies. Contamination mainly stems from agriculture, sewage, industry, and urban settlements.[8] Common contaminants include

[5] Both examples relate to production externalities, but pollution externalities can also arise from consumption.

[6] Pollution externalities can affect human well-being through various channels, either by impacting market outcomes (e.g., income, profits, production cost, prices) or by affecting non-marketed goods (e.g., health, environmental amenities) (Freeman III, Herriges and Kling, 2014).

[7] For example, an environmental tax must reflect the marginal damages incurred by third parties to achieve efficient allocations. To set the optimal tax rate, these marginal damages in terms of the economy, human health, or the environment must be known. A permit trading scheme creates a market for the externality by issuing allowances to emit (permits) that can be freely traded among polluting parties. In that case, the total amount of permits must be set correctly for effective abatement.

[8] The sources of water pollution are grouped into two categories: Point-source pollution originates from a specific source with localized effects, e.g., an industrial plant discharging

pathogens (e.g., bacteria, viruses), toxic substances (e.g., pesticides, oil, metals), nutrients (e.g., nitrate, phosphate), biodegradable organic matter (e.g., plant or animal matter) and other forms of pollution (e.g., thermal energy) (Von Sperling, 2007). These contaminants have a wide range of adverse effects on human health and the environment. For example, pathogens are responsible for waterborne diseases, pesticides can be toxic for humans and wildlife, and nutrients can lead to excessive algae growth (eutrophication). Human health impacts typically arise from consumption of contaminated drinking water, but can also be related to consumption of plant or animal products affected by water pollution or recreational activities in polluted waters, e.g., swimming and fishing.

The health impacts of water pollution have been studied for centuries. Early research dates back to John Snow, a physician who studied the causes of cholera outbreaks in the 19th century. At the time, it was commonly believed that cholera is transmitted through poisonous particles in the air (miasma), but John Snow could not find evidence to corroborate this belief.[9] Anecdotal evidence led him to suspect contaminated drinking water as a cause of cholera, so he tested his hypothesis using a quasi-experiment: Water supply companies served distinct areas in London using contaminated water from the Thames River. One company relocated their intake pipes further upstream, where the river stream was not yet contaminated by cholera victims' evacuations. John Snow used this variation in pollution exposure and compared death rates between households served by different water suppliers. He discovered that the death rate for dirty-water users was eight to nine times higher than for clean-water users (Snow, 1855).

Since then, epidemiologists, environmental scientists, and health and environmental economists have contributed to a plethora of empirical evidence on the health impacts of water pollution. Many studies focus on microbial pathogen pollution of drinking water that arises from contamination with sewage and causes infectious diseases, such as cholera and other diarrheal diseases. This type of pollution is still a significant risk to safe drinking water in low- and middle-income countries.[10] Epidemiologists have consistently found that improvements in drinking water quality and sanitation decrease the prevalence of diarrheal disease

chemicals, a sewage company draining wastewater into a river, or an oil spill. Non-point source pollution cannot be attributed to a specific emitter; it has diffuse sources and can enter the water body at various locations, e.g., agricultural run-offs cannot be traced back to a specific farm, similar to urban run-offs (Von Sperling, 2007).

9 Today we know that cholera is a waterborne disease that is caused by bacteria and leads to severe diarrhea, nausea, and dehydration. If untreated, it can be fatal within hours.

10 Although more prevalent in poorer countries, waterborne diseases are also a challenge in rich countries like the US, where local outbreaks due to pathogen polluted waters frequently occurred in the last decades (Pandey et al., 2014).

(Luby et al., 2015; Wolf et al., 2014). Recent contributions from the economics domain include, for example, Cutler and Miller (2005) showing that mortality decreases during the 19th and 20th centuries in the US were driven to a large extent by improvements in water quality preventing deaths from typhoid fever. These short-term mortality decreases had long-lasting impacts on human capital formation, as indicated by large increases in earnings and educational attainment among those not exposed to typhoid in early life (Beach et al., 2016).[11,12]

Pathogen pollution from sewage and wastewater is not the only threat to water quality. Another serious problem is nutrient water pollution from nitrogen and phosphate, with intensive conventional agriculture being a major contributor to nutrient inputs (Singh and Craswell, 2021).[13] The application of mineral fertilizer and animal manure often leads to over-fertilization, i.e., more nutrients being applied than the plant can absorb. Excess nutrients can leach into the soil and run off into surrounding surface and groundwater bodies. Nutrient pollution in surface waters harms the ecosystems by accelerating harmful algal blooms and creating low-oxygen waters that are toxic to wildlife. It can also directly affect humans, e.g., through decreased recreational value or health risks, like gastrointestinal and dermatological diseases (Smith and Schindler, 2009).

Nutrient pollution in groundwater bodies is particularly worrisome. Groundwater resources serve as the only source of drinking water in many parts of the world (Shukla and Saxena, 2019), and water pollution might become irreversible due to the prohibitive cost of remediation in groundwater bodies (Lall, Josset and Russo, 2020). Groundwater nitrate pollution, for example, has been increasing in recent decades all over the world.[14] This trend is generally linked to the increasing use of fertilizer nitrogen, and there is ample empirical evidence to support that claim (e.g., Bawa and Dwivedi, 2019; Gallagher and Gergel, 2017; Wick, Heumesser and Schmid, 2012). Nitrate polluted drinking water poses a risk to human health when

[11] Another strand of economic literature focuses on infant health and child mortality. For example, Currie et al. (2013) present a quasi-experimental design exploiting a panel of mothers with multiple children; they find that contaminated drinking water has significant and substantive impacts on birth weight and gestation among less-educated mothers. Brainerd and Menon (2014) show that exposure to fertilizer agrichemicals dissolved in drinking water causes higher mortality rates among infants, using seasonal variation in crop planting in India.

[12] Note that the economic literature on water pollution is relatively scarce, in contrast to the numerous studies exploring the consequences of air pollution. This is a consequence of limited data availability, as data on water contamination is harder to obtain even in high-income countries such as the US (Currie et al., 2013).

[13] Other sources of nutrient water pollution are fossil fuel combustion (nitrogen oxides), urban run-offs from densely populated areas, and industry discharge.

[14] Globally, mean nitrate levels have risen by about 36 percent since 1990; in some regions in the Eastern Mediterranean and Africa, nitrate concentrations have more than doubled in the last decades (Shukla and Saxena, 2019).

permissible limit values are exceeded.[15] Consumption of nitrate-contaminated water causes methemoglobinemia among infants (blue baby syndrome) and is suspected of having carcinogenic effects on adults (Shukla and Saxena, 2019).

Polluted groundwater bodies impose costs on society not only through their detrimental consequences on human health, but also by raising the costs of drinking water production. When water supply companies abstract raw water from polluted groundwater bodies to produce drinking water, they must take preventive measures to protect human health. If raw water nitrate surpasses the legal threshold, the companies must take additional processing steps to ensure that the drinking water is safe for human consumption, requiring more chemical inputs, electricity, or even investments in denitrification plants (Westling, Stromberg and Swain, 2020). This raises the cost of drinking water production, which are typically passed through to water consumers in the form of price increases.

The fifth chapter of this dissertation adds to this literature by empirically investigating the relationship between organically farmed land and nitrate concentrations in surrounding groundwater bodies, contributing to a better understanding of the determinants of groundwater quality. Moreover, the chapter quantifies the impact of groundwater nitrate pollution on the cost function of water suppliers, which is necessary to comprehensively assess the external effects of agricultural fertilizer use.

1.2.2 Air pollution

Air pollution is a consequence of releasing various gases and particles into the atmosphere. Many air pollutants are directly emitted from burning fossil fuels, e.g., carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM).[16] These primary pollutants originate from different sources, e.g., CO stems from incomplete combustion in gasoline-powered vehicles and residential heating systems, while SO_2 is mostly emitted from coal- or oil-fired power plants. NO_2 belongs to the group of highly reactive nitrous oxides (NO_x) and forms mostly from motor vehicle exhaust, while PM is also a by-product of combustion (Seigneur, 2019).[17] A notable exception is ground-level ozone (O_3), which is a secondary pollutant that is not directly emitted but forms in the lower

[15] The WHO limit value amounts to 50 mg/l. The same limit applies in the EU, whereas the US limit is 45 mg/l.

[16] Other sources are mechanical processes, e.g., in transportation where braking and tire wear release particulate matter, or natural processes, e.g., forest fires and volcanic eruptions.

[17] PM also originates from mechanical processes (e.g., construction activities, farming, braking) and from natural sources (e.g., dust, sea salt, pollen) (Seigneur, 2019).

atmosphere as a consequence of chemical reactions between different pre-cursor pollutants, such as NO_2 and volatile organic compounds (VOCs).[18] All of these air pollutants deteriorate human health via inhalation or ingestion. Moreover, air pollution damages the ecosystem, e.g., SO_2 and NO_2 cause acid rain that harms forests and freshwater resources, and NO_2 emissions contribute to the eutrophication of surface waters.

Anthropogenic air pollution started with the discovery of fire tens of thousand of years ago (Hardy et al., 2012). At that time, human exposure to air pollution resulted from burning wood and other biomass in poorly ventilated areas. The health impacts of air pollution were first documented at least 2400 years ago by Hippocrates in Greece, but it was not until the Industrial Revolution during the 18th and 19th centuries that outdoor air pollution became a major public health concern (Fowler et al., 2020). The large-scale burning of coal and oil led to the emission of significant amounts of air pollution, degrading air quality in urban areas and in proximity to industrial facilities. In the early 20th century, industrial centers in Europe and the US suffered from extreme pollution episodes that caused notable spikes in mortality rates. For example, the London Fog of December 1952, where smoke from combustion mingled with fog and became smog, resulted in tripled death rates with more than 3,000 excess deaths during the first three weeks after the event (UK Ministry of Health, 1954).[19,20] These extreme air pollution episodes changed the public perception of the air pollution problem and served as a catalyst for epidemiological air pollution research and policy initiatives to mitigate air pollution (Bell and Davis, 2001).

The field of epidemiology has contributed a vast number of empirical studies on the health effects of air pollution. It is well established that short-term exposure to high concentrations and long-term exposure to low concentrations of air pollution causes cardiovascular and respiratory diseases (Brunekreef and Holgate, 2002; Kampa and Castanas, 2008). Inhaling polluted air affects the respiratory system, causing chronic obstructive pulmonary disease, asthma, and lung cancer (Kurt, Zhang and Pinkerton, 2016). Particulate matter can also penetrate the lung tissue and cause systemic inflammations in different parts of the body, affecting

[18] Ozone occurs naturally in the earth's stratosphere, where it forms the ozone layer and protects life on earth from the sun's ultraviolet radiation. In contrast, ozone in the lower atmosphere is harmful to human health.

[19] Recent estimates suggest even greater numbers of up to 12,000 excess deaths in the three months after the smog episode (Bell and Davis, 2001).

[20] Other examples include the Meuse Valley (Belgium) in 1930, where stable atmospheric conditions and the accumulation of industrial emissions resulted in mortality rates being ten times as large as normal, or Donora (PA, US) in 1948, where atmospheric inversions trapped air pollutants in a valley leading to sixfold increases in death rates (Bell and Davis, 2001).

blood clotting, obstructing cardiac vessels, and consequently increasing the risk for heart attacks or failures (Rajagopalan, Al-Kindi and Brook, 2018). Moreover, evidence of neurodegenerative effects of air pollution is accumulating, showing that particulate matter can infiltrate the brain, potentially causing strokes, Alzheimer's and dementia, and Parkinson's disease (Block and Calderón-Garcidueñas, 2009; Grande et al., 2020).

These numerous health impacts of air pollution lead to increases in mortality (Brunekreef and Holgate, 2002; Hoek et al., 2013), especially among vulnerable populations like children and infants (Jayachandran, 2009; Knittel, Miller and Sanders, 2016). The adverse effects also materialize through higher hospitalization rates (Iskandar et al., 2012; Lleras-Muney, 2010), and medicine intake (Ostro et al., 2001), resulting in direct costs in the health care system for treating and curing patients.

Recently, economists have contributed empirical evidence pointing towards the negative consequences of air pollution exposure for a range of related outcomes. For example, air pollution exposure affects the process of human capital formation by increasing school absences (Currie et al., 2009; Komisarow and Pakhtigian, 2022). It also diminishes the labor productivity of workers, both at the extensive margin by increasing employee absenteeism (Aragon, Miranda and Oliva, 2017; Hanna and Oliva, 2015), and at the intensive margin by decreasing cognitive capabilities (Chang, Graff Zivin and Neidell, 2016; Chang et al., 2019; Graff Zivin and Neidell, 2013). Further, air pollution reduces the subjective well-being of exposed individuals, either directly by deteriorating their health, or through indirect channels, like housing costs (Levinson, 2012; Luechinger, 2009). These adverse effects on labor market outcomes, human capital formation, and well-being impose indirect costs on society that go beyond direct health care costs. These costs need to be considered when quantifying the losses from air pollution exposure, to aid policymakers in designing effective mitigation strategies.

The third chapter of this thesis contributes to this literature by exploring the mechanism underlying the negative relationship between air pollution and human well-being, showing that parents are indirectly affected in their well-being through pollution-induced health impacts on their children. The fourth chapter contributes by evaluating the effects of the environmental externalities from resource extraction on the labor market outcomes of individuals living close to a hydraulic fracturing site.

1.2.3 Environmental policies

In recent years, increasingly stringent environmental mitigation policies have been implemented all over the world, especially with respect to local pollutants (Brunel and Johnson, 2019). These policies aim to minimize the damages incurred by individuals, firms, and the environment, and consist of many different approaches, e.g., command-and-control instruments, taxes, subsidies, pollution permits, or a combination of these instruments. Implementing these policies is costly since it requires government expenditures for administrative efforts. Furthermore, policy enforcement causes adaption costs for firms and households that stem from, e.g., expenditures for pollution control equipment or fines to be paid in the case of non-compliance. To offset these costs, the policy measures need to offer sufficiently large benefits in terms of damage reductions. Hence, it is crucial to assess whether these policies achieve their goals of reducing pollution. This subsection reviews the empirical evidence on the effectiveness of important policies combating water and air pollution in Europe and the US.

Water pollution policies

An important step toward protecting water bodies in the US was the passing of the federal Clean Water Act (CWA) in the 1970s. The CWA aims to reduce surface water pollution from point sources, and relies on non-tradable pollution permits and subsidizing the use of pollution control equipment: It regulates the amount of pollutants that can be discharged from industrial plants and wastewater treatment facilities by issuing permits to polluters, and it offers federal grants to municipalities for improving their wastewater treatment facilities (Keiser and Shapiro, 2019b). The introduction of the CWA led to substantial improvements in surface water quality in the following decades, although improvements were not necessarily achieved in a cost-efficient way (Keiser and Shapiro, 2019a). However, since the CWA focuses on point-source pollution, the policy could not significantly reduce pollution from non-point pollution, such as nutrient pollution from agricultural run-offs.

In addition to the ambient surface water quality regulations, the US government issued the Safe Drinking Water Act in 1974. It sets and enforces drinking water standards, authorizes actions to protect groundwater sources, and grants subsidies for cleaner drinking water (Keiser and Shapiro, 2019b). Empirical evidence on its effectiveness is scarce because long-term data on actual pollution concentrations in drinking water systems are not available in the US,[21] but some evidence links decreases in water quality violations to mandatory information disclosure requirements (Bennear and Olmstead, 2008).

In contrast to the US, water regulations in the EU have more holistic goals. The main water quality policy is the Water Framework Directive (WFD) which seeks to improve water quality in all types of water bodies, including ground- and surface waters (EU, 2000a). However, the WFD delegates implementation and enforcement to the member states of the EU, leading to delays in the enforcement process in single member states (European Commission, 2021b), hence there are no empirical studies on its overall effectiveness.

An integral part of the WFD is the EU Nitrates Directive, which aims to protect ground- and surface waters from agricultural pollution (EU, 1991).[22] The directive sets a legally binding limit value of 50 mg/l for nitrate concentrations in water bodies; member states' governments are obliged to implement action plants if nitrate concentrations exceed this value. Moreover, it defines voluntary guidelines for farmers on the amount and timing of nitrogen application and the adoption of modern nitrogen management tools. Chabé-Ferret, Reynaud and Tène (2021) find that the EU Nitrates Directive reduced the concentration of nitrates in French surface water bodies by eight percent. Large-scale empirical evidence on its impact on groundwater bodies is lacking so far.[23]

Air pollution policies

Concerning air pollution control, one of the earliest policies of the 20th century was the US Clean Air Act (CAA), initially enacted in 1963 and amended several times since then. It aimed at developing a federal program to address air pollution problems and fostered research into abatement and monitoring techniques. A major amendment occurred in 1970, which included the adoption of National Ambient Air Quality Standards (NAAQS) for ambient concentrations of several criteria pollutants, e.g., SO_2, O_3, or coarse particulate matter (PM_{10}). If ambient pollution

[21] Keiser and Shapiro (2019b) note that given the importance of water quality, surprisingly little economic research analyzes policy effectiveness. There are only a few papers studying the effect of regulations on water quality providing causal inference. The main reasons are limited data availability on pollution levels and policy implementation. Moreover, policies are often uniform without spatial variation, spatial computation involves modeling the water networks, and it is not clear which pollutants are most relevant.

[22] The Nitrates Directive mandates regular national monitoring and reporting on nitrate concentrations in all EU member states. Data from German groundwater bodies is used in the fifth chapter of this dissertation.

[23] Velthof et al. (2014) conduct an ex-ante modeling exercise suggesting that the Nitrates Directive reduces agricultural nitrate leaching by up to 16 percent in the EU-27, but they do not explore consequences for groundwater quality.

levels in an area, typically a county, exceed these standards, the area is designated into non-attainment status. As a consequence, the federal state government must implement stricter regulations to reduce emissions from stationary and mobile sources.[24]

Evidence from ex-post studies using quasi-experimental designs suggests that the increased policy stringency in non-attainment areas led to significant reductions in ambient O_3 and PM_{10} concentrations:[25] Henderson (1996) shows that O_3 levels in non-attainment counties decreased by 8 percent relative to attainment counties. Auffhammer, Bento and Lowe (2009) find that PM_{10} concentrations in non-attainment areas dropped by 11 to 14 percent. These ex-post estimates are three times larger than the ex-ante estimates of the Environmental Protection Agency (Aldy et al., 2022), highlighting the importance of conducting ex-post evaluations.

Further amendments to the CAA also introduced market-based environmental policies, e.g., the national cap-and-trade program on SO_2 emissions that was implemented in the 1990s to address the acid rain problem. These market-based instruments are typically more cost-effective in achieving emission reductions by abating emissions where it is cheapest. Indeed, ex-post analysis on the SO_2 cap-and-trade program suggests cost savings of about 20 percent relative to a uniform performance standard (Chan et al., 2018).[26]

In the European context, the current basis for air pollution control is laid out in the EU Directive on Ambient Air Quality and Cleaner Air (EU, 2008b).[27, 28] The directive sets legally binding limit values for ambient concentrations of twelve air pollutants that have to be attained by member states. If member states fall out of attainment, they are obliged to propose air quality plans listing

[24] The NAAQS are enforced by the federal states via so-called State Implementation Plans to ensure attainment of the standards.

[25] Concerning SO_2, Greenstone (2004) finds that the CAA had a modest effect with significant reductions of up to 11 percent in the early 1990s.

[26] A comprehensive review of regulations implemented under the CAA and related empirical evidence is given by Aldy et al. (2022).

[27] Air pollution control has been a focus of EU policy since the 1980s. After the Convention on Long-range Transboundary Air Pollution was signed in 1979, more directives targeting local air pollution came into place in the 1980s, e.g., for SO_2 (Directive 80/779/EEC) and NO_2 (Directive 85/203/EEC). In 1996, the Air Quality Framework Directive (EU, 1996) established a comprehensive strategy describing the basic principles of air quality assessment and listing relevant several pollutants to be regulated. Subsequently, several daughter directives set monitoring standards and limit values for these pollutants (Directives 96/62/EC, 2000/69/EC, 2002/3/EC, and 2004/107/EC). In 2008, these directives were consolidated and replaced by the Ambient Air Quality Directive (EU, 2008b).

[28] Moreover, sector-specific legislation establishes standards to improve air quality, e.g., concerning industrial emissions (EU, 2001, 2010, 2015), road vehicles (EU, 2008a, 2009b, 2016a), fuels (EU, 2003, 2016b) and product-design standards (EU, 2009a).

policy measures to improve air quality.[29] These air quality plans are typically implemented on a local level, e.g., in cities or regions, and consist of a variety of (mostly command-and-control) policy instruments targeting different sectors.

In recent years, air pollution in the EU frequently exceeded the limit values for NO_2 and PM_{10}, mostly in urban areas, with almost two-thirds of NO_2 exceedances being linked to dense traffic or proximity to major roads (EEA, 2022). Consequently, most air quality plans focus on the traffic sector and consist of policy measures targeting reductions in traffic volumes and a modal shift to cleaner modes of transport, e.g., by improving public transport, adopting low emission zones, and promoting cycling (EEA, 2018). Empirical evidence on the effectiveness of these policy measures is relatively scarce, presumably due to their fragmented nature and limited data availability. A notable exception are low emission zones, which are driving restrictions based on motor vehicle emission intensity, that have been shown to effectively decrease traffic-related pollution inside their boundaries (Gehrsitz, 2017; Wolff, 2014; Zhai and Wolff, 2021).

The second chapter of this dissertation contributes to the growing literature on the effectiveness of environmental policies by studying one of the most common command-and-control policies to reduce traffic-related air pollution. Specifically, it examines the impacts of low emission zones on air pollution, individual well-being, and health, while taking policy spillovers into account.

1.3 Methodology

All chapters of this dissertation apply econometric estimation techniques using micro-level panel data.[30] Chapters 2, 3, and 4 use methods to analyze treatment effects: Chapter 2 focuses on estimating causal policy effects using a novel estimator robust to time-varying effects developed by Callaway and Sant'Anna (2021). Chapters 3 and 4 aim at recovering causal effects from observational data with fixed effects regression models, while Chapter 4 combines this regression approach with propensity score matching. Chapter 5 estimates dynamic panel data models using the Generalized Methods of Moments (GMM) estimator. These methods are briefly introduced in this section.

[29] Between 2014 and 2020, 944 air quality plans were reported to the regulatory agency, out of which 557 were implemented (EEA, 2022).

[30] Panel data consist of repeated observations at different points in time on the same set of cross-sectional units of interest (e.g., firms, individuals, pollution monitors). In terms of notation, the cross-sectional units are denoted by $i = 1, \ldots, N$ and the time periods by $t = 1 \ldots T$.

1.3.1 Treatment effect analysis

Treatment effect analysis focuses on estimating the causal effects of a policy or an intervention on an outcome variable of interest. The standard way of thinking about treatment effects originates from the potential outcome framework of Rubin (1974). The basic idea is that the observed outcome, Y_{it}, is only one of several potential outcomes associated with different treatment states. Suppose the intervention is of binary nature, where unit i either receives the treatment at time t, $D_{it} = 1$ (treatment group), or remains untreated, $D_{it} = 0$ (control group). In this case, unit i has two potential outcomes for the treatment, Y_{1it}, and the no-treatment state, Y_{0it}. Researchers are often interested in the average effect of receiving the treatment, i.e., the Average Treatment Effect on the Treated (ATT):

$$\text{ATT} = \mathbb{E}[Y_{1it}|D_{it} = 1] - \mathbb{E}[Y_{0it}|D_{it} = 1] \tag{1.1}$$

The fundamental problem of evaluation arises because only one potential outcome is observed, $\mathbb{E}[Y_{1it}|D_{it} = 1]$, while the other unobserved outcome remains counterfactual, $\mathbb{E}[Y_{0it}|D_{it} = 1]$. When treatment assignment is random across units and compliance with the treatment is perfect, potential outcomes are independent of treatment assignment.[31] In this case, we can estimate the ATT by replacing the conditional expectations in equation 1.1 with their sample analogues, i.e., the average outcomes in the treatment and the control group.

Without random treatment assignment, units can self-select into the treatment based on their potential outcomes, introducing selection bias and preventing identification of causal effects. With observational data, treatment assignment is typically not random, such that additional assumptions are necessary to find a valid counterfactual for the treated group. One possibility is to evoke the conditional independence assumption, i.e., potential outcomes are independent of treatment assignment conditional on a set of observable covariates, X_{it}.[32] If the conditional independence assumption holds, we can estimate the ATT based on conditional-on-X comparisons between treatment and control groups. This can be achieved either through regression analysis, matching approaches, or both (Angrist and Pischke, 2008).[33]

[31] Formally: $\mathbb{E}[Y_{1it}|D_{it} = 1] = \mathbb{E}[Y_{0it}|D_{it} = 1]$.

[32] Formally: $(Y_{0it}, Y_{1it}) \perp D_{it}|X_{it} \Rightarrow \mathbb{E}[Y_{1it}|X_{it}, D_{it} = 1] = \mathbb{E}[Y_{0it}|X_{it}, D_{it} = 1] = \mathbb{E}[Y_{0it}|X_{it}]$.

[33] A common matching approach is propensity score matching, which is applied in combination with regression analysis in Chapter 4 of this thesis. Caliendo and Kopeinig (2008) provide an overview of the most common matching approaches, their benefits, and pitfalls.

In practice, the conditional independence assumption might not be credible in the presence of unobserved confounders that are correlated with treatment assignment. If these confounders are unit specific and do not vary over time, we can use an alternative identifying assumption, where assignment is random conditional on time-varying observable covariates, X_{it}, and time-invariant unit-level heterogeneity, A_i.[34] If we are willing to assume that the conditional expectation function is linear in parameters, i.e., $\mathbb{E}[Y_{0it}|A_i, X_{it}, t] = \alpha + \lambda_t + A_i'\gamma + X_{it}\delta$, and the treatment effect is additive and constant across units and time (homogeneous treatment effects), i.e., $\mathbb{E}[Y_{1it}|A_i, X_{it}, t] = \mathbb{E}[Y_{0it}|A_i, X_{it}, t] + \rho$, we can use a two-way fixed effects regression to recover the ATT:

$$Y_{it} = \underbrace{\alpha_i}_{=\alpha + A_i'\gamma} + \lambda_t + \rho D_{it} + X_{it}\delta + \epsilon_{it} \tag{1.2}$$

Equation 1.2 depicts a two-way fixed effects (TWFE) model: The individual fixed effects α_i capture the unobserved time-invariant heterogeneity across individuals. The time fixed effects λ_t capture the unobserved heterogeneity across time periods. Equation 1.2 can be estimated using the standard within estimator[35] to obtain unbiased and consistent estimates of the causal parameter ρ, under the identifying assumption of strict exogeneity.[36] Note that regardless of whether the treatment assignment is random or not, the Stable-Unit-Treatment-Value-Assumption needs to be satisfied. It requires that the potential outcomes of unit i, are not affected by the treatment assignment of any other unit j, i.e. there are no relevant interactions (spillovers) between the members of the population.[37]

The TWFE model in equation 1.2 has been frequently applied in the empirical literature to recover causal effects.[38] The popularity of the TWFE model stems from the belief that it is equivalent to a difference-in-differences (DD) design, but this holds only for the case with two time periods and two groups. In the case of a

[34] Formally, this implies $\mathbb{E}[Y_{1it}|X_{it}, A_i, t, D_{it} = 1] = \mathbb{E}[Y_{0it}|X_{it}, A_i, t, D_{it} = 1] = \mathbb{E}[Y_{0it}|X_{it}, A_i, t]$.

[35] The within estimator removes the unit fixed effects, α_i, by subtracting off unit-level averages across time from equation 1.2 and applies Ordinary Least Squares (OLS) to the time-demeaned model. It is also known as Fixed Effects estimator, see Section 10.5 in Wooldridge (2010).

[36] Formally: $\mathbb{E}[\epsilon_{it}|D_{it}, X_{it}, A_i, t] = 0$.

[37] Formally: $(Y_{1it}, Y_{0it}) \perp D_{jt}\ \forall i \neq j\ \forall t$. Chapter 2 presents an empirical example where spatial spillovers between treated and controls are present.

[38] This is true for environmental economics, but also other economics disciplines: 19 percent of all empirical papers published by the American Economic Review between 2010 and 2012 have used a TWFE regression to estimate treatment effects (De Chaisemartin and d'Haultfoeuille, 2020).

binary treatment with two periods, the TWFE model in equation 1.2 corresponds to the classical DD model, where the treatment effect is estimated as the difference between changes in outcomes before and after treatment in a treatment and a control group.[39] The DD identifying assumption relies on parallel trends between treatment and control group, i.e., the average outcomes in treatment and control group would have followed the same trend in the absence of treatment.[40] However, identification is not straightforward in the presence of multiple time periods, multiple treatment groups, or variation in treatment timing.

Recent econometrics literature has pointed out that the TWFE model cannot recover the causal parameter if treatment effects are heterogeneous across time or cohorts/groups (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Goodman-Bacon (2021) shows that under staggered treatment adoption, i.e., when units receive the treatment at different points in time, and under time-varying treatment effects, the TWFE model cannot recover the ATT. Instead, the parameter estimate of ρ in 1.2 represents a weighted average of all possible two-group two-period estimates, where the weights are determined by sample sizes in each group and the variance in the treatment variable. De Chaisemartin and d'Haultfoeuille (2020) show that these weights can even be negative. Following this criticism, Callaway and Sant'Anna (2021) developed an estimator that yields unbiased estimates under staggered treatment adoption and treatment effect heterogeneity. Their approach estimates separate treatment effects for each time period and treatment group and aggregates these estimates using strictly positive weights based on treatment group sizes.

1.3.2 Dynamic panel data models

Many economic relationships are dynamic in nature, where today's outcome depends on its own past realizations. The availability of panel data enables empirical researchers to model these dynamic relationships. The standard approach is to include a lagged dependent variable as a regressor to capture persistence in the dependent variable.

[39] Angrist and Pischke (2008) introduce the difference-in-differences model as a useful alternative when treatment varies at a more aggregate level, e.g., across federal states. In that case, conditioning on state-level fixed effects instead of individual-level fixed effects is sufficient, and the model can be estimated using cross-sectional data (instead of panel data).

[40] In general, the strict exogeneity assumption of the TWFE model is stricter than the parallel trends assumption of the DD model. In the two-period, two-group case, both are equivalent.

$$y_{it} = \beta y_{it-1} + \mu_i + \epsilon_{it} \tag{1.3}$$

Equation 1.3 depicts a dynamic panel data model, where the current outcome, y_{it}, depends on the outcome of the last period, y_{it-1}, and unobserved time-invariant heterogeneity captured by unit fixed effects, μ_i. The inclusion of the lagged dependent variable violates the assumption of strict exogeneity of regressors since y_{it-1} depends on past values of the error term, ϵ_{it}. This causes a correlation between the lagged dependent variable and the residuals of the (time-demeaned) model, essentially creating an endogeneity issue.[41] Estimating equation 1.3 with the standard within estimator will typically be biased and inconsistent when using micro-level panel data, where the number of units N is large while the number of time periods T is small (Nickell, 1981).[42]

To correct for the bias stemming from the correlation between the lagged dependent variable and the error term, instrumental variable approaches can be applied.[43] Anderson and Hsiao (1982) propose to estimate equation 1.3 in first-differences to eliminate the unit-level fixed effects, and then use twice lagged values of the dependent variables as instruments for the differenced lagged dependent variable.

$$\Delta y_{it} = \beta \Delta y_{it-1} + \Delta\epsilon_{it} \tag{1.4}$$

Equation 1.4 is the first-differenced version of equation 1.3. Under the assumptions that the lagged dependent variable is independent from current disturbances, i.e., $\mathbb{E}[y_{it-1}\epsilon_{it}] = 0$, and that the error terms are serially uncorrelated, y_{it-2} is a valid instrument for $\Delta y_{it-1} = y_{it-1} - y_{it-2}$ as it is correlated with Δy_{it-1} and orthogonal to $\Delta\epsilon_{it}$. In this framework, the endogenous regressor is instrumented with one instrumental variable so that the model is just identified. The Anderson and Hsiao (1982) estimator is consistent, but not necessarily efficient as it relies only on one moment condition, although there are additional moment conditions available that could be exploited. Arellano and Bond (1991) developed this idea further and proposed to use all available lags, $y_{it-h}, h \geq 2$, as instruments in

[41] Formally: $\mathbb{E}[\epsilon_{it}|y_{it-1}, ..., y_{i0}, \mu_i] \neq 0$ since $\mathbb{E}[y_{it}\epsilon_{it}] = \beta\mathbb{E}[y_{it-1}\epsilon_{it}] + \mathbb{E}[\mu_i\epsilon_{it}] + \mathbb{E}[\epsilon_{it}^2] = \mathbb{E}[\epsilon_{it}^2] > 0$.

[42] The asymptotic bias of the within estimator does not disappear with $N \to \infty$. Alvarez and Arellano (2003) demonstrate that the asymptotic bias disappears if $lim(\frac{N}{T}) = 0$, meaning that consistency could be achieved if a longer time span was available.

[43] Instrumental variable estimators rely on employing instruments that are correlated with the endogeneous explanatory variable, but independent from the error terms.

a first-differenced Generalized Methods of Moments (GMM) procedure. This approach is consistent if T is fixed and N tends to infinity.

The approach was extended by Blundell and Bond (1998). They combined equations 1.3 and 1.4 into a system of equations in levels and first differences, and obtained additional instruments for the levels equation (BB system-GMM). Specifically, the equations in levels are instrumented by first-differenced lagged values, assuming that these first-differenced instruments are orthogonal to the unit-specific fixed effects. This improves efficiency by using more information relative to the first-difference Arellano and Bond (1991) estimator, especially if the dependent variable is highly persistent, i.e., when β is close to one.

1.4 Outline and contributions

Table 1.1 lists the scientific articles associated with each chapter of this dissertation, including co-authors, own contribution, and current publication status. The subsequent sections outline each chapter's motivation and relevance, contributions, and main results.

1.4.1 The air quality and well-being effects of low emission zones

The second chapter, entitled *The Air Quality and Well-Being Effects of Low Emission Zones* and co-authored with Luis Sarmiento and Aleksandar Zaklan, analyzes the effectiveness and well-being consequences of driving restriction policies. Specifically, we study the most common form of command-and-control policies targeting urban air pollution in Europe, namely low emission zones (LEZs).

The article contributes to the literature in several ways: First, by comprehensively analyzing the policies' impacts on traffic-related pollution, ground-level ozone, and overall air quality. Second, by analyzing spatial policy spillovers that affect pollution levels in neighboring areas, and by uncovering seasonally heterogeneous effects. Third, by providing the first evidence of adverse well-being effects of driving restriction policies.

We identify causal impacts of the policy by exploiting staggered adoption of LEZs across different cities. In doing so, we use difference-in-differences designs robust to staggered implementations and time-varying treatment effects. The identification assumption is that conditional on observables, the implementation of LEZs is orthogonal to unobserved determinants of air pollution, health, and

Table 1.1: Overview of chapters and author's contributions

Ch.	Title	Co-Authors	Contribution	Publication status
2	The Air Quality and Well-Being Effects of Low Emission Zones	Luis Sarmiento, Aleksandar Zaklan	Author was responsible for designing and implementing the analysis of well-being and health. Initiation of research, data preparation, design and implementation of the pollution analysis, and writing and revising the manuscript was collaborative.	Submitted to "Journal of the Association of Environmental and Resource Economists" (March 2022)
3	Indirect Effects of Ground-Level Ozone on Well-Being	Julia Rechlitz, Luis Sarmiento, Aleksandar Zaklan	Author was responsible for preparing the data, implementing the empirical analysis, and revision of the manuscript.*	Unpublished
4	Fracking and Health-Related Absenteeism of Employees	Luis Sarmiento	Author was responsible for initiating research, implementing the analysis, and writing of the manuscript. Data preparation and design of the empirical strategy was collaborative.	Submitted to "Energy Economics" (June 2022)
5	Organic farming, water quality and drinking water supply costs – An empirical analysis for Germany	Greta Sundermann, Astrid Cullmann	Author was responsible for designing the empirical strategy and implementing the estimations. Proposal of the research question, data preparation and writing of the manuscript was collaborative.	Unpublished

* The chapter is based on the DIW Discussion Paper No. 1877 "Make Sure the Kids are OK: Indirect Effects of Ground-Level Ozone on Well-Being" by Julia Rechlitz, Luis Sarmiento, and Aleksandar Zaklan (2020). This chapter presents an improved version of the analysis, where the results on the mechanism are strengthened through linking parents' well-being to children's health outcomes, the inverse-distance weighting approach to calculate pollution exposure is correctly implemented, and the data is extended to cover two additional years.

subjective well-being. The analysis of LEZs' effectiveness is based on air pollution data on the most frequently measured traffic-related contaminants (CO, PM_{10}, NO_2) and ground-level ozone provided by the German Environmental Agency. To comprehensively assess the effects on overall air quality, we construct an air quality index (AQI) based on hourly concentrations of these pollutants. Individual-level data for the analysis of well-being and health comes from the German Socio-Economic Panel.

The results confirm that LEZs decrease traffic-related air pollutants, like PM_{10} and NO_2. In contrast, O_3 levels increase after policy implementation, both inside and outside the LEZs' boundaries. Overall air quality improves inside of the zones, indicating that the increases in O_3 are not large enough to offset the decreases in traffic-related pollutants. We also show that the frequently used two-way fixed effects difference-in-differences models tend to underestimate the policy's effectiveness due to time-varying policy effects. Moreover, the analysis uncovers substantial seasonal heterogeneity in LEZs' air quality impacts, with decreases in traffic-related pollution being more pronounced in winter. In contrast, ozone increases mainly occur during summer, when warmer temperatures and longer sunshine hours accelerate the ozone formation process.

Concerning the effect on individual-level outcomes, we find decreases in self-reported life satisfaction among people living inside a LEZ after policy implementation. Decreases are especially pronounced for owners of diesel cars – the engine class facing the most stringent restrictions – and for working-age individuals. We further find significant reductions in hypertension cases among LEZ inhabitants, in line with the empirical evidence showing that LEZs decrease cardiovascular diseases. Moreover, we find similar-sized reductions in life satisfaction for individuals dwelling near a LEZ. However, the health outcomes of neighboring individuals are not significantly affected, indicating that people living in the vicinity of LEZs bear the costs of restricted mobility but do not benefit from improvements in air quality.

Our findings suggest that policymakers should consider refining the design of LEZs to minimize pollution spillovers and to mitigate the unintended increases in ozone, e.g., by imposing seasonal driving restrictions or enlarging coverage. The negative well-being effects might be reduced by increasing policy acceptance, e.g., through information campaigns about the policy's health benefits.

1.4.2 Indirect effects of ground-level ozone on well-being

The third chapter *Indirect Effects of Ground-Level Ozone on Well-Being*, written collaboratively with Julia Rechlitz, Luis Sarmiento, and Aleksandar Zaklan, explores the heterogeneous impacts of ground-level ozone exposure on human well-being. The main contribution lies in disentangling the mechanisms through which air pollution affects individual well-being and eliciting the indirect channel of children's health.

Using geo-referenced data on individuals and households from the German Socioeconomic Panel (SOEP) and air pollution data from the German Environmental Agency from 2005 to 2018, this study examines the relationship between ozone exposure, subjective well-being, and child health. Based on substantial literature on the pernicious effects of ozone exposure on child and infant health, we hypothesize that ozone indirectly affects parents' life satisfaction through their children's health impacts. We test this indirect channel by comparing the well-being effects of ozone on parents and childless persons. We also examine the direct channel ozone by estimating the impact on subjective health satisfaction of exposed adults. Further insights into the mechanism are gained from distinguishing between parents with children with respiratory illness and parents of healthy children.

The empirical strategy relies on seasonal variation in ozone exposure to identify the effect of air pollution on well-being and health satisfaction. We exploit the exact interview date of SOEP individuals and their residential location to calculate average ozone concentrations for different exposure windows, i.e., the week, month, and quarter before the interview. We use fixed effects regression models to estimate the impact of ozone exposure on subjective life and health satisfaction, controlling for individual- and household-level covariates, weather impacts, interview month and weekday fixed effects, and individual and year fixed effects. We estimate separate effects for parents and childless people, assuming that the sensitivity of individuals' life satisfaction to ozone is not affected by childbirth.

Results suggest a consistently negative relationship between ozone exposure and the well-being of parents, whereas childless people are not significantly affected in their well-being. Health satisfaction of both groups is never significantly impacted by ozone, indicating that the well-being impacts on adults' health are too subtle to notice or stem from another channel. Exploring the mechanism behind the well-being effect on parents, we find that parents of children with respiratory illness are driving the effect, whereas parents of healthy kids are not significantly affected in their well-being. This provides direct evidence that children's health affects the well-being of their parents, either through empathy, worries about missing work, or costs of providing care. Moreover, the negative well-being effects are concentrated among below-median earning parents, in line with the literature showing that children from low-income families are generally less healthy than children from high-income households. The results suggest that a cost-benefit analysis of ozone-related environmental policies should take this indirect channel into account.

1.4.3 Fracking and health-related absenteeism of employees

The fourth chapter, *Fracking and Health-Related Absenteeism of Employees* written in collaboration with Luis Sarmiento, focuses on the adverse labor market impacts of local pollution externalities stemming from resource extraction. Specifically, we quantify the impact of pollution externalities from hydraulic fracturing on surrounding households' labor market outcomes by analyzing health-related employee absenteeism. This chapter contributes to the empirical evidence on environmental pollution and its impacts on individuals' labor supply.

Hydraulic fracturing, commonly referred to as fracking, is a technique to extract natural gas and oil from shale rock formations by injecting high volumes of water, sand, and chemicals into the ground. If hydraulic fracturing leads to significant negative environmental externalities, then individuals living in close proximity to fracking sites will have poorer health outcomes and a higher number of sick leave days than comparable individuals.

We combine 2000 to 2014 individual- and household-level data from the Panel Study of Income Dynamics (PSID) with oil and gas well data from Pennsylvania. We infer causality by using a differences-in-differences design that exploits intertemporal and geographical variation in construction dates and locations of fracking wells. We compare households located within a specific distance to a fracking well to similar households located further away. Propensity-score matching on socio-economic characteristics ensures comparability between both groups. Moreover, our difference-in-differences specification controls for time-varying confounders on the individual- and household-level, for time-invariant unobserved heterogeneity by including individual fixed effects and for time fixed effects.

Our results provide the first evidence of a significant negative labor market effect of fracking, indicating that exposure to a well increases absenteeism by two to three days. The magnitude of the effect is comparable to literature estimates on the impacts of having a chronic illness, e.g., diabetes or obesity. The results inform the cost-benefit perspective of natural resource extraction activities, pointing towards costs in terms of decreased labor supply that have been previously overlooked.

1.4.4 Organic farming, water quality, and drinking water supply costs

The fifth chapter, *Organic Farming, Water Quality, and Drinking Water Supply Costs*, which is co-authored with Greta Sundermann and Astrid Cullmann, provides empirical evidence on the relationships between agricultural farming practices, groundwater pollution, and the cost of drinking water supply. The paper contributes to the literature by linking organic farming practices and groundwater nitrate pollution and by quantifying the impact of nitrate-polluted groundwater on the cost of drinking water supply in Germany.

We merge seven administrative data sources containing geo-referenced information on groundwater nitrate pollution, organic farming, mineral fertilizer application, land cover, settlement structure, weather, and firm-level data on drinking water supply firms. We use a panel of groundwater nitrate monitors from 2008 to 2016 to quantify the impact of organic farming on nitrate pollution in groundwater bodies. We model annual nitrate levels as an auto-regressive process that depends on the share of organically farmed land, conditional on other factors affecting groundwater nitrates, such as mineral fertilizer application, land use, weather, and time-invariant hydro-geological characteristics at the nitrate sampling site. We estimate the auto-regressive model with monitor-level fixed effects using the system GMM estimator proposed by Blundell and Bond (1998). Results suggest that an additional percentage point in the share of organically farmed land decreases nitrate concentrations in surrounding groundwater bodies by 0.3 mg/l on average.

We quantify the impact of groundwater nitrate pollution on the cost of drinking water supply based on a panel of groundwater-abstracting water supply companies. Since water supply firms use different technologies and processes to remove nitrate from abstracted raw water, we estimate separate effects for water treatment costs, composed of expenditures for chemical and energy inputs, and total costs, encompassing treatment costs, labor costs, and capital costs. We model treatment cost as a function of water quality, conditional on the quantity of water abstracted, the composition of source intake, and weather impacts. Estimates are obtained using a two-way fixed effects model that accounts for unobserved firm-level heterogeneity and common time trends. Our results suggest that an increased groundwater nitrate concentration increases firms' treatment costs. More precisely, a one percent increase in groundwater nitrate is associated with an increase in treatment cost by about 0.04 to 0.05 percent. We acknowledge that the process of nitrate removal might not only increase treatment costs but also labor and capital costs. Therefore, we quantify the effect of groundwater nitrate pollution on the total costs of water supply based on a total cost model accounting for labor and capital prices, physical outputs, and environmental factors like pollution. Our findings reveal that groundwater nitrate pollution significantly increases total costs. The estimates show increases in total costs of 0.02 percent for an additional percentage point in groundwater nitrate pollution.

From a policy perspective, our results suggest that organic farming systems can contribute to improving groundwater quality. Expanding the share of organically farmed areas, relative to conventionally farmed agricultural land, could reduce groundwater nitrate pollution in the long run. This would be beneficial for drinking water supply firms and their customers because improved water quality lowers the costs of water supply. This could redeem the current situation, where water consumers ultimately pay the price for pollution externalities stemming from the agricultural sector.

Chapter 2

The Air Quality and Well-Being Effects of Low Emission Zones

2.1 Introduction

Air pollution is a well-known cause of welfare losses, mainly through its impacts on health and human capital (e.g. Graff Zivin and Neidell, 2013; Sarmiento, 2022; Simeonova et al., 2021). Pollution levels are especially high in urban areas, with tailpipe emissions from motorized vehicles being one of the primary sources (Davis, 2008; Gallego, Montero and Salas, 2013). Governments have responded to the mitigation challenge through various policy measures aimed at reducing traffic-related emissions. One increasingly popular approach are low emission zones (LEZs), which restrict vehicles from entering specific geographical areas based on their emission intensity.

While the benefits of LEZs regarding traffic-related pollution are well-understood (e.g. Gehrsitz, 2017; Pestel and Wozny, 2021; Wolff, 2014), the current literature has yet to broaden its scope to a more general assessment of spatial spillovers and overall air quality effects. Examining the zones' impact on overall air quality is necessary, as air quality goes beyond traffic-related pollution by incorporating highly relevant secondary pollutants like ozone (O_3) currently under-researched in the LEZ literature.[1] Moreover, looking at spatial spillovers is relevant because behavioral adaptations of drivers and chemical interactions in the lower atmosphere can lead to unintended changes in air pollution outside the zones' borders, raising questions of environmental justice and policy effectiveness.

Furthermore, although current studies provide convincing evidence that LEZs improve health outcomes (Margaryan, 2021; Pestel and Wozny, 2021), the literature is yet to provide a fuller picture of their overall well-being effects. Again, a broader scope is warranted, as driving restriction policies do not only imply benefits in the form of improved health outcomes but also costs by restricting individual mobility, forcing changes in transportation modes, or imposing costly retrofits on private vehicles. Evaluating the impact of LEZs on self-reported life satisfaction allows us to understand whether the cost or the benefit side plays a more prominent role in determining the policy's impact on individuals' well-being. We estimate the impact of LEZs on affected individuals' health and subjective well-being outcomes with data from the German Socio-Economic Panel (SOEP).

Like previous studies, we identify the causal effect of LEZs by exploiting the spatio-temporal variation arising from the staggered implementation of the

[1] Primary (point source) pollutants are emitted directly from a source, whereas secondary (non-point source) pollutants form when other pollutants react in the atmosphere. Examples of primary pollutants are carbon monoxide (CO) and sulfur dioxide (SO_2). Examples of secondary pollutants are O_3 and coarse particulate matter (PM_{10}). It is also worth noting that nitrogen dioxide (NO_2) can both work as a primary and secondary pollutant.

policy across different cities using difference-in-differences (DD) designs. The identification assumption is that conditional on observables, the implementation of LEZs is orthogonal to unobserved determinants of air pollution, health, and subjective well-being. Furthermore, recent advances in the DD literature show that two-way fixed effects difference-in-differences (TWFE-DD) estimates are potentially biased under staggered policy adoption and dynamic treatment effects (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). We confirm the existence of this bias in the case of LEZs by decomposing the TWFE-DD estimate with the methodology outlined by Goodman-Bacon (2021). Specifically, TWFE-DD point estimates are biased towards zero because of the comparison of later vs. earlier treated units. To avoid this source of bias, we use the Callaway and Sant'Anna difference-in-differences (CS-DD) methodology (Callaway and Sant'Anna, 2021), which allows us to estimate unbiased group and time-specific average treatment effects on the treated (ATTs).

Our results confirm previous studies on the effectiveness of LEZs at decreasing the concentrations of coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2) (Gehrsitz, 2017; Pestel and Wozny, 2021; Wolff, 2014). Furthermore, we also find robust evidence of an increase in O_3, providing, to the best of our knowledge, the first evidence of LEZs' unintended effects arising from the inverse relationship between NO_2 and O_3 in nitrous-rich regions like urban centers (Monks et al., 2015) (cf. Section A.1). This O_3 increase is quite relevant given the intrinsic relationship between ozone exposure and exacerbated morbidity. For instance, the 2019 Global Burden of Disease Study estimates 365,000 ozone-related deaths per year around the world (DeLang et al., 2021). Nevertheless, even with the rise in O_3, we provide evidence of overall air quality improvements as captured by the zones' effect on the air quality index (AQI). Concerning spatial spillovers, we show increments in the concentration of O_3 and CO outside the zones' borders and no effects regarding PM_{10} and NO_2.

Examining the effect on individual-level outcomes, we find a significant decrease in individuals' self-reported levels of life satisfaction. Decreases are especially pronounced for owners of diesel cars – the engine class facing the most stringent restrictions – and for working-age individuals. On average, the life satisfaction of individuals living inside a LEZ decreases by 0.19 points after policy adoption. This effect is substantive as it amounts to about 20% of the life satisfaction effect of becoming unemployed found in the literature (Kassenboehmer and Haisken-DeNew, 2009). We further show that the drop in life satisfaction is immediate, lasts for several years after policy implementation but is ultimately transient.

Additionally, we provide evidence of improvements in objective health outcomes. Focusing on the subset of individuals with available health data, we estimate a significant decrease in hypertension cases, while confirming the negative impact on well-being for this smaller sample. Therefore, our results suggest that the implicit cost of restricting mobility outweigh the well-being benefits of improved health outcomes, at least on average. Looking at heterogeneous effects by age groups reveals that the decrease in hypertension cases accrues mostly to people aged 60 or older, while the life satisfaction decrease is less pronounced within this age group.

Concerning policy spillovers to outside areas, we find similar-sized reductions in life satisfaction for individuals dwelling near a LEZ, which is not surprising given that persons living outside the zone's borders likely need to enter the neighboring zone at some point in time for leisure or work-related activities. However, health outcomes for these individuals show no significant changes after policy implementation, implying that people in the vicinity of LEZs bear the costs of restricted mobility but do not benefit from improvements in air quality.

From a policy perspective, our findings suggest that policymakers should consider refining the design of LEZs to minimize the impact of harmful spatial spillovers and the unintended effects on secondary air pollutants. Possible strategies could be to increase LEZs' coverage area, anticipate the impact on ozone for regions with high ozone levels, or contemplate restricting traffic only in the winter months when traffic-related pollution is more elevated. Our well-being results imply that policymakers should look at both the costs and benefits of driving restriction policies, as only focusing on the benefits can present a distorted picture of their actual effects. Particularly for LEZs, policymakers could potentially reduce their adverse well-being effects through information campaigns about the policy's health benefits, nudging, transfer mechanisms like tax credits to purchase cleaner vehicles, or public transport waivers.

Related literature

Previous studies on the effects of LEZs provide compelling evidence of a statistically significant reduction in the concentration of traffic-related contaminants within the zones' borders. For instance, Wolff (2014) is an important earlier contribution estimating a significant PM_{10} decrease with TWFE-DD; a result later confirmed by Malina and Scheffler (2015) with fixed-effects panel regressions. Gehrsitz (2017) and Pestel and Wozny (2021) update Wolff (2014)' estimates regarding PM_{10} and provide additional evidence of a negative effect for NO_2. Finally, Ellison, Greaves and Hensher (2013) and Zhai and Wolff (2021) uncover similar PM_{10} effects for the London LEZ.

Regarding spillovers, although Wolff (2014) finds beneficial PM_{10} spillovers for the case of the Berlin LEZ, he obtains no significant estimate when looking at average effects across Germany. Gehrsitz (2017) analyzes PM_{10} spillovers using a larger data set covering more LEZs over a longer time period and finds only suggestive evidence of beneficial effects, with point estimates at outside stations being negative but insignificant.

Concerning the effects of the policy on objective health outcomes, Margaryan (2021) uses detailed register data on outpatient and inpatient health care to show that LEZs have clear health benefits, Pestel and Wozny (2021) provides evidence of an adverse effect on extreme health outcomes like hospitalizations due to cardiovascular and respiratory conditions, and Rohlf et al. (2020) provide evidence of reductions in pharmaceutical expenses. Notably, Gehrsitz (2017) deviates from the overall positive policy implications by concluding that LEZs' pollution reductions are too small to affect infant health.

A related but distinct stream of the literature analyzes the effectiveness of the second dominant type of driving restriction, alternate-day travel policies. Our results suggest that LEZs are more effective than alternate-day restrictions at reducing traffic-related air contaminants, as the evidence on the effectiveness of alternate-day travel policies is mixed. Davis (2008, 2017) analyzes the effect of driving restrictions in Mexico City and concludes that the program was ineffective and even counterproductive with respect to pollution. Gallego, Montero and Salas (2013) echoes this for similar transport reforms in Santiago de Chile. The evidence on similar instruments in China, however, suggests greater effectiveness. Zhong, Cao and Wang (2017) show that alternate-day travel policy in Beijing reduces air pollution. Chen et al. (2013) show that Beijing temporarily improved air quality with alternate-day travel restrictions on the eve of the 2008 Olympic games. In the same vein Viard and Fu (2015) show that the same restriction policy in Beijing is effective at reducing air pollution despite limited compliance (Wang, Xu and Qin, 2014). To our knowledge, there is currently no evidence on the well-being effects of any type of driving restriction policy in the literature.

2.2 Background on LEZs

Policymakers in the European Union try to minimize air pollution's health risks by setting limit values to pollutant concentrations.[2] The limit values are legally binding. In the case of non-attainment, the member states must propose and implement action plans to reduce the risk or duration of future limit violations; if the member states fail to implement sufficient measures to reduce pollution, repeated non-attainment results in financial penalties. Table 2.1 portrays current exposure limits in the European Union.

Table 2.1: EU air quality regulations

Pollutant	Concentration	Avg. period	Legal nature	Permitted exceedance days per year
CO	10 mg/m^3	Max. daily 8 h mean	Limit value as of 1.1.2005	NA
NO_2	200 μg/m^3	1 hour	Limit value as of 1.1.2010	18
NO_2	40 μg/m^3	1 year	Limit value as of 1.1.2010	NA
O_3	120 μg/m^3	Max. daily 8 h mean	Target value as of 1.1.2010	25 days averaged over 3 years
PM_{10}	50μg/m^3	24 hours	Limit value as of 1.1.2005	35
PM_{10}	40μg/m^3	1 year	Limit value as of 1.1.2005	NA

Source: EU (2008b).

Germany implemented the 22nd Ordinance of the Federal Immission Control Act (Bundes-Immissionsschutzgesetz - BImSchG) to comply with EU legislation. This law made EU limit values legally binding as of January 2005. In the following years, many cities could not adhere to the limit values for NO_2 and PM_{10}. Between 2005 and 2007, 89 urban centers violated the daily PM_{10} limit of 50 μg/m^3 on more than 35 days in at least one year. Among these, 52 were large cities with more than 100,000 inhabitants, which amounts to 65 percent of all large cities in Germany. 54 cities exceeded the annual NO_2 limit of 40 μg/m^3 for at least one year. Consequently, German federal states and local administrations had to draw up clean air action plans (CAAPs) for improving air quality. These action plans targeted traffic exhaust-related pollutants and consisted of bundles of policy measures, commonly involving the introduction of a low emission zone (LEZ).[3]

The Ordinance on the marking of vehicles (35th BImSchV) provides the legal basis for introducing low emission zones by giving state and local governments the

[2] Directive 1999/30/EC (EU, 1999) defines permissible concentrations for NO_2, SO_2 and PM_{10}, Directive 2000/69/EC (EU, 2000b) set limits for carbon monoxide (CO), and Directive 2002/3/EC (EU, 2002) focuses on O_3. These legislations were revised in 2008 and unified into the single Directive 2008/50/EC (EU, 2008b) that defines current limit values and detailed measurement procedures for all criteria pollutants.

[3] Other frequently applied policy measures include the procurement of cleaner public transport vehicles, closing of heavy traffic roads for commercial vehicles, building of ring roads, and traffic re-routing.

right to restrict access to specific city areas for cars not complying with predefined emission standards. Germany enforces LEZs through colored stickers on car's windshields: Only automobiles with a specifically colored sticker can enter the LEZ. Red stickers represent the highest emitting vehicles, and green stickers the least emitting ones; Table 2.2 lists details on the stringency of emission standards and stickers. The policy is enforced by police and municipal authorities and infringement results in fines for the vehicle driver.[4]

Table 2.2: Relevant emission standards for LEZ sticker categories

	No Sticker	Red	Yellow	Green
Diesel	Euro 1 or older	Euro 2 / Euro 1 with particle filter	Euro 3 / Euro 2 with particle filter	Euro 4 or better / Euro 3 with particle filter
Gasoline	Without catalytic converter	–	–	Euro 1 with catalytic converter or better

Notes: Relevant emission standards for LEZ sticker categories defined in the Ordinance on the marking of vehicles (35th BImSchV). The Euro standards represent the EU emission regulations for new light duty vehicles based on Directive 70/220/EEC and its amendments.

2.3 Data

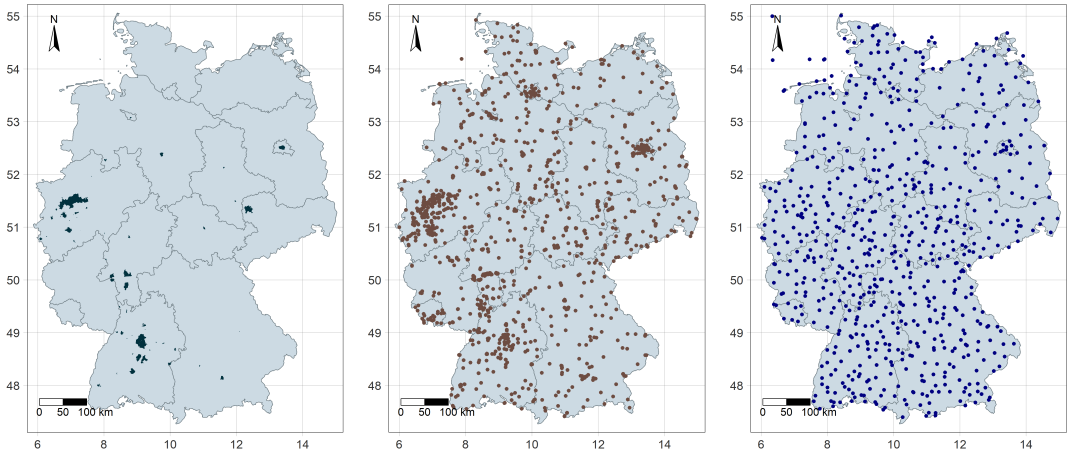
We collect granular pollution measures from the German Environment Agency (UBA) covering 659 monitoring stations scattered throughout Germany. The data contains daily averages of CO, NO_2, O_3, and PM_{10} between 2005 and 2018. Furthermore, we also obtain hourly pollution readings to calculate the AQI according to the formula of the U.S. Environmental Protection Agency (EPA) (EPA, 2018). The AQI maps the concentration of all criteria pollutants into an index between zero and five hundred units, the higher the index, the worse the air quality conditions.

Figure 2.1 shows the spatial distribution of LEZs, air pollution measuring stations, and weather stations in Germany. Information on the location and implementation dates of LEZs comes from UBA's website. We further collect data on the implementation of Clean Air Action Plans (CAAP), which are bundes of local air pollution mitigation policies introduced by city governments that can come with or without LEZs. In 2018, there were 58 active LEZs that concentrate in the country's most populated urban areas around Berlin, Munich, Stuttgart,

[4] In 2008, the fine for entering a LEZ without the appropriate sticker amounted to 40 Euro plus one penalty point at the driving license office. In 2014, the fines were doubled whereas the penalty point was abolished.

Frankfurt, Cologne, and the Ruhrgebiet region. In contrast, monitoring and weather stations are more scattered throughout the country.

Figure 2.1: Spatial distribution of low emission zones, pollution, and weather stations

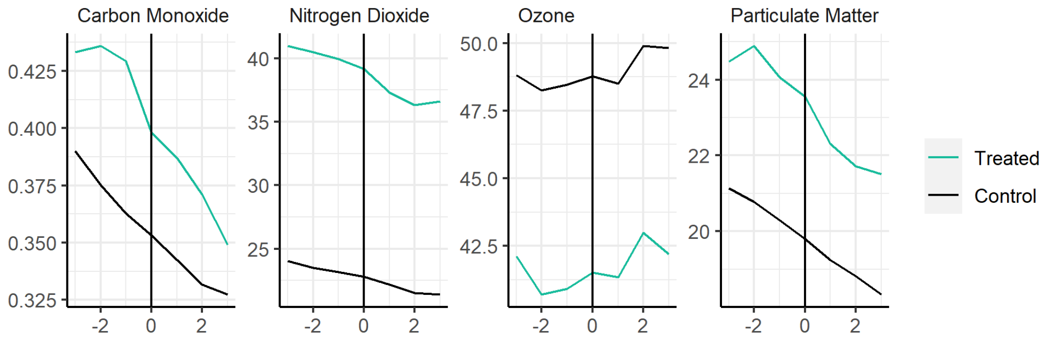


(a) Low Emission Zones (b) Air pollution stations (c) Weather stations

Notes: The left-hand panel depicts all low emission zone (LEZ) introduced between 2008 and 2018, the center panel shows all pollution monitors active during the study period between 2005 and 2018, and the right-hand side panel plots all weather monitors between 2005 and 2018.

Figure 2.2 compares the evolution of CO, NO_2, O_3, and PM_{10} levels between treated and control stations inside and outside active LEZs, accounting for the staggered introduction of LEZs. Note that Figure A.1 shows the same common trends for all specifications of the control group used in our empirical design, while Table A.1 lists overall average pollutant concentrations for treatment and control stations. This figure is different from standard common trends plots because of the staggered introduction of LEZs. In it, we average the values of all possible event-time combinations across treatment and control groups. For instance, the value at $t = -1$ for the treated group is the average value one year before implementing LEZs across all treatment groups, i.e., all groups of stations where LEZs were implemented in the same year. Furthermore, we avoid compositional changes in the treatment group by restricting the time window to three years around treatment, this is necessary because not restricting the time-window change the sample of treated stations, i.e., stations treated in 2016 would drop from the sample at $t = -4$.[5] We observe similar trends between treated and control units before the introduction of LEZs.

Figure 2.2: Pre- and post-treatment averages for treated and control stations



Notes: Inter-temporal comparison of average pollution between treated and control units. The vertical axis contains the average of each criteria pollutant and the horizontal axis the time to treatment, i.e., number of years to the introduction of a LEZ. Each data point corresponds to the average value of all possible event-time combinations across treated and control units. We restrict the horizontal axis to two periods before and after treatment because these are the only ones without compositional changes..

To assess the effect of LEZs on individual-level outcomes, we use data from the German Socio-Economic Panel Study (SOEP) between 2005 and 2018. The SOEP is a representative longitudinal survey that collects information on persons and households in Germany since 1984. The data contains our primary outcome variable; self-rated individual life satisfaction measured on an 11-point Likert scale,[6] as well as a wide range of health and socio-demographic characteristics. Importantly, we observe the geographic location of households at the street-block level and the exact interview date of individuals, allowing us to determine whether they live within LEZs and whether the SOEP interviewed them before or after the zone became active. For individuals residing outside of LEZs, we observe the distance to the closest LEZ and the corresponding implementation date.

The SOEP incorporated several enlargements and refreshment samples in recent years, such that individuals can already live in an active LEZ at the time of their first interview. Hence, we exclude the always treated because their pre-treatment outcomes are unobserved and do not contribute to identification in our empirical setting. By dropping these cases, we avoid unnecessary compositional

[5] Specifically, the exposure value τ periods to the treatment date is: $\hat{Pol}_{\tau}^{Treated} \mid \hat{Pol}_{\tau}^{Control} = \frac{1}{N^{\tau}} \sum_{\tau=-15}^{6} \frac{1}{N^{c}} \sum_{c} Pol\tau^{c} \quad \forall\, \tau = (Y - G)$. Y indicates the year of the observation and G the treatment group, i.e., the year of LEZ implementation. N^{τ} is the number of times τ takes an specific value, e.g., for $\tau = -1$, there are six different combinations of Y and G; (2009-2010, 2010-2011, ... 2016-2017). Finally, N^{c} refers to the number of stations.

[6] SOEP individuals rate how satisfied they are with their lives overall on a scale from 0 (“completely dissatisfied”) to 10 (“completely satisfied”).

changes in our treatment group that hinder the causal interpretation of point estimates. For similar reasons, we also drop individuals surveyed for one single year and individuals outside of LEZs who were interviewed by SOEP after the closest LEZ came into effect. Additionally, we also exclude individuals that changed their place of residence during our study period to avoid confounding effects from residential sorting.[7]

Table 2.3 lists descriptive statistics on all treated and control individuals in the selected sample described above, while descriptives on two alternative control groups used in the empirical analysis are shown in Table A.2. Individuals residing inside LEZs are, on average, more educated, have a higher income, and fewer children. Moreover, fewer households inside the zones own a motor vehicle. Regarding health variables, we observe on average one additional doctor visit per year among treated subjects, while hypertension and cancer shares are very similar in both groups.

Panel A in Figure 2.3 depicts the number of individuals per treatment group. We define treatment groups as the first year after treatment, i.e., the year of the first SOEP interview after LEZ implementation. The fact that new persons are treated every year between 2008 and 2016 illustrates the variation in treatment timing induced by the staggered adoption of LEZs. Early LEZs affect around 42% of all treated persons, with large cities like Berlin and Munich introducing LEZs between 2008 and 2009.[8] Panel B depicts the annual averages of life satisfaction in the treatment and the control group centered around LEZ implementation dates, based on the same methodology as for the pollution outcomes. Figure A.2 shows the same graph for all control samples used in the empirical analysis. In the first three years prior to LEZ adoption, average life satisfaction develops in parallel for the treated and control sample. In the year of LEZ implementation, the average well-being of treated individuals drops visibly. Furthermore, section 2.7.3 provides further evidence that the common trends assumption between treatment and control groups cannot be rejected.

[7] Results are robust to the inclusion of movers and are listed in Table A.5. Around 30 percent of SOEP individuals change their place of residence during the study period.

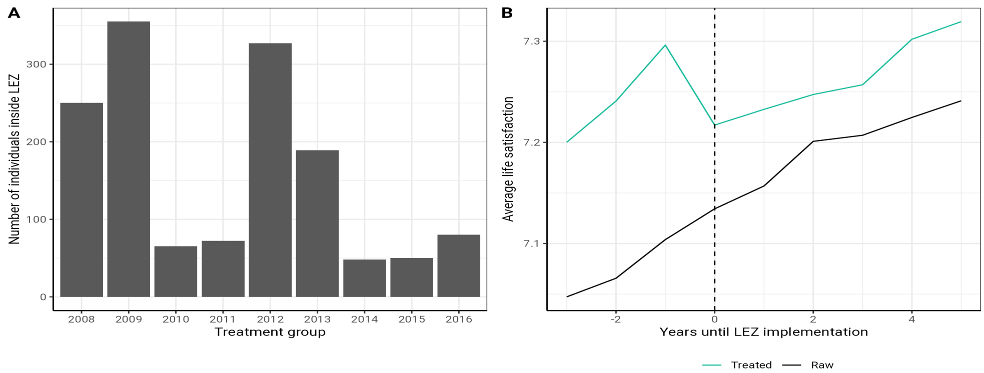
[8] We exclude LEZs introduced in 2017 and 2018 because they were all implemented in relatively small towns, where we observe fewer than 20 treated individuals per treatment group. The small number of units in these treatment cohorts hinders reliable estimation of group-time ATTs.

Table 2.3: Descriptive statistics on SOEP individuals

	Inside LEZ			Outside LEZ
	Total	Before	After	Total
Life satisfaction [0-10]	7.11	7.08	7.14	7.10
	(1.73)	(1.73)	(1.73)	(1.76)
Age [years]	54.47	52.86	55.65	54.11
	(16.64)	(16.04)	(16.98)	(17.04)
Is female [%]	0.53	0.53	0.53	0.52
	(0.50)	(0.50)	(0.50)	(0.50)
Is employed [%]	0.56	0.54	0.57	0.56
	(0.50)	(0.50)	(0.50)	(0.50)
Income [Thsd Euro]	44.99	43.90	45.79	42.20
	(35.11)	(34.61)	(35.45)	(33.81)
Education [years]	12.89	12.69	13.04	12.26
	(3.06)	(3.02)	(3.08)	(2.63)
Number children	0.44	0.51	0.39	0.48
	(0.90)	(0.93)	(0.87)	(0.92)
Owns motor vehicle [%]	0.81	0.83	0.80	0.90
	(0.39)	(0.38)	(0.40)	(0.30)
Number motor vehicles	1.26	1.28	1.26	1.58
	(0.95)	(0.91)	(0.97)	(1.06)
Owns diesel car [%]	0.32	0.33	0.31	0.33
	(0.47)	(0.47)	(0.46)	(0.47)
Number doctor visits	11.09	11.30	10.94	10.08
	(15.19)	(15.60)	(14.88)	(15.08)
Has hypertension [%]	0.31	0.32	0.31	0.32
	(0.46)	(0.47)	(0.46)	(0.47)
Has cancer [%]	0.06	0.06	0.06	0.06
	(0.24)	(0.23)	(0.25)	(0.24)
Number individuals	1436	1436	1436	19578
Number observations	12634	5348	7286	141411

Notes: This table shows the average characteristics of treated and control SOEP individuals observed between 2005 and 2018. Treated persons reside within the LEZs area and control individuals outside. For the treated sample, we present overall, pre-treatment, and post-treatment averages. For control persons, we present overall averages.

Figure 2.3: Number of individuals per treatment group and average well-being of treated and control individuals



Notes: Panel A shows the number of persons per treatment group between 2008 and 2016. We define treatment groups as the first year we observe individuals after treatment. Panel B shows annual averages of life satisfaction between treated and control units. The vertical axis contains the average of life satisfaction, and the horizontal axis the time to treatment (τ). Each data point corresponds to the average value of all possible event-time combinations across treatment and control groups three years around policy adoption.

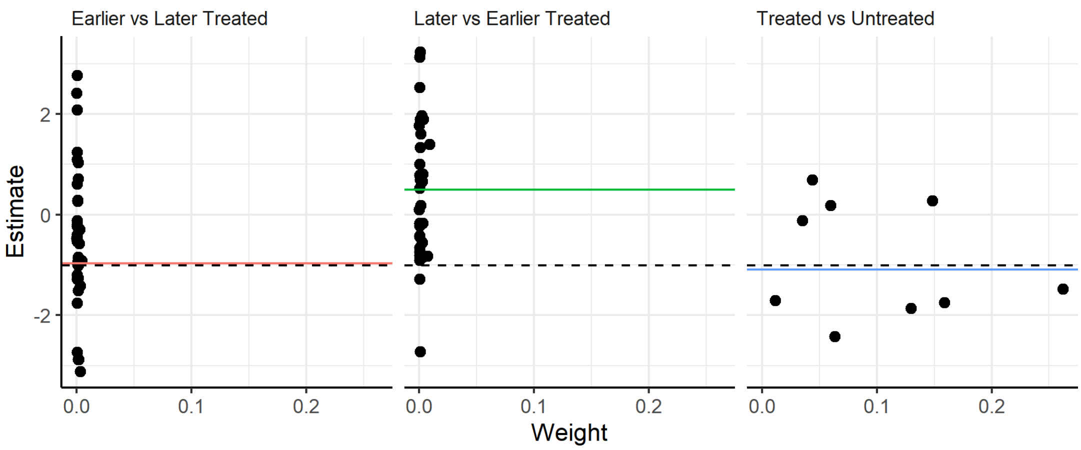
2.4 Research design

2.4.1 Empirical methodology

Identifying the effect of LEZ is not trivial as their implementation across Germany is not random (see Section 2.2). If we do not consider this systematic difference between treated and control stations, it can lead to biased estimates of the true treatment effect. Like previous studies analyzing the impacts of LEZs, we address the identification challenge by leveraging the spatiotemporal variation in the zones' implementation date using DD designs.

Additionally, our research design explicitly takes into account that when implementing DDs with more than two periods and variation in treatment timing, the weights used to compute ATTs with standard TWFE-DD can lead to biased estimates (De Chaisemartin and d'Haultfoeuille, 2020). For instance, Goodman-Bacon (2021) shows that the coefficient of the TWFE-DD design is the weighted average for all possible two-group two-period combinations of three different comparison groups: earlier vs. later treated, later vs. earlier treated, and treated vs. untreated. Figure 2.4 portrays our sample's PM_{10} estimates across the three comparison groups. The dotted line is the weighted TWFE-DD estimate across all comparison groups, and the solid horizontal lines are average coefficients for each comparison group.

Figure 2.4: Goodman-Bacon decomposition for the effect of LEZs on the concentration of coarse particulate matter (PM_{10})



Notes: Goodman-Bacon (2021) decomposition. Solid horizontal lines represent TWFE-DD estimates on the impact of LEZs on annual PM_{10} levels. Treated stations are inside the zone and control stations between 25 and 75 km from the zone's border. Each estimation sample consists of a balanced panel of stations measuring the respective pollutant between 2005 and 2018.

Because already-treated stations ("Earlier Treated" in Figure 2.4) experienced substantial decreases in pollutant levels after implementation, their results bias the TWFE-DD towards zero, resulting in an underestimation of the LEZs' true impact. In our setting, the bias is so severe that for most Later vs. Earlier Treated comparisons, the sign of the coefficient reverses relative to other comparisons.[9]

To obtain unbiased estimates under staggered policy adoption and time-varying treatment effects, we use the CS-DD estimator that allows us to estimate and flexibly aggregate group-time ATTs across multiple groups and time periods (Callaway and Sant'Anna, 2021). Other advantages of CS-DD are that it lets us compute unbiased event-time estimates suitable to examine time-varying treatment effects and formally assess the common trends assumption while considering the effects of selective treatment timing. Equation 2.1 shows the CS-DD empirical model:

$$y_{itg} = \beta_{ge} LEZ_{itg} + \lambda_i + \gamma_t + \epsilon_{it} \,, \tag{2.1}$$

where y_{itg} is the yearly average pollution level for unit i, treated in year g, measured at time t. The treatment group g corresponds to all units treated in $t = g$, e.g., all units initially treated in 2008 are part of the 2008 treatment group. β_{ge} are the point estimates of interest and represent the ATT for stations in group g at time since treatment $e = t - g$. LEZ_{itg} is a dummy variable equal to one if, in period t, unit i in group g is treated. Finally, λ_i and γ_t are unit and year fixed effects.

To estimate dynamic treatment effects in the vein of TWFE-DDs event study designs, we aggregate β_{ge} according to equation 2.2. In it, β_e is the average treatment e periods after treatment and $P[G = g|G + e \leq T]$ the probability of being first treated in period g, conditional on being observed e periods after treatment. Note that because the length of treatment can vary across stations, treatment groups' composition can change with e. We provide estimates robust to this potential pitfall by balancing the groups with respect to e, i.e., we only aggregate β_{ge} for a subset of stations treated for at least n periods.

$$\beta_e = \sum_{g \in G} \omega^e_{gt} \beta_{ge} \quad \forall \quad \omega^e_{gt} = 1[g + e \leq T] \times P[G = g|G + e \leq T] \,, \tag{2.2}$$

[9] On average, the 2x2 DD estimates for the Later vs. Earlier Treated comparisons amount to 0.49 micrograms per cubic meter (μg/m^3) for PM_{10}. These comparisons get a weight of 12 percent, indicating that this timing group is relatively influential for the overall TWFE-DD parameter.

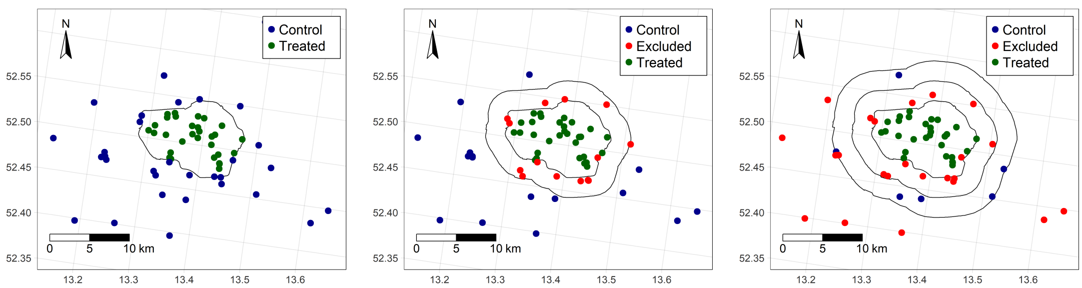
Finally, equation 2.3 aggregates individual group and event-time ATTs into an average ATT across all treatment group and time periods, where β is the weighted sum of β_{ge} with strictly positive weights and larger weights for larger group sizes.

$$\beta = \frac{1}{\kappa} \sum_{g \in G} \sum_{e=1}^{T} \omega_{gt} \beta_{ge} \quad \forall \quad \omega_{gt} = 1[t \geq g] \times P[G = g | G \leq T] \,, \tag{2.3}$$

2.4.2 Specifying the control group

Figure 2.5 illustrates the construction of our baseline control samples. First, the raw sample encompasses all stations outside LEZs. Second, we restrict the raw sample with a 25 km exclusion area between the treatment and control group to avoid spatial spillovers threatening the validity of SUTVA; treated stations are inside the zone (green), excluded stations are all stations between 0 and 25 km from the zone's border (red), and the control group consists of all stations further away from the 25 km buffer (blue). Third, in the doughnut design, we increase the comparability of treatment and control units by restricting the outer edge of the control group to 50 km from the start of our buffer area.[10]

Figure 2.5: Control group specifications of the CS-DD design (Berlin low emission zone)



(a) Raw (b) Buffer (c) Doughnut

Notes: These figures illustrate the raw, buffer, and doughnut specifications of the CS-DD using Berlin's LEZ.

Moreover, we also provide estimates for a fourth specification by restricting the control group to stations in cities with a CAAP but no LEZ. This final sample allows us to increase the similarity of treated and controls regarding pre-treatment pollution levels. We choose the doughnut design as our preferred specification because it balances the threat of spillovers with a closer geographical

[10] Very similar results hold at other distances, i.e., 100, 150, 200 km. They are available upon request.

match between the treatment and control groups. However, all specifications are consistent with the common trend assumption and deliver similar ATT estimates.[11]

2.5 Effects on air pollution

2.5.1 Average treatment effect on the treated

Table 2.4 shows the ATT for the raw, buffer, doughnut, and CAAP specifications.[12] Concerning CO, coefficients are negative and on the verge of being statistically significant across specifications. For NO_2, all estimates are negative and statistically significant at the one percent level. They range from 2.85 to 4.09 $\mu g/m^3$ in the CAAP and doughnut specifications, confirming the findings of previous studies like Pestel and Wozny (2021) and Gehrsitz (2017) who estimate respective reductions of 1.6 and 0.5 $\mu g/m^3$. The difference in magnitude between our estimates and Pestel and Wozny (2021) or Gehrsitz (2017) likely comes from the inherent Goodman-Bacon (2021) bias depicted in Figure 2.4.

Next, there is evidence of O_3 increases across specifications. In the doughnut design, we estimate that LEZs increase the concentration of O_3 by 1.18 $\mu g/m^3$. Also in line with previous TWFE-DD estimates, all specifications point to a significant PM_{10} reduction ranging between 1.51 and 1.97 $\mu g/m^3$. For instance, Pestel and Wozny (2021) and Gehrsitz (2017) estimate a reduction of 1.4 and 0.7 $\mu g/m^3$, while Wolff (2014)'s log-linear TWFE-DD model uncovers a 9.1% reduction, equivalent to a decrease of about 2.1 $\mu g/m^3$.[13]

2.5.2 Dynamic treatment effects

Figure 2.6 plots event-time ATTs for the preferred doughnut specification, which are similar for the raw, buffer, and CAAP samples (see Figures A.3, A.4, and A.5). Each estimate corresponds to the ATT at each time period before and after treatment. The grey shaded areas represent 95% confidence intervals.

[11] Our choice of control group is in line with an alternative data-driven approach, in which regression discontinuity (RD) models with time as the running variable are used to estimate the local average treatment effect (LATE) of LEZs at pollution monitors outside the restriction area within a narrow time window around their implementation date. We refer the interested reader to the working paper version (Sarmiento, Wägner and Zaklan, 2021) for further information.

[12] For the curious reader, in section A.4.2 we provide results by type of measuring station, i.e., UBA divides stations into traffic and background. Traffic stations are often next to major roads at street level. Background stations are often on top of buildings in background areas.

[13] We obtain a reduction by 2.1 $\mu g/m^3$ by taking 9.1% of the 2007 average PM_{10} level of 23.1 reported by Wolff (2014) in Table 1.

Table 2.4: Effect of the introduction of LEZ on air pollution

(a) Raw

	CO	NO_2	O_3	PM_{10}
	−0.03	-3.78^{***}	0.96^{+}	-1.77^{***}
	(0.02)	(0.72)	(0.58)	(0.50)
N.Obs	1759	5799	3914	5051
N.Stations	255	556	365	508
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(b) Buffer

	CO	NO_2	O_3	PM_{10}
	−0.03	-3.81^{***}	1.27^{**}	-1.90^{***}
	(0.02)	(0.77)	(0.59)	(0.53)
N.Obs	1394	4504	2943	3849
N.Stations	197	425	271	383
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(c) Doughnut

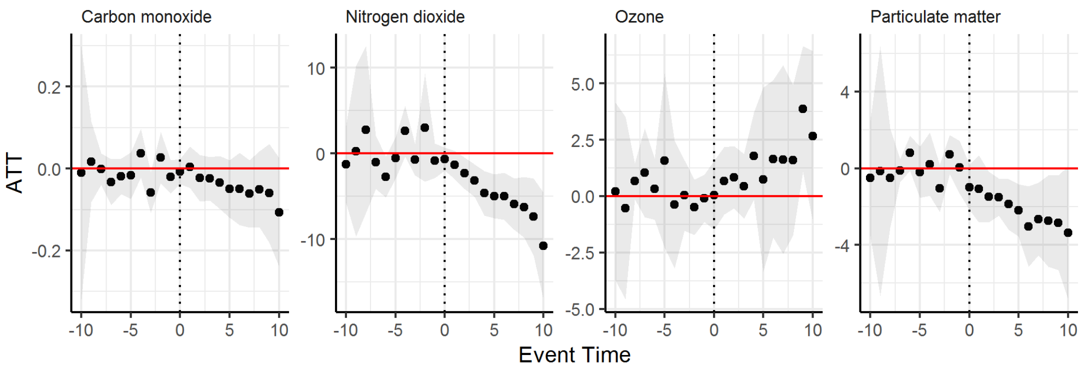
	CO	NO_2	O_3	PM_{10}
	−0.03	-4.09^{***}	1.18^{*}	-1.97^{***}
	(0.02)	(0.87)	(0.65)	(0.51)
N.Obs	906	2832	1704	2502
N.Stations	134	266	157	248
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(d) CAAP

	CO	NO_2	O_3	PM_{10}
	−0.02	-2.85^{***}	1.21	-1.51^{***}
	(0.02)	(0.83)	(0.80)	(0.53)
N.Obs	1016	2588	1087	2163
N.Stations	131	244	106	220
N.Groups	8	8	8	8
N.Periods	14	14	14	14

Notes: CS-DD estimates for the impact of LEZs on annual air pollution concentrations across four different specifications of the control sample. The raw control group contains all stations outside LEZs. The buffer design restricts the raw sample to stations beyond 25 km from LEZs' borders. The doughnut sample further trims the control group by restricting its outer edge to 75 km. Finally, the CAAP control group contain only stations in cities with CAAP but no LEZ. The CS-DD model controls for station and year fixed effects. Standard errors are clustered at the municipality level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Figure 2.6: Event-time ATTs



Notes: Event-time CS-DD estimates for the impact of LEZs on annual air pollutant concentrations. Event time measured in years before/after policy implementation. Treated stations are inside the zone and control stations between 25 and 75 km from the zone's border. The CS-DD model controls for station and year fixed effects. Grey ribbons represent 95% confidence intervals. We cluster standard errors at the municipality level. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Concerning, CO, although all post-treatment coefficients are negative, we find no significant effects after the implementation. For NO_2, on the other hand, we observe statistically significant reductions from the second period onward, with pollutant levels decreasing by 10.3 $\mu g/m^3$ during the last time interval. Point estimates for O_3 are positive in every post-treatment period but with wide confidence bands. Finally, the event-time ATTs for PM_{10} are negative and statistically different from zero from the second period onward.[14] Reassuringly, we cannot reject the common trends assumption for any pollutant as there are no significant pre-treatment effects.

2.5.3 Heterogeneous seasonal effects

Working with annual averages can mask seasonal heterogeneity in the effectiveness of LEZs. For instance, O_3 is more predominant during the spring and summer months because of its interaction with solar radiation, while NO_2 and PM_{10} are higher during the winter months because of residential heating and the lower efficiency of internal combustion engines at low temperatures. Table 2.5 shows the seasonal results using the doughnut specification.[15]

Table 2.5: Seasonal effects of the introduction of LEZs on air pollution

(a) Carbon monoxide (CO)

	Winter	Spring	Summer	Fall
	-0.05^{*}	-0.04^{**}	-0.02	-0.03
	(0.03)	(0.02)	(0.02)	(0.03)
N.Obs	906	874	868	871
N.Stations	134	133	131	131
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(b) Nitrogen dioxide (NO_2)

	Winter	Spring	Summer	Fall
	-3.61^{***}	-4.54^{***}	-3.96^{***}	-4.91^{***}
	(0.74)	(1.15)	(0.85)	(0.93)
N.Obs	2832	2797	2789	2792
N.Stations	266	266	266	266
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(c) Ozone (O_3)

	Winter	Spring	Summer	Fall
	0.66	1.79^{*}	1.99^{**}	0.76^{*}
	(0.54)	(0.93)	(0.87)	(0.45)
N.Obs	1703	1682	1672	1677
N.Stations	156	155	154	155
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(d) Coarse particulate matter (PM_{10})

	Winter	Spring	Summer	Fall
	-1.83^{***}	-1.92^{***}	-2.02^{***}	-2.65^{***}
	(0.68)	(0.69)	(0.63)	(0.74)
N.Obs	2502	2456	2450	2459
N.Stations	248	247	247	248
N.Groups	8	8	8	8
N.Periods	14	14	14	14

Notes: CS-DD estimates for the impact of LEZs on seasonal air pollution concentrations across four different seasons. Treated stations are inside the zone and control stations between 25 and 75 km from the zone's border. We calculate the average exposure in each season by averaging daily pollution values. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipality level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter (μg/m^3) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Results reveal substantial seasonal heterogeneity in the effectiveness of LEZs. We estimate significant reductions in the concentration of CO, NO_2, and PM_{10} during the winter months of -0.05, -3.61 , and -1.83 μg/m^3. The significant winter estimate for CO arises because the lower efficiency of internal combustion engines

[14] Note that compositional changes may affect the results of the CS-DD estimates. For robustness, we restrict the sample underlying the event-time ATTs to contain only stations with five post-treatment periods. Figure A.6 shows the results for the balanced version of the doughnut specification and confirms that compositional changes do not drive point estimates.

[15] Figure A.7 further contains point estimates for the other control group specifications.

at cold temperatures increases the effectiveness of driving restriction (Suarez-Bertoa and Astorga, 2018). The result is in line with the literature analyzing the effectiveness of seasonally differentiated traffic restrictions (Rivera, 2021). In the spring, estimates for CO, NO_2, and PM_{10} remain broadly unchanged. At the same time, the coefficient for ozone increases in magnitude and becomes statistically significant, suggesting that LEZs increase spring concentrations of O_3 by 1.79 $\mu g/m^3$. During summer and autumn, our results for all contaminants except for CO are statistically significant.

2.5.4 Spillovers

We now estimate the spillover effects of LEZs by considering their impact on stations between zero and 25 km from the zones' borders in table 2.6.[16] As with the results for inside stations we provide estimates for four different control samples; the raw sample contains all stations further away than 25 km; the buffer draws a 25 km buffer zone between treated and control stations; the doughnut further excludes from the buffer sample all stations further away than 100 km from LEZs; and the CAAP only considers stations between 0 and 25 km from CAAP cities and excludes all control stations within 25 km from LEZs.

In line with existing literature we do not find evidence of spillovers for NO_2 or PM_{10} (Pestel and Wozny, 2021; Wolff, 2014). However, for O_3, we obtain evidence of harmful spillovers as indicated by statistically significant increases across all specifications. The O_3 increases in adjacent areas are similar in magnitude to those obtained inside the LEZs, in line with the observation that O_3 may be transported over long distances (Hov, Hesstvedt and Isaksen, 1978). For CO, the preferred specification hints at harmful pollution spillovers likely due to a re-direction of traffic flows around LEZs.

Figure 2.7 depicts the results of estimating season-specific spillover effects. Point estimates reveal that O_3 spillovers concentrate in the summer months with increases as high as 2.37 $\mu g/m^3$. Moreover, likely due to the higher pollution intensity of internal combustion engines at cold temperatures, we uncover significant spillovers for CO during the winter months.

[16] Results are qualitatively similar for rings of other thickness, i.e., (0-1), (0-5), and (0-10) km. They are available upon request

Table 2.6: Spillovers across different control samples

(a) Carbon monoxide (CO)

	Raw	Buffer	Doughnut	CAAP
	0.03*	0.04*	0.03^{+}	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
N.Obs	1205	1014	831	774
N.Stations	175	136	110	114
N.Groups	8	7	7	7
N.Periods	14	14	14	14

(b) Nitrogen dioxide (NO_2)

	Raw	Buffer	Doughnut	CAAP
	0.05	−0.13	−0.19	−0.51
	(0.60)	(0.60)	(0.65)	(0.66)
N.Obs	4192	3367	2647	2782
N.Stations	395	308	235	252
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(c) Ozone (O_3)

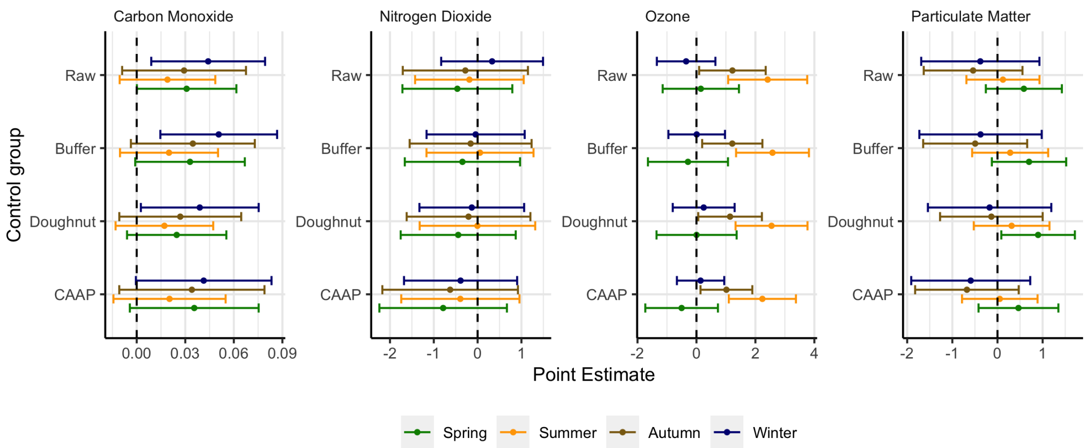
	Raw	Buffer	Doughnut	CAAP
	1.33*	1.05^{+}	1.15*	1.09^{+}
	(0.61)	(0.54)	(0.60)	(0.49)
N.Obs	3187	2503	1948	2091
N.Stations	293	227	174	181
N.Groups	8	8	8	8
N.Periods	14	14	14	14

(d) Coarse particulate matter (PM_{10})

	Raw	Buffer	Doughnut	CAAP
	−0.05	0.06	0.29	−0.10
	(0.36)	(0.40)	(0.41)	(0.42)
N.Obs	3672	2957	2374	2398
N.Stations	364	282	220	233
N.Groups	8	8	8	8
N.Periods	14	14	14	14

Notes: CS-DD estimates for the impact of LEZs on annual air pollution concentrations for stations between zero and 25 km from the zone borders. We provide estimates of four different specifications of the control group. The raw control sample contains all stations further away than 25 km. The buffer excludes all stations within a 25 km buffer zone. The doughnut further excludes from the buffer sample all stations further away than 100 km from LEZs. And the CAAP only considers stations between 0 and 25 km from CAAP cities. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipality level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter (μg/m^3) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Figure 2.7: Seasonal spillovers (CS-DD)



Notes: CS-DD estimates of the impact of LEZs on seasonal air pollution concentrations for stations between zero and 25 km from the zones' borders. We provide estimates of four different specifications of the control group. The raw sample contains all stations further away than 25 km, the buffer excludes all stations within a 25 km buffer zone, the doughnut further excludes from the buffer sample all stations further away than 100 km from LEZs, and the CAAP only considers stations between 0 and 25 km from CAAP cities. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipality level; 95% confidence intervals depicted. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter (μg/m^3) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

2.6 Effects on overall air quality

Finally, we investigate the overall air quality effects of LEZs using the composite air quality index (AQI). Table 2.7 shows the ATTs of LEZs on the annual averages of the AQI, for pollution monitors inside and nearby a LEZ.

Table 2.7: Effectiveness and spillovers of LEZ introduction on the air quality index (AQI)

		Outside LEZ			
	Inside LEZ	Raw	Buffer	Doughnut	CAAP
	-5.17^{***}	0.44	-0.17	-0.05	-0.16
	(1.62)	(1.46)	(1.37)	(1.43)	(1.41)
N.Obs	2970	4602	3714	2875	3023
N.Stations	277	424	329	248	267
N.Groups	8	8	8	8	8
N.Periods	14	14	14	14	14

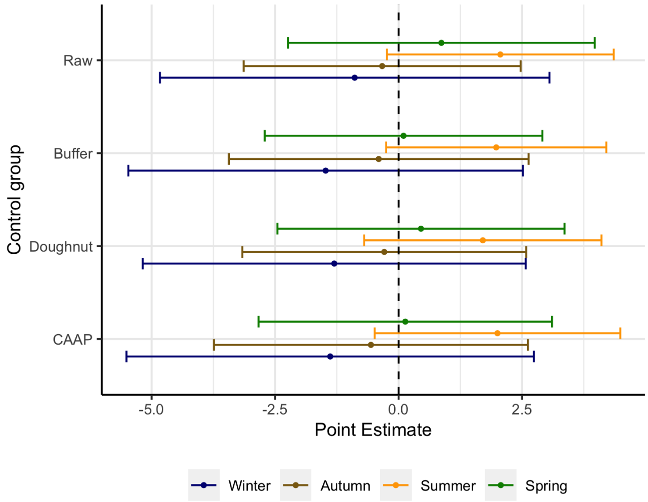
Notes: CS-DD estimates for the impact of LEZs on annual average AQI values for stations inside and outside LEZs. For inside stations, treated units are inside the zone and controls between 25 and 75 km from the zones' borders. For outside stations, treated units are between 0 and 25 km from the zones' borders and we provide results for four different specifications of the control group. The raw sample contains all stations further away than 25 km, the buffer excludes all stations within a 25 km buffer zone, the doughnut further excludes from the buffer sample all stations further away than 100 km from LEZs, and the CAAP only considers stations between zero and twenty-five kilometers from CAAP counties. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipality level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$.

The results show that LEZs improve overall air quality inside their borders, as the value of the AQI decreases by 5.17 units after the implementation in the doughnut specification. This amounts to a reduction of 11.4 percent relative to pre-treatment AQI levels.[17] Concerning air quality effects outside the zones' borders, results are overall statistically insignificant, indicating that the O_3 and CO increases do not translate to overall air quality reductions as measured by the AQI.

Figure 2.8 depicts seasonal effects for pollution monitors inside and outside LEZs. Regardless of the season, LEZs consistently reduce the value of the AQI, suggesting that they are indeed effective at improving air quality within the zones' borders despite the unintended increases in the concentration of O_3. Furthermore, the analysis of season-specific spillover suggests that LEZs cause statistically significant increase in summertime AQI values, by about ten percent, in line with the policy-induced increase in O_3 levels during summer months. These results suggest that persons living outside LEZs bear the costs of the driving restriction without experiencing the benefits of improved air quality and even suffering a deterioration in air quality during summertime.

[17] Table A.3 shows the AQI results for all four different control groups. Point estimates are stable in terms of magnitude and significant across specifications.

Figure 2.8: Seasonal LEZ effects on air quality index (AQI)



Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β) of the impact of low emission zones on seasonal average air quality for stations inside and outside LEZs. For inside stations, treated stations are all those stations inside the zone. For outside stations, treated stations are all those stations within the pre-specified distance. Control stations are all stations further away than 25 km from the zone's border and up until 75 km. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipality level; 95% confidence intervals depicted.

2.7 Well-being and health effects

2.7.1 Well-being effects

To analyze LEZs' impact on individual well-being and health outcomes, we estimate ATTs for three different control samples. First, we include all SOEP individuals that do not move and are not always treated, as descriped in Section 3.3. Second, we exclude control persons residing within 25 km from an LEZ to account for potential spatial spillovers. Third, we further restrict the control group to individuals living in CAAP cities to increase the similarity between treatment and control units. As the sample with the 25 km buffer accounts for spillovers, is moderately sized, and exhibits parallel pre-trends, we focus on this sample in the remaining of the study. Appendix A.6 lists the results for the most restrictive CAAP control group. Table 2.8 shows the estimated effects of LEZ on life satisfaction for all three samples.

All point estimates are negative and statistically significant, indicating that LEZs decrease life satisfaction. This negative effect is remarkable as it occurs despite the policy's overall effectiveness at improving air quality. In the preferred buffer specification, LEZs decrease life satisfaction by 0.19 points, or 2.7% of average pre-treatment values. The magnitude of the effect is quite substantial. For example, also using SOEP data, Kassenboehmer and Haisken-DeNew (2009)

Table 2.8: Effect of LEZ introduction on life satisfaction

	(1)	(2)	(3)
ATT	-0.162^{**}	-0.190^{***}	-0.114^{+}
	(0.057)	(0.054)	(0.065)
N.Obs	154062	94248	25901
N.Individuals	20963	12588	3343
N.Groups	9	9	9
N.Periods	14	14	14

Notes: CS-DD estimates of the impact of LEZs on the life satisfaction. The first column lists results obtained on the full sample, the second restricts the control group to individuals living further away than 25km from LEZs, and the third further restricts the control group to persons living in cities with a CAAP but no LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

find that becoming unemployed decreases life satisfaction by up to 0.9 points, suggesting that the impact of LEZ amounts to about 20% of the unemployment effect. Further restricting the control group to persons living in cities with CAAP quarters the sample size, attenuates point estimates, and increases standard errors. Nevertheless, we still observe a statistically significant 0.11 point decrease in life satisfaction.

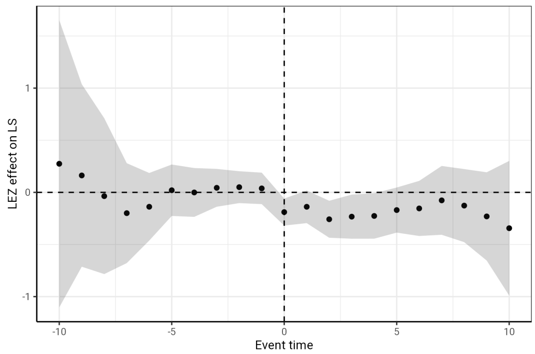
Although life satisfaction is an ordinal variable, Table 2.8 treats it as continuous. To alleviate concerns regarding the scale of our outcome measure, and to elicit the effect of LEZs across the distribution of life satisfaction, we estimate the impact on different threshold values on the scale by transforming our dependent variable into a binary indicator equal to one if life satisfaction is larger or equal to two, four, six, and eight. Table A.4 lists the results of this exercise, indicating that people who score higher on the well-being scale experience larger decreases in well-being following LEZ adoption, whereas people at the lower end of the well-being distribution are less affected.

Figure 2.9 plots event-time ATTs for the preferred specification, while Figure A.10 depicts dynamic event-time ATTs for all samples. Results show a significant decrease in life satisfaction in the first year after the LEZ is activated. The negative impact on life satisfaction is slightly weaker in the second year, but it persists in subsequent years before reverting to insignificance some five years after the treatment.[18]

To highlight potential mechanisms through which LEZs affect life satisfaction, we analyze heterogeneous effects for various subsamples. In panel (a) of Table 2.9 we split the sample based on motor vehicle ownership and estimate separate ATTs for persons with and without cars. Note that the SOEP only surveyed

[18] Results also hold when controlling for compositional changes of the treatment group at different event times; $e \in (1, ..., 5)$. They are available upon request.

Figure 2.9: Dynamic LEZ effects on life satisfaction



Notes: Dynamic CS-DD point estimates and 95% confidence bands on the impact of LEZs on life satisfaction. The sample of control individuals is restricted to residences further than 25km away from the nearest LEZ. Standard errors clustered at the household level.

mobility-related information in 2015. Consequently, we base the sample split on cross-sectional differences. As expected, motor vehicle owners' life satisfaction declines significantly after LEZ implementation. The point estimate for the sample of individuals not owning a motor vehicle is around the same magnitude as in the full sample, but imprecisely estimated. Additionally, panel (b) splits the subsample of motor vehicle owners into households with and without diesel cars. In both samples, individuals' life satisfaction decreases, but the effect on diesel car owners is almost twice as large as in the other group. This is in line with LEZs' stricter standards for diesel engines than for gasoline engines (see Table 2.2).

Table 2.9: Heterogeneous LEZ effects on life satisfaction by motor vehicle ownership

(a) By motor vehicle (MV) ownership

	With MV	Without MV
ATT	-0.186^{**}	-0.162
	(0.058)	(0.169)
N.Obs	55704	7235
N.Individuals	5227	709
N.Groups	9	9
N.Periods	14	14

(b) By diesel car ownership

	Diesel	Other Fuels
ATT	-0.276^{**}	-0.151^{*}
	(0.099)	(0.071)
N.Obs	17917	37626
N.Individuals	1739	3473
N.Groups	9	9
N.Periods	14	14

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction. The control group consists of individuals living further away than 25km from the nearest LEZ. Subsamples are split based on motor and diesel vehicle ownership. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

Table 2.10 panel (a) further shows that the negative effect on life satisfaction persists at similar magnitudes across all income quartiles.[19] Still, the impact is lowest in the first income quartile, which is plausible given that more than a third

[19] Quartiles are based on annual net household income (after taxes) averaged over the whole sample period; the cutoffs are [0; 27,000], (27,000; 34,300], (34,300; 48,700] and > 48,700 Euros.

of households in this income quartile do not own a motor vehicle; this sample consists of low-paid workers, retirees, and welfare recipients who typically cannot afford a car. The largest impact occurs in the second quartile, where the share of vehicle owners is much higher at over 90%. Effects on the third and fourth quartiles are lower than in the second, potentially because these individuals can more easily adapt to the driving restrictions. Nevertheless, LEZs still have a statistically significant negative effect on their life satisfaction.

Table 2.10: Heterogeneous LEZ effects on life satisfaction by income and age

(a) By income quartiles

	Q1	Q2	Q3	Q4
ATT	-0.186	-0.265^{*}	-0.204^{+}	-0.197^{**}
	(0.142)	(0.119)	(0.122)	(0.077)
N.Obs	21858	22910	24433	25033
N.Individuals	3145	3145	3146	3144
N.Groups	9	9	9	9
N.Periods	14	14	14	14

(b) By age groups

	$\geq$ 65 years old	$<$ 65 years old
ATT	-0.097	-0.240^{***}
	(0.112)	(0.063)
N.Obs	28856	65392
N.Individuals	4163	9953
N.Groups	9	9
N.Periods	14	14

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction. The control group consists of individuals living further away than 25km from the nearest LEZ. Subsamples are split based on income quartiles and age groups. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

Panel (b) of the same table also lists results across age subgroups. We focus on a cutoff of 65 years. People older than 65 are retirees or near retirement - they are less likely to own a car and, on average, own fewer cars than working-age individuals. In contrast, people younger than 65 have very different mobility requirements, e.g., due to the need to commute to work or due to children in the household. These differences appear in the point estimates, with strong effects on life satisfaction for individuals younger than 65 and no significant effect for people aged 65 or older.

Changes in house and rent prices could drive the estimated well-being effects if these changes are induced by LEZ adoption. Therefore, Table 2.11 splits the sample into home owners and renters. Life satisfaction of individuals who own their dwelling decreases significantly, indicating that the well-being effects are not driven by increases in rents. The effect on renters is more pronounced, but not statistically different from the effect on owners. Nevertheless, the larger effect on renters could be potentially attributed to increasing rent prices: We estimate the impact of LEZ adoption on monthly rent payments in our data and find positive, but imprecisely estimated coefficients.[20]

[20] Results are available upon request.

Table 2.11: Heterogeneous LEZ effects on life satisfaction of renters and owners

	Owner	Renter
ATT	-0.192^{**}	-0.269^{***}
	(0.072)	(0.081)
N.Obs	62448	31724
N.Individuals	8357	5381
N.Groups	9	9
N.Periods	14	14

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction. The control group consists of individuals living further away than 25km from the nearest LEZ. Subsamples are split based on home ownership status. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

2.7.2 Health effects

We complement our results by analyzing the impact of LEZs on objective health measures and utilization of the health care system as proxied by the number of doctor visits.[21] Since 2009, the SOEP bi-annually surveys several illness categories and the number of doctor visits within the last twelve months prior to the interview. We restrict our sample to individuals and time periods where information on specific illnesses is available. Since health outcomes are only available since 2009, we drop individuals initially treated in 2008 and 2009 because we do not observe their pre-treatment outcomes. Since the recent empirical literature shows that LEZs decrease cardiovascular diseases (Margaryan, 2021; Pestel and Wozny, 2021), we focus on hypertension as a risk factor for cardiovascular conditions. Moreover, as a falsification test, we analyze the effect of LEZs on the occurrence of cancer. Cancer often develops over long time periods and it is unlikely that the effect of LEZs on pollution would trigger changes in the cancer rate during our sample period.

Table 2.12: LEZ effect on health care utilization and health outcomes

	LS	Doctor visits	Hypertension	Cancer
ATT	-0.163^{+}	-1.292	-0.046^{*}	0.010
	(0.087)	(0.938)	(0.022)	(0.013)
N.Obs	28814	28718	28814	28814
N.Individuals	9218	9208	9218	9218
N.Groups	4	4	4	4
N.Periods	5	5	5	5

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction and objective health outcomes. The control group consists of individuals living further away than 25km from the nearest LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

[21] We also looked at subjective health satisfaction that is measured using the same ordinal scale as for subjective life satisfaction. However, results are largely insignificant, presumably because the objective health benefits are, on average, too subtle to manifest in overall improvements of subjective health.

Table 2.12 reports point estimates of the effect of LEZs on life satisfaction, doctor visits, hypertension, and cancer. The negative effect on life satisfaction persists in this smaller sample with a magnitude comparable to our baseline results. Moreover, there is suggestive evidence that LEZs decrease the number of doctor visits, although we cannot establish statistical significance at conventional levels. Concerning objective health outcomes, we estimate a significant decrease in the likelihood of hypertension. The probability of developing hypertension drops by 4.6 percent after implementation. The effect on hypertension is immediate, manifesting itself in the first year after LEZ implementation, and point estimates are rather stable in later years (Figure A.11). Using the pre-treatment hypertension rate of 31 percentage points among LEZ individuals (cp. Table 2.3) to calculate the potential reduction in hypertension cases yields an estimate of 1.4 percentage points. Given that more than 6.6 million people lived inside a LEZ in 2018, a simple back-of-the-envelope calculation suggests that these driving restrictions avoided at least 93,000 hypertension cases in Germany. The point estimate of the LEZ effect on the probability of developing cancer is, as expected, statistically insignificant.

Lastly, we validate our results by analyzing heterogeneous health effects for different age groups in Table 2.13. The decrease in the number of doctor visits is especially pronounced for middle-aged adults and older individuals, with almost two avoided doctor visits per year for individuals in these age groups. Next, the decrease in the probability of developing hypertension is visible across all age groups, with the effect becoming stronger for older individuals. People aged 60 to 80 years benefit the most from LEZs, as their probability for hypertension decreases by 8.2%, which is in line with recent empirical evidence showing that health benefits of LEZs accrue mostly to the older population (Margaryan, 2021). Finally, the probability of developing cancer is not significantly affected by LEZ implementation in any age group.

2.7.3 Spillovers in life satisfaction and health outcomes

Our results in Section 2.5 show that LEZs generate O_3 spillovers in adjacent areas, which can even cause diminished overall air quality during the summer months. This implies that individuals living in the affected areas not only have to bear restricted mobility but also potential costs arising from increased air pollution. To investigate whether individuals living near LEZs experience life satisfaction

Table 2.13: LEZ effect on health outcomes by age groups

	Number of Doctor Visits			Hypertension			Cancer		
Age group	(20-40]	(40-60]	(60-80]	(20-40]	(40-60]	(60-80]	(20-40]	(40-60]	(60-80]
ATT	−0.08	-1.83^{+}	−1.79	−0.02	−0.03	-0.08^{*}	−0.005	0.003	0.023
	(1.27)	(1.10)	(2.10)	(0.04)	(0.03)	(0.04)	(0.004)	(0.015)	(0.030)
N.Obs	5157	12736	10954	4113	11463	10954	4113	11463	10954
N.Individuals	2519	4520	3618	2054	4256	3613	2054	4256	3613
N.Groups	4	4	4	4	4	4	4	4	4
N.Periods	5	5	5	5	5	5	5	5	5

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on objective health outcomes across different age groups. The control group consists of individuals living further away than 25km from the nearest LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

and health effects, we estimate LEZs' ATTs for individuals within 25 km distance to a zone.[22] Table 2.14 lists the results for the same outcomes as Table 2.12.[23]

Table 2.14: LEZ spillovers in well-being and health

	LS	Doctor visits	Hypertension	Cancer
ATT	-0.192^{**}	0.379	−0.001	−0.003
	(0.042)	(0.383)	(0.010)	(0.005)
N.Obs	41079	40935	41079	41079
N.Individuals	12989	12973	12989	12989
N.Groups	4	4	4	4
N.Periods	5	5	5	5

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on the life satisfaction and health outcomes of individuals living between zero and twenty five kilometers from LEZs. The control group consists of individuals living further away than 25km away from the nearest LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

The negative well-being effect is also present outside the zones' limits, with decreases comparable to those of LEZ residents. This reduction in subjective well-being for outside dwellers is not surprising, given that people living within 25 km from a LEZ will likely travel into the corresponding city center at some point in time. In addition, these individuals are affected by harmful pollution spillovers. In contrast to our findings for residents of LEZs, health outcomes of neighboring individuals are not impacted by LEZ implementation, implying that the adverse pollution spillovers are not sufficient to trigger negative health effects, as measured by healthcare utilization, hypertension, and cancer rates. Our results therefore suggest that people residing in the vicinity of LEZs bear the costs of restricted mobility without the health benefits of improved air quality.

[22] Using a smaller distance for the treated group, e.g. individuals within 1km, 5km, 10km etc., yields point estimates that are very similar in magnitude to the 25km specification.

[23] Table 2.14 uses the the bi-annual SOEP sample starting in 2009. Table A.6 lists results for the full SOEP sample (2005-2018), and suggests a life satisfaction effect of similar magnitude as in the reduced sample.

Overall, our results suggest that LEZs decrease subjective well-being of individuals living inside their borders. This negative life satisfaction effect is immediate but transitory as it disappears several years after policy implementation. We show that adverse life satisfaction effects are heterogeneous and especially pronounced among diesel car owners and younger individuals, who are more likely to be affected by the policy. In addition, we provide evidence that LEZs decrease the likelihood of developing hypertension, mostly in the older population, though these health benefits do not seem sufficient to counteract the drop in life satisfaction due to LEZ implementation. Concerning people living nearby LEZs, we find comparable decreases in life satisfaction without any significant impacts on health outcomes.

2.8 Conclusion

This paper contributes to the growing literature on the effects of low emission zones by providing a comprehensive analysis of their effectiveness concerning overall air quality and subjective well-being. Moreover, we advance our understanding of LEZs by paying particular attention to spatial spillovers and seasonal heterogeneity. Looking at overall air quality instead of specific traffic-related contaminants allows us to broaden our scope to other determinants of air quality besides traffic-related pollutants. Notably, we also analyze the impact of the zones on self-reported life satisfaction and objective health outcomes of individuals in Germany. To the best of our knowledge, this is the first study looking at the life satisfaction effects of driving restriction policies. To identify the causal effects of the zones, we use recent advances in difference-in-differences (DD) designs that are robust to the potential bias of staggered implementation and time-varying treatment effects.

Results show that LEZs improve overall air quality, despite causing an unintended increase in ground-level ozone. Confirming the previous literature, the air quality improvement is driven by a decrease in traffic-related pollutants. Our analysis of seasonal heterogeneity shows that LEZs are especially effective at reducing traffic contaminants during the winter when the zones' marginal effects are more prominent due to a higher pollution intensity of vehicles. In contrast, they increase ozone levels most during the summer months when greater solar radiation supports the creation of ozone. We also find that LEZs cause spatial spillovers, increasing both ozone and carbon monoxide outside the zone limits. Again, these effects are stronger during summer and winter months, respectively.

Our analysis of well-being outcomes shows that LEZs cause a significant decrease in well-being for individuals residing inside the zones. Effects are more pronounced for owners of diesel cars, which are more restricted than gasoline vehicles, and for working-age individuals below the age of 65. We further confirm previous studies looking at the health effects of the zones by showing that they improve self-reported health outcomes of individuals in our sample. These results suggest that the average well-being costs of restricting mobility potentially outweigh the well-being benefits of improved health outcomes. Concerning policy spillovers to outside areas, we find similar-sized reductions in life satisfaction for individuals dwelling outside but near an LEZ, while health outcomes of persons living outside the restriction area are not affected by LEZs adoption. These results imply that people in the vicinity of LEZs bear the costs of restricted mobility without benefiting from improvements in air quality.

Our findings suggest that policymakers should consider refining the design of LEZs to minimize the impact of harmful spatial spillovers and unintended effects on secondary air pollutants. Possible strategies could be to increase LEZs' coverage area, or focus on restricting traffic mainly during the winter months when traffic-related pollution is more elevated and the marginal effectiveness of LEZs on air pollution is highest. Policymakers should also view the drop in subjective well-being as a cost to the policy and think about ways how to mitigate it, for example, by more effectively communicating the health benefits of LEZs or strengthening transfer mechanisms to support the purchase of cleaner vehicles and the use of public transportation.

An important avenue for future research concerns the mechanisms behind the reduction in self-reported life satisfaction. For instance, this decrease could be driven by financial burdens arising from car replacement or the adverse psychological effects of restricting mobility stemming from various factors like attitudes towards environmental policies or general trust in the government. Case studies at the city level that include rich data on mobility behavior and expenses, vehicle ownership, and political attitudes could be one way to deepen our understanding of the negative well-being effect.

Chapter 3

Indirect Effects of Ground-Level Ozone on Well-Being

3.1 Introduction

Understanding the link between local air pollution, human health, and well-being is a relevant issue for economists. Air pollution causes economic costs through exacerbated morbidity (Kampa and Castanas, 2008), increases in mortality (Jayachandran, 2009; Knittel, Miller and Sanders, 2016), expenditures on health services (Barwick et al., 2018; Moretti and Neidell, 2011), disruptions to human capital formation through school absenteeism (Chen, Guo and Huang, 2018; Currie et al., 2009), shocks to labor supply (Aragón, Miranda and Oliva, 2017; Hanna and Oliva, 2015), adverse effects on labor productivity (Chang et al., 2019; Zivin and Neidell, 2012), and reductions in self-reported measures of well-being (Levinson, 2012; Luechinger, 2009).

This paper considers the effect of air pollution on subjective well-being for the case of ground-level ozone.[1] Surprisingly, even though ozone is the second-most deadly air pollutant in Europe after particulate matter (Wolff, 2014), to the best of our knowledge, there is no evidence of its effect on self-reported well-being measures. One possible reason for this counter-intuitive lack of evidence is that ozone concentrations may not be high enough to affect the life satisfaction of the average person, although relevant for specific population groups more susceptible to the negative consequences of exposure.

In this study, we propose that ozone levels can affect adults' well-being directly through their health, and indirectly through the effect of exposure on family members. If the indirect mechanism is present, we expect stronger effects on the well-being of persons with sensitive family members in their household. We disentangle the direct and indirect channels by investigating heterogeneous effects between parents and non-parents. The indirect channel is particularly relevant in places where ozone levels are not sufficiently high to affect adults' health but powerful enough to impact the health of more susceptible household cohabitants like children. Understanding whether such an indirect effect exists contributes to a fuller understanding of air pollution's welfare consequences.

To our knowledge, this paper is the first to examine the indirect effect of family environments on the relationship between pollution and well-being and the first to find a consistently negative impact of ozone exposure. We further contribute by focusing on the mechanisms behind the well-being result, i.e., the health

[1] In contrast to ground-level ozone, which is primarily human-made and harmful to flora and fauna, the bulk of ozone in the earth's atmosphere occurs naturally in the stratosphere, between about 10 km and 50 km above the earth's surface. This ozone layer is vital for protecting life from the sun's ultraviolet radiation. In the remainder of the paper, we write ozone instead of ground-level ozone for brevity.

of sensitive family members and the role of heterogeneous family environments proxied by income.

Focusing on the well-being effects of ozone is advantageous for three reasons: First, substantial epidemiological evidence shows that ozone exposure decreases objective health outcomes for both adults and children, with children being especially affected.[2] Second, ozone is particularly relevant because while the concentrations of other pollutants decreased in recent years due to policy interventions, average ozone levels have remained stable. Furthermore, current levels of ozone are likely to increase because of climate-change-induced heatwaves (Rosenzweig et al., 2004; Selin et al., 2009). Third, the correlation of ozone with other contaminants is often negative, allowing us to provide lower-bound estimates and alleviate spurious correlation concerns.

We analyze the effects of ozone on two measures of subjective well-being: satisfaction with one's health, and satisfaction with one's life. Health satisfaction targets the health channel of air pollution, whereas the broader measure of life satisfaction encompasses further factors affecting an individual's well-being, such as indirect welfare effects stemming from the impact of ozone on the environment, the family, and the community. Evaluating subjective well-being is informative, especially in contexts of moderate ozone concentrations and healthy populations. If ozone affects the health of individuals, they may increase their demand for health services, decrease labor supply, or suffer productivity losses, which leads to additional economic costs. Conversely, if ozone only moderately deteriorates objective health outcomes, it may not lead to immediate economic costs when the individual generally *feels* well.[3] Furthermore, life satisfaction measures are also attractive from an identification perspective as they respond to short and medium-term shocks, like the variation in air pollution. Existing literature has already successfully exploited this sensitivity of life satisfaction to short-term events (e.g. Levinson, 2012; Luechinger, 2009).

We identify the effect of ozone on individuals from short and medium-term variations in ozone levels. Specifically, we combine geo-coded data on daily ozone levels from measuring stations across Germany with geo-coded individual-level data on subjective health and life satisfaction between 2005 and 2018 from the German Socio-Economic Panel Study (SOEP), a representative survey of German

[2] Additional direct losses in well-being may occur through aesthetic effects, such as foggy air due to pollution (Levinson, 2012).

[3] Validating the results for the subjective variables (well-being and health) using objective data is beyond this paper's scope due to data availability. Especially in Germany, administrative data on children's objective health outcomes are not publicly available. However, we refer the reader to the extensive body of literature linking air pollution and objective outcomes.

individuals. We exploit information on the precise date of the SOEP interview to assign weekly, monthly, and quarterly exposure levels to each individual through inverse distance weighting. Our preferred specification estimates the effects of ozone on the health and life satisfaction of parents and non-parents, controlling for time and individual fixed effects, individual-level sociodemographic covariates, and weather impacts.

The study also explores the channels through which parents experience losses in life satisfaction by analyzing the impact of ozone exposure on parents of children with respiratory disease, as these children are particularly vulnerable to exposure. Moreover, we explore heterogeneous effects between high and low-income households and examine the sensitivity of our results through several robustness tests. First, we randomize pollution exposure across individuals and across time allowing us to rule out spurious correlations. Second, we are mindful of the need to ascertain that estimations are robust to the cardinalization of the ordinal well-being outcomes (e.g. Bond and Lang, 2019). As such, we re-formulate the 11-point outcome scales for life and health satisfaction as binary variables and re-estimate our main specification using a fixed-effects Probit model to check whether our results depend on the ordinal nature of the well-being outcomes.

Results show statistically and economically significant adverse effects of ozone on parents' life satisfaction. In contrast, such effects are absent for childless persons. The economic significance in families with children increases with the level of temporal aggregation: point estimates grow in absolute value between weekly, monthly, and quarterly time windows. This result is in line with the epidemiological literature, which shows that the effects of ozone on health become more pronounced with prolonged exposure, suggesting that – under the assumption that the sensitivity of individuals' life satisfaction to ozone is not affected by childbirth – ozone pollution diminishes the well-being of parents while not significantly affecting childless persons. In contrast to our results on life satisfaction, we do not find any effect of ozone on health satisfaction, neither for parents nor for persons without children. Our findings suggest that ozone concentrations in Germany are not high enough to affect the subjective health of adults in general, but are suggestive regarding the negative consequences of ozone on children's health, and their indirect effect on the life satisfaction of the adult population.

Exploring the mechanism behind the well-being effect, we find that parents who have a child with a respiratory disease experience decreases in their life satisfaction, while parents of healthy children are not affected by ozone exposure. This result provides direct evidence that the children's health is one of the elements driving the well-being effect, either through empathy, worries about missing work, or costs of providing care. Moreover, below-median earning parents are more affected in their well-being. This result aligns with the literature showing that children from low-income families are generally less healthy than children from high-income households (Currie and Lin, 2007; Reinhold and Jürges, 2012). The indirect influence of ozone on parents should be taken into account in further research and policy debates regarding the costs and benefits of reducing air pollution.

In our view, the two contributions most relevant to ours are Luechinger (2009) and Levinson (2012). Luechinger (2009) analyzes the effect of SO_2 on the subjective life satisfaction of SOEP households using a quasi-experimental design. His study finds a significant negative impact of SO_2 pollution on individuals' life satisfaction. Levinson (2012) uses data from the General Social Survey (GSS), collected by the National Opinion Research Center and daily variation in air pollution to show that PM_{10} also diminishes life satisfaction of U.S. individuals. Our paper adds to the literature compared to Luechinger (2009) and Levinson (2012) in several respects: First, it studies the effects of a different pollutant, ozone. Second, it explores the channels through which pollution affects life satisfaction. Third, it leverages the higher quality of our data, mainly better coverage compared to Levinson (2012) and better regional granularity compared to Luechinger (2009), to pursue a more precise identification, and fourth, it explores how different time aggregations of pollution affect the coefficients of our causal variable.

Further studies on the link between air pollution and life satisfaction provide additional evidence on the relationship between these variables: Rehdanz and Maddison (2008) use SOEP data to find a negative association between people's claim to be affected by higher air pollution and their levels of life satisfaction. Ferreira and Moro (2010) use the same method at the level of Irish electoral districts and find similar results. Cunado and De Gracia (2013), Ferreira et al. (2013) and Ambrey, Fleming and Chan (2014) also find a negative association between life satisfaction and air pollution. Zhang, Zhang and Chen (2017) find that an air pollution index composed of SO_2, NO_2, and PM_{10} decreases subjective mental health and increases hedonic unhappiness. However, to our knowledge, this literature does not explicitly explore channels through which air pollution affects well-being.

3.2 Background: Ozone and health

There is a significant literature on the *direct* impacts of ozone pollution on objective health outcomes. Empirical evidence shows that exposure increases the morbidity and mortality of affected persons (Knittel, Miller and Sanders, 2016; Schwela, 2000). Short-term effects include decreases in lung capacity, inflammations of the respiratory tract, and a higher frequency of asthma attacks. At the same time, long-term exposure increases the risk of developing chronic lung disease (EPA, 2016), and potentially increases the probability of developing lung cancer (Kim, Shin and Choi, 2018; Rocks et al., 2017). The health effects of ozone are most potent among vulnerable populations, like children, the elderly, and individuals suffering from respiratory ailments. Gryparis et al. (2004) use data from 24 different European urban agglomerations to conclude that an increase of 10 milligrams per cubic meter (mg/m^3) in the levels of 1-hour maximum daily ozone concentrations raises total mortality rates by 0.31%. Regarding morbidity, Devlin et al. (1991) conclude that even at ambient levels as low as eight particles per billion (ppb), ozone exposure has negative impacts on the respiratory system. Koken et al. (2003) find that ozone correlates with hospitalizations of elderly adults due to cardiovascular ailments, while Friedman et al. (2001) uses variations in environmental policies during the Atlanta summer games to infer that the associated drops in peak daily ozone levels (81.3 to 58.6 ppb) lead to fewer asthma-related emergency room admissions. Moretti and Neidell (2011) use instrumental variable techniques to estimate the financial costs of ozone on hospital admissions. They determine that ozone exposure causes annual costs of US$ 55m from respiratory hospitalizations and avoidance behavior.

Studies focusing on the effect of ozone on children's health have also produced substantial evidence regarding the damaging impact of ozone on respiratory health, lung capacity, long-term inadequacy of lung growth, increases in hospitalizations, mortality, and use of asthma medicine (Bates, 1995). The literature shows that ozone affects children more strongly than adults. Lleras-Muney (2010) studies the effect of air pollution on children's hospitalization rates by using the relocation of military personnel as a source of exogenous variation in exposure. She finds that an increase in ozone exposure by one standard deviation increases the hospitalization rates of military children between 8% and 23%. Burnett et al. (2001) analyze the effects of ozone on the hospitalization rates of children under two years of age. They find that increasing the average ozone concentration to one-hour maximum values typically found in summertime (45 ppb) would increase daily hospitalizations due to respiratory ailments by 35%. Coneus and Spiess (2012) analyze SOEP data on children's health outcomes and find that ozone exposure leads to bronchitis and other respiratory illnesses among toddlers. Thurston et al. (1997) find significant correlations between lower lung capacity and high levels of atmospheric ozone when studying the effect of ozone in children between seven and thirteen years old. Ostro et al. (2001) find that asthmatic children between the ages of eight and thirteen increase medicine use during higher ozone episodes. Lee et al. (2002) observe that, for South Korean children under the age of fifteen, the risk of asthma-related hospitalization increases between 7% to 13% when atmospheric ozone rises by 21 ppb. Tolbert et al. (2000) find that increasing the 8-hour maximum ozone level by 20 ppb increases pediatric emergency room visits due to asthma by 4%. Finally, Gent et al. (2003) show that asthmatic children are particularly vulnerable to ozone exposure, with levels well below the regulatory limit values leading to increased shortness of breath and use of rescue medication use.

Based on the epidemiological evidence and under the reasonable assumption that the utility of children enters the utility function of their parents, we hypothesize that there are two channels for ozone to affect adults' well-being: The first channel captures the direct effect of ozone through their health, which is the channel investigated in the existing literature. The second channel is through family effects: Parents' outcomes are affected by their childrens' welfare. We hypothesize that in the case of ozone, the second channel is worth examining because children are a sensitive group to the effects of ground-level ozone.

3.3 Data

3.3.1 Data sources

We obtain household and personal data from the German Socio-economic Panel Study (SOEP). The SOEP is a representative longitudinal panel study that started in West Germany in 1984. Our primary outcome variables are responses to questions asking individuals to rate their life and health satisfaction. The questions are as follows: "How satisfied are you with your life, all things considered?" and "How satisfied are you with your health, all things considered?" Respondents provide answers on an eleven-point scale from zero (completely dissatisfied) to ten (completely satisfied) (Richter et al., 2013). SOEP also provides two critical pieces of information necessary for the causal identification of the effects of ground-level ozone on life and health satisfaction: First, it contains the geo-coordinates of surveyed households on a strictly confidential basis. We use these geo-codes and inverse distance weighting to match surveyed individuals to nearby pollution measuring stations, enabling a clean spatial matching of exposure and individuals.[4] Second, the survey also contains information on the exact day of the interview, allowing for a precise temporal match of individuals and their ozone exposure. Additionally, the SOEP also has information on a broad set of sociodemographic and economic controls, such as marital status, age, gender, income, and employment.

Moreover, the SOEP surveys the birth biography of respondents, including the month and year of childbirth, allowing us to distinguish between parents and childless persons. We focus on parents living in the same household with their minor children, and compare them to childless people.[5] Information on children's health outcomes is collected via "mother and child" questionnaires that survey doctor-diagnosed diseases and conditions of the child, e.g., respiratory diseases such as asthma or bronchitis.[6] After matching kids' health information to their parents' responses, we can differentiate between parents with healthy and sick kids.

Data on the daily concentration of ozone and other air pollutants come from the German Environmental Agency (*Umweltbundesamt*, henceforth UBA). UBA maintains an extensive network of monitoring stations measuring different types of contaminants. In total, UBA has 387 stations measuring the concentration of ozone in the environment.[7] Figure 3.1 shows the spatial distribution of ozone monitoring stations across Germany. Stations concentrate in urban clusters such as Berlin in the northeast, Hamburg in the north, and the Ruhr area in the west.

Additionally, the German meteorological service (*Deutscher Wetterdienst, DWD*) provides weather data from its monitoring stations. We also match the weather data to the individual-level data with inverse distance weighting.

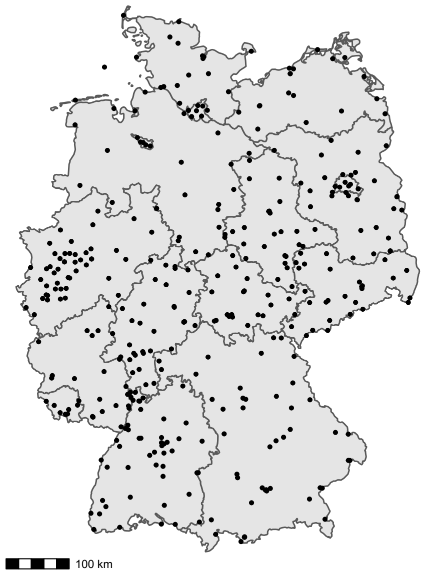
[4] Specifically, the inverse distance weighting is based on pollution measuring stations within a radius of twenty kilometers to a SOEP household. Results are robust to using a ten-kilometer radius, although estimates are often less precise due to smaller sample size.

[5] Childless people are those who have not given birth before the end of our sample period. We discard childless people who live with children in the same household, e.g., adult siblings. We also eliminate responses of (future) parents if the child is not yet born, and responses of (former) parents whose children have reached the legal age or have moved out of their parent's household.

[6] Mothers/fathers of children younger than eleven years are prompted the question "Has your child been diagnosed by a doctor as having one of the following health conditions or impairments?". Answers are either yes or no for specific disease categories, e.g., respiratory disease (asthma, bronchitis or similar), allergies, neurodermatitis, or vision impairment.

[7] Because of malfunction and routine maintenance, stations measuring ozone have missing values around 10% of the time.

Figure 3.1: Ozone monitoring stations in Germany



Notes: The figure depicts the locations of ozone monitoring stations in Germany between 2005 and 2018.
Source: German Environmental Agency.

3.3.2 Ground-level ozone in Germany

Our primary explanatory variable is ground-level ozone. In Germany, over the period 2005-2018, ozone had an average annual concentration of 48.3 micrograms per cubic meter ($\mu g/m^3$), with a standard deviation of 24.4 $\mu g/m^3$ and a maximum of 199.9 $\mu g/m^3$. Ozone levels are higher in rural areas (58.7 $\mu g/m^3$) than in suburban (45.9 $\mu g/m^3$) and urban (42.7 $\mu g/m^3$) districts. Furthermore, the annual average concentration of ozone has remained stable throughout our sample period, whereas the concentration of traffic-related pollutants like nitrogen dioxide (NO_2) and coarse particulate matter (PM_{10}) decreased (Figure 3.6, right panel), mostly because of the adoption of environmental policies such as clean air action plans and low emission zones.

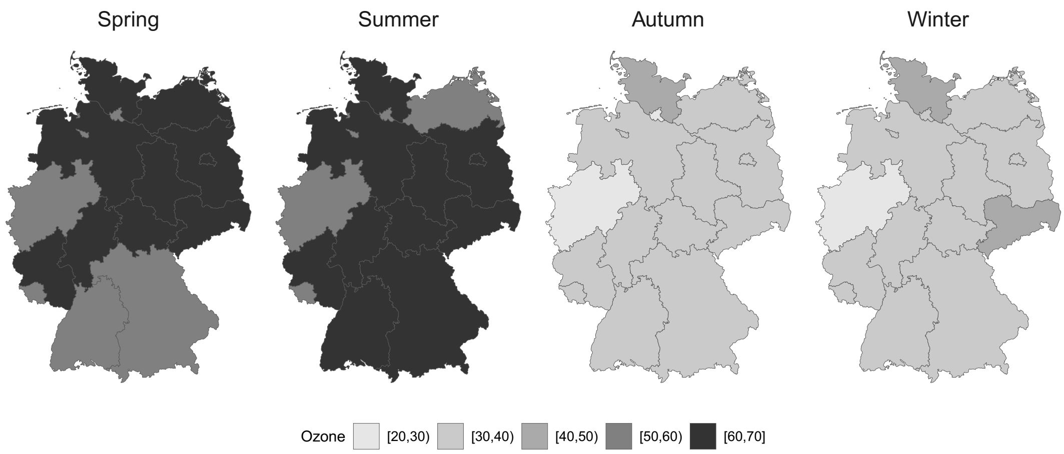
Both the higher level of ozone in rural areas and its steady long term trend mirror the fact that ozone is a secondary environmental pollutant.[8] On the one hand, ozone is formed through solar radiation in combination with precursor contaminants, such as nitrogen oxides (NO_x) and volatile organic compounds. On the other hand, NO_x also degrades ozone into oxygen, leading to a non-linear relationship between ozone and its precursors. For example, in areas with high levels of NO_x, such as urban centers and traffic areas, ozone degrades at faster

[8] In contrast to primary pollutants (e.g., carbon monoxide or sulfur dioxide), secondary pollutants are not directly emitted from a source. Instead, secondary pollutants form in the lower atmosphere through chemical interactions with different precursor pollutants.

rates, leading to lower ozone levels than in rural areas with lower levels of ozone precursors. This phenomenon is referred to as the ”ozone paradox” (Monks et al., 2015).

Despite its stable trend in annual average values, ozone still varies significantly within the year. Given that primary contaminants’ interaction with solar radiation triggers the creation of ozone, its levels are higher during the summer months (center panel in Figure 3.6). Moreover, as the levels of primary pollutants and solar radiation vary across locations, the ozone concentration also varies substantially across space. Figure 3.2 shows the spatial distribution of average ozone levels across German federal states during the year’s four seasons. We observe lower ozone levels in densely populated states such as North Rhine-Westphalia, Hamburg, and Bremen, and higher levels in more rural areas, such as Schleswig-Holstein and Saxony. Regional concentrations vary significantly by season. In the winter, the states with higher ozone levels are the more rural Eastern and Northern states. In the summertime, due to the influence of solar radiation on ozone formation, southern states such as Baden-Wuerttemberg and Bavaria exhibit higher exposure levels.

Figure 3.2: Ozone concentrations in Germany by season



Notes: The figure depicts seasonal average ozone levels across German federal states. Seasonal ozone averages are calculated by averaging over daily values in the respective season over the period 2005-2018. Ozone averages are reported in micrograms per cubic meter (μg/m^3).
Source: German Environmental Agency.

We assign daily ozone exposure to individuals using inverse distance weighting (IDW) between ozone monitoring stations and individuals’ dwellings. IDW is a spatial interpolation technique that approximates the value of a point in space by weighting the values of comparable neighbors.[9] It assigns location-specific pollution averages to each person by providing more weight to stations located near the person's dwelling.

3.3.3 Individual-level data

Table 3.1 presents basic descriptive statistics for the subsample of SOEP individuals residing within twenty kilometers of ozone measuring stations. The mean of both life and health satisfaction is in the upper part of their categorical distribution, with a mean value of 7.25 for life satisfaction and 6.93 for health satisfaction. On average, surveyed individuals have an income of 43.6 thousand Euro, are in their 40s, and are employed 68% of the time. We observe differences between individuals by child status. Parents are younger, generate a higher income, and are employed more frequently than childless people. We control for these differences in the regression analysis. In terms of pollution, parents are exposed to higher ozone levels because they live in more rural areas relative to childless people.

Figure 3.3 shows the distribution of answers for health and life satisfaction. For both variables, the highest frequency of responses is between seven and nine. On average, individuals were mostly satisfied with their life during the sample period. We observe that life and health satisfaction are correlated, although the correlation is not perfect. Scores for health satisfaction are spread across the scale more than for life satisfaction. Table B.1 shows that the distributions of life and health satisfaction ratings are very similar among parents and non-parents.

Figure 3.4 portrays the temporal evolution of life and health satisfaction. The graphs exhibit similarities and differences in the evolution of both variables over time. Both life and health satisfaction decrease during the financial and economic crisis in 2008/2009. In the ensuing years, they increase in line with the positive development of the German business cycle and the concurrent rise in employment.

[9] Formally, IDW interpolation takes the form:

$$V_{jt} = \left\{ \begin{array}{c} \frac{\sum_i^N \omega(dist_{ij}) * pol_{it}}{\sum_i^N \omega(dist_{ij})} \\ pol_{it} \rightarrow dist_{ij} = 0 \end{array} \right\} \Longrightarrow \omega(dist_{ij}) = \frac{1}{distance(x_i, x_j)^p}$$

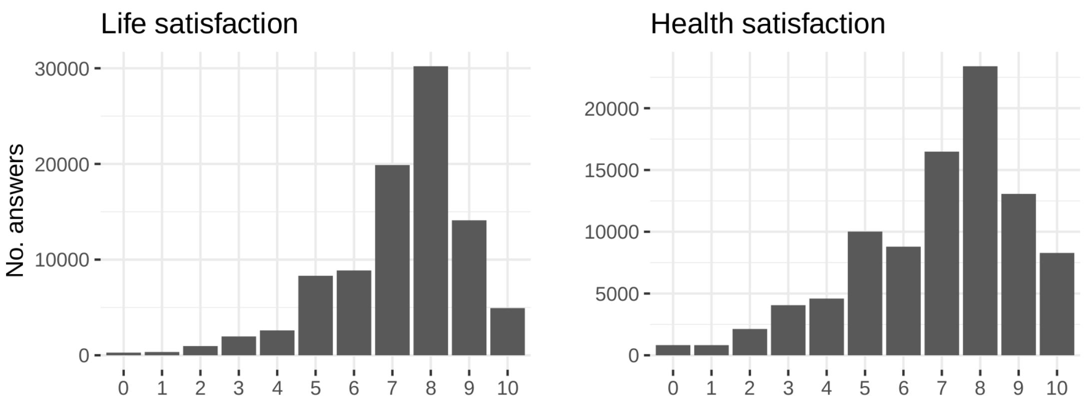
where V_{jt} is the weighted value of pollution at household j at time t, pol_{it} is the value of pollution at station i at time t, x_i and x_j the geographical coordinates of station i and households j, and $dist_{ij}$ is the distance between pollution station i and household j. The power factor p modifies the weighting load; the greater p, the greater the weight of closer stations. We use a weight of two, as recommended by De Mesnard (2013) for air pollution. To focus on local ozone concentration, we cut off stations located further away than twenty kilometers. Finally, we use the great circle distance formula for maximum precision in calculating the distance between coordinate points (Shumaker and Sinnott, 1984).

Table 3.1: Descriptive overview

	Full sample		*Parents*		*Childless*	
	Mean	SD	Mean	SD	Mean	SD
SOEP variables						
Life satisfaction	7.25	1.72	7.39	1.65	7.07	1.79
Health satisfaction	6.93	2.15	7.07	2.05	6.76	2.26
Age	43.79	14.95	41.92	7.47	46.16	20.63
Income	43.60	32.23	46.63	31.33	39.75	32.93
Is employed	0.67	0.47	0.79	0.41	0.53	0.50
Is married	0.60	0.49	0.80	0.40	0.35	0.48
Number kids	1.07	1.18	1.91	0.95	0.00	0.00
Pollution						
Ozone (O_3)	49.57	17.32	51.62	17.28	46.96	17.01
Nitrogen dioxide (NO_2)	32.05	15.04	30.61	14.61	33.88	15.38
Coarse particulate matter (PM_{10})	23.59	10.95	22.37	10.03	25.15	11.82
Weather						
Temperature	7.72	6.70	9.19	6.66	5.87	6.27
Precipitation	1.84	1.11	1.91	1.17	1.77	1.02
Sunshine	4.62	2.29	5.05	2.25	4.08	2.23
Individuals	16,423		9,600		6,823	
Observations	86,101		48,100		38,001	

Notes: The table lists descriptives on socio-demographic variables and pollution exposure of SOEP individuals, averaged over the period 2005-2018. Employment (marriage) is a binary variables indicating if the person is employed (married) in each year or not. Income is monthly net household income measured in thousand Euro. All pollutants are measured in $\mu g/m^3$.
Source: SOEP, version 35, and German Environmental Agency.

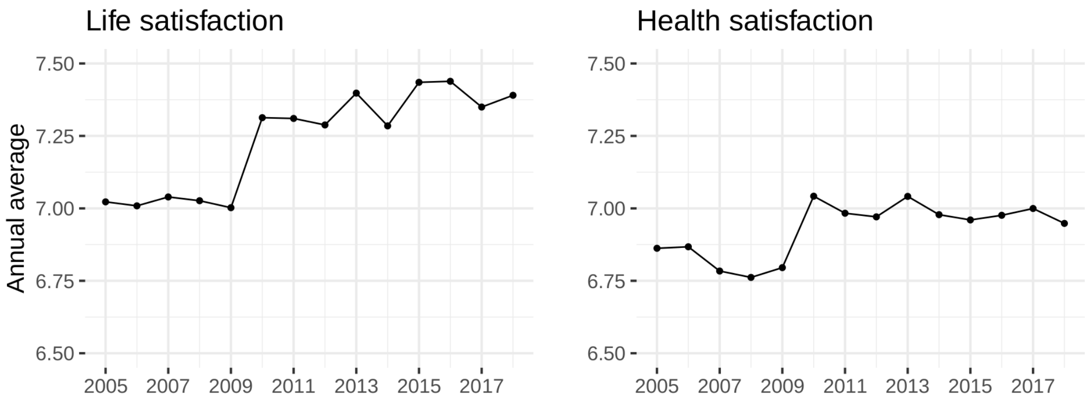
Figure 3.3: Life and health satisfaction of SOEP individuals



Notes: The figure depicts the number of SOEP responses per category of life and health satisfaction, respectively, for the period 2005-2018.
Source: SOEP, version 35.

Since then, average life and health satisfaction have remained relatively stable. Average life and health satisfaction of parents are higher than for non-parents, but both groups exhibit similar trends (Table B.2).

Figure 3.4: Life and health satisfaction of SOEP individuals over time



Notes: The figure depicts annual average values of life and health satisfaction of SOEP individuals for the period 2005-2018.
Source: SOEP, version 35.

3.4 Research Design

3.4.1 Identification

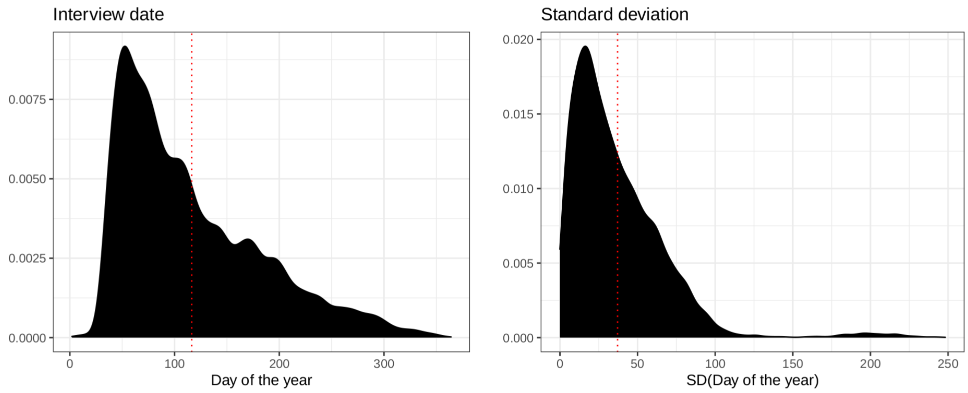
The research design identifies the effect of ozone on individuals from within-year variation in ozone levels at weekly, monthly, and quarterly frequencies.[10] Our identification strategy helps mitigate concerns about the endogeneity of pollution levels, and it is similar to the approach by Levinson (2012), except that the higher quality of our data allows us to exploit more variation in ozone concentrations across space and time (Figure 3.2). The design controls for unobservable heterogeneity through individual, year, month, and day-of-the-week fixed effects. Additionally, we control for differences in observables at the individual level, as well as for weather conditions that play a role in ozone generation.

SOEP interviews take place at different times of the year all over Germany. Roughly half of the surveys take place between September and March — months with low ozone concentrations — while the other half occurs from April to August when ozone levels are higher (Figure 3.5, left panel). Besides, the interview dates also vary at the individual level across the years. On average, SOEP interviews for each person occur with a standard deviation of 37 days (Figure 3.5, right panel). In addition to variation across the year, interviews also vary by weekday. Even if the questionnaire were filled on the same date in two consecutive years, ozone

[10] Our data only allow us to map ozone levels to each person's dwelling. However, especially kindergartens and primary schools are usually close to people's homes. We thus consider our assumption that ozone levels at individuals' dwellings are similar to those at schools and kindergartens to be fair.

values likely change because of differences in ozone concentrations depending on the day of the week (Figure 3.6, left panel). Together, these sources of temporal variation provide significant in-person variation in exposure.

Figure 3.5: Distribution of SOEP interviews over days of the year

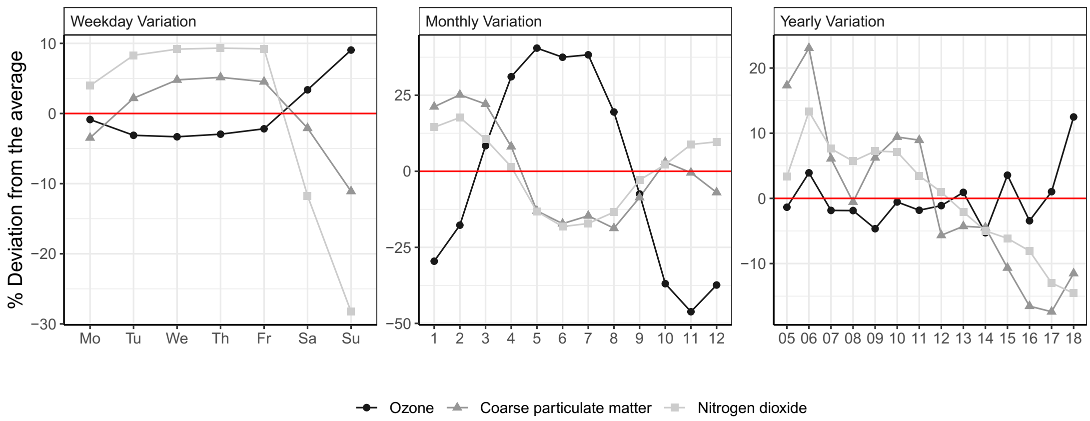


Notes: The left panel shows the distribution of the day-of-the-year of SOEP interviews for the period 2005-2018. The right panel depicts the distribution of individual-level standard deviations of interview dates.
Source: SOEP, version 35.

One concern is self-selection through moving behavior. Some individuals may move to areas with less pollution. To avoid this issue from contaminating our results, we exclude individuals that moved dwellings during the sample period: By eliminating movers, we estimate a lower bound of the effect of ozone, as people that relocate due to ozone exposure are likely to be more sensitive than those who remain in their prior location. Another potential concern is that ozone levels may be highly correlated with other pollutants so that multicollinearity may hinder the identification of effects. Figure 3.6 shows that ozone variation differs strongly from PM_{10} and NO_2 across the week, the year, and over our sample period. In addition to differences in variation over shorter intervals, ozone is the only air pollutant that has not seen a significant decrease throughout the study period (Figure 3.6, right panel). We check the robustness of our results using a multi-pollutant specification that controls for other relevant contaminants besides ozone.[11]

[11] We include additional pollutants that are highly correlated with ozone, i.e., coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2). Results for the multi-pollutant specification are listed in Tables B.2, B.3, and B.4.

Figure 3.6: Temporal variation in ozone, fine particulate matter and nitrogen dioxide



Notes: The figure depicts percentage deviations of weekday, monthly, and annual average pollution concentrations from their overall average for the period 2005-2018.
Source: German Environmental Agency.

3.4.2 Empirical model

Our main analysis estimates the following equations:

$$LS_{it} = \alpha + \rho \; Ozone_{it} + \boldsymbol{X'_{it}}\alpha + \boldsymbol{W'_{it}}\beta + \boldsymbol{\Gamma_t} + \lambda_i + \epsilon_{it}, \tag{3.1}$$

$$HS_{it} = \alpha + \rho \; Ozone_{it} + \boldsymbol{X'_{it}}\alpha + \boldsymbol{W'_{it}}\beta + \boldsymbol{\Gamma_t} + \lambda_i + \epsilon_{it}, \tag{3.2}$$

LS_{it} and HS_{it} are subjective life and health satisfaction values for each individual i on the interview date t. $Ozone_{it}$ is the exposure of individual i to ozone. ρ represents the coefficient of interest on pre-interview ozone exposure of different lengths. We estimate short-term effects by using the ozone exposure during the week prior to the interview as the main explanatory variable and capture longer-term effects by using rolling averages of ozone concentrations during the month and quarter before the interview. $\boldsymbol{X'_{it}}$ is a matrix of time-varying individual level controls and $\boldsymbol{W'_{it}}$ contains weather controls based on weekly, monthly, or quarterly rolling averages prior to the interview. $\boldsymbol{\Gamma_t}$ contains the matrix of year, month, and weekday fixed effects. λ_i are individual fixed effects, and ϵ_{it} is the error term, clustered at the household level. Finally, we address the dependent variable's ordinal nature using panel probit models with individual and year fixed effects in the robustness section.

3.5 Results

3.5.1 Full sample

We begin our analysis by considering if variation in exposure to ozone concentrations during the week before the interview affects the life or health satisfaction of individuals in the full sample. For each outcome, we run six different specifications, building up from a model containing only the level of ozone and individual and year fixed effects (Table 3.2, column 1) to the full specification corresponding to Equation 3.4.2 (column 6). The latter is our preferred specification, controlling for differences in income, marital and employment status, and five-year age bins allowing for non-linear relationships between age and life satisfaction, and interview month and weekday fixed effects. Additionally, it flexibly controls for weather impacts by including indicator variables for weather quintiles.

Table 3.2: Short-term effect of ozone on life satisfaction, full sample

	Dependent Variable: Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Ozone	-0.0010*	-0.0010*	-0.0008	-0.0008	-0.0013*	-0.0011*
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Income		0.0008*	0.0009*	0.0009*	0.0009*	0.0009*
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Is married		0.2442***	0.2435***	0.2435***	0.2433***	0.2438***
		(0.0570)	(0.0569)	(0.0568)	(0.0568)	(0.0568)
Is employed		0.0588**	0.0550*	0.0552*	0.0568**	0.0562**
		(0.0215)	(0.0214)	(0.0214)	(0.0214)	(0.0214)
Fixed-effects						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
Day-of-the-week	No	No	No	Yes	Yes	Yes
Control variables						
Age bins	No	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	Linear	Non-linear
Fit statistics						
Individuals	16,423	16,423	16,423	16,423	16,423	16,423
Observations	86,101	86,101	86,101	86,101	86,101	86,101
Adjusted R^2	0.53711	0.53809	0.53844	0.53848	0.53856	0.53848

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on average ozone exposure during the week prior to the SOEP interview. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. Column (2) adds the sociodemographic covariates income, employment status, marital status, and categorical five-year age bins; (3) adds fixed effects for the month of the interview; (4) adds day-of-the-week fixed effects; (5) adds linear weather controls (sunshine duration, temperature, precipitation); (6) controls for non-linear weather impacts through indicator variables for weather quintiles. Robust standard errors clustered at the household level in parentheses.

Table 3.2 lists results for the impact of average ozone exposure during the week prior to the SOEP interview on life satisfaction. The point estimate for ozone is consistently negative across all specifications, and statistically significant in the preferred specification. The results for other covariates are as expected and in concordance with Frijters, Haisken-DeNew and Shields (2004): Income, being employed, and being married are positively related to life satisfaction. The point estimates on the five-year age bins suggest a U-shaped relationship between life satisfaction and age, consistent with the evidence presented by Baetschmann (2013).[12] As we are not only interested in the effect of ozone on subjective evaluations of people's lives but also their subjective health, we run the same specifications with health satisfaction as the dependent variable.[13] In line with Levinson (2012), we find that ozone has no short-term effect on individuals' health satisfaction.

Next, we analyze the effect of different time aggregations of exposure to ozone on life satisfaction. Doing so is of interest as the epidemiological literature suggests that the adverse effects of ozone accumulate over time. We run additional estimations for average ozone concentrations during the month and quarter before the interview. Table 3.3 shows the coefficients on ozone for the weekly, monthly, and quarterly time aggregations and across all models.[14] Again, there is some evidence of a negative link between ozone and life satisfaction in the full sample, with varying significance levels across specifications. The impact on life satisfaction appears to accumulate over time because coefficient magnitude increases with longer exposure windows. In contrast, the results for health satisfaction are never significant for any time aggregation of ozone exposure.

These initial results for the full sample show that ozone levels are negatively related to how individuals assess their life satisfaction. In contrast, ozone exposure does not affect adults' health satisfaction, potentially because health effects on adults are rather moderate and too subtle to impact their self-rated health. Nevertheless, we cannot rule out that these health effects translate to decreases in life satisfaction. Next, we test whether this direct health effect, or the hypothesized indirect effect operating through children's health, is driving the negative relationship between ozone and life satisfaction. We revisit our hypothesis by studying if ozone has differential impacts on life and health satisfaction of parents and childless people. All further analyses focus on our preferred specification.

[12] For brevity, we do not list the coefficients on age bins. They are available upon request.
[13] Table B.1 lists the results for health satisfaction.
[14] We also run our regressions using daily pollution data. Ozone is never found to be significant. We believe this result is reasonable due to the short measurement period. The results are available upon request.

Table 3.3: Effect of ozone on life and health satisfaction, full sample and different time aggregations of pollution

	Dependent Variable: Life satisfaction					
Ozone average	(1)	(2)	(3)	(4)	(5)	(6)
Weekly	-0.0010*	-0.0010*	-0.0008	-0.0008	-0.0013*	-0.0011*
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Monthly	-0.0013**	-0.0013**	-0.0013	-0.0012	-0.0015+	-0.0014+
	(0.0005)	(0.0005)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Quarterly	-0.0020**	-0.0019**	-0.0021+	-0.0021+	-0.0023+	-0.0024+
	(0.0006)	(0.0006)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
	Dependent Variable: Health satisfaction					
Weekly	0.0000	0.0001	0.0001	0.0001	-0.0003	-0.0002
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Monthly	0.0000	0.0000	-0.0005	-0.0005	-0.0011	-0.0009
	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0010)	(0.0009)
Quarterly	0.0011	0.0011	0.0010	0.0010	-0.0002	0.0006
	(0.0007)	(0.0007)	(0.0014)	(0.0014)	(0.0015)	(0.0014)
Fixed-effects						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
Day-of-the-week	No	No	No	Yes	Yes	Yes
Control variables						
Age bins	No	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	Linear	Non-linear
Fit statistics						
Individuals	16,423	16,423	16,423	16,423	16,423	16,423
Observations	86,101	86,101	86,101	86,101	86,101	86,101

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on ozone exposure. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. Column (2) adds the sociodemographic covariates income, employment status, marital status, and categorical five-year age bins; (3) adds fixed effects for the month of the interview; (4) adds day-of-the-week fixed effects; (5) adds linear weather controls (sunshine duration, temperature, precipitation); (6) controls for non-linear weather impacts through indicator variables for weather quintiles. Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

3.5.2 Parents and childless individuals

Recall that our central hypothesis is that ozone affects adults' well-being through the impact of ozone on their children's health. If it holds, we expect the point estimate of ozone exposure on the life satisfaction of parents to be significant and negative in sign, while the same point estimate for persons without children should remain insignificant. Table 3.4 contains the estimation results from our preferred specification across three different time aggregations of ozone exposure, for the subsamples of parents and childless persons, and for both life and health satisfaction.

Table 3.4: Effect of ozone on life and health satisfaction, by child status

Dependent Variables:	*Life satisfaction*		*Health satisfaction*	
Ozone average	Parents	Childless	Parents	Childless
Weekly	-0.0018*	-0.0003	0.0010	-0.0016+
	(0.0007)	(0.0008)	(0.0009)	(0.0009)
Monthly	-0.0025*	0.0002	-0.0005	-0.0007
	(0.0011)	(0.0013)	(0.0013)	(0.0014)
Quarterly	-0.0041*	0.0001	0.0004	0.0012
	(0.0017)	(0.0019)	(0.0019)	(0.0022)
Individuals	9,600	6,823	9,600	6,823
Observations	48,100	38,001	48,100	38,001

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure among parents and non-parents. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

We find a statistically significant effect of ozone on the life satisfaction of parents. In contrast, we find no significant results for persons without children. Results show that a marginal increase in ozone decreases parents' life satisfaction between 0.002 and 0.004 points, depending on the level of temporal aggregation. When extending the time interval for measuring exposure before the interview, the coefficient grows in size, pointing to time accumulation of adverse outcomes. Our results suggest that a one-standard-deviation increase in ozone exposure decreases life satisfaction of parents by 0.04 to 0.07 points. This effect corresponds to about 4-8% of the impact of becoming unemployed, as estimated by Kassenboehmer and Haisken-DeNew (2009). Given that job loss is one of the strongest shocks on life satisfaction found in the literature, the magnitude of the ozone impact on well-being appears substantive.

Concerning health satisfaction, we do not find any significant effects for parents.[15] This result implies that the effect of ozone on the well-being of parents works - at least partially - indirectly: Ozone exposure diminishes parents' well-being due to the negative impact of ozone on their children, a well-known high-risk group.

[15] For childless people, the impact of weekly ozone exposure on health satisfaction is borderline significant. A possible explanation is that the childless people are on average older than the parents in our sample and, hence, more vulnerable to the health impacts of ozone.

3.6 Mechanism

3.6.1 The role of parents' income

We have shown that ozone affects parents' life satisfaction while remaining innocuous to childless persons. An intuitive explanation is that children's health influences parents' well-being. We investigate this claim by using household income as a proxy for kids' health. There is consensus in the empirical literature that children from low-income households have generally worse health status, and are more likely to suffer from chronic and acute medical conditions (Currie and Lin, 2007). The negative relationship between children's health and parents' income has also been confirmed for Germany (Reinhold and Jürges, 2012). Hence, we expect more pronounced well-being effects on parents in low-income households, because their children are more vulnerable to ozone exposure due to worse health status. We investigate this hypothesis by examining heterogeneous life and health satisfaction effects of ozone in high- and low-income households.[16] To do so, we split the sample of parents into above-median and below-median earners and estimate separate effects for each subsample.

Table 3.5: Effect of ozone on life and health satisfaction of parents, by income group

Dependent Variables:	*Life satisfaction*		*Health satisfaction*	
Ozone average	Low income	High income	Low income	High income
Weekly	-0.0024^{+}	-0.0014	0.0012	0.0005
	(0.0013)	(0.0009)	(0.0014)	(0.0012)
Monthly	-0.0046*	-0.0008	-0.0001	-0.0012
	(0.0018)	(0.0014)	(0.0021)	(0.0018)
Quarterly	-0.0039	-0.0004	0.0013	-0.0014
	(0.0029)	(0.0022)	(0.0032)	(0.0027)
Individuals	6,640	5,723	6,640	5,723
Observations	24,048	24,052	24,048	24,052

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure among below-median and above-median income parents. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

The results in Table 3.5 show that the well-being effect of weekly and monthly ozone exposure is more pronounced for low-income parents than for high-income

[16] Using income as a proxy for kids' health is advantageous because it also captures undiagnosed illnesses of children. This circumvents the "diagnosis bias" where children from high-income households are more likely to be diagnosed with chronic conditions even if they are healthier on average (Reinhold and Jürges, 2012).

parents. In contrast to above-median earners, the well-being of below-median earning parents significantly declines. This supports the hypothesis that children in low-income households have a lower health status, and react more strongly to ozone exposure.

3.6.2 The impact of children's respiratory health

We have provided evidence that the negative relationship between ozone and parents' well-being is more pronounced in low-income households, presumably due to worse child health. Next, we corroborate this claim by directly relating parents' well-being to objective health outcomes of their children. As shown in section 3.2, a large stream of epidemiological literature demonstrates the negative consequences of ozone exposure for kids' health. Ozone exposure does not only increase the prevalence of respiratory diseases among children (Coneus and Spiess, 2012), it can also exacerbate pre-existing respiratory conditions like asthma (Gent et al., 2003). Hence, we expect children with a respiratory disease to be more vulnerable and react more strongly to ozone exposure. We exploit these findings by differentiating between parents of children with a doctor-diagnosed respiratory disease and parents of healthy children.[17]

Table 3.6 lists the regression results on life and health satisfaction for parents with sick children and parents with healthy children.[18] Effects on health satisfaction are never significantly different from zero, confirming again that parents' health assessment is unaffected by ozone exposure. Concerning life satisfaction, we observe pronounced decreases among parents of kids with a respiratory condition: Across all exposure lengths, point estimates obtained from the subsample of sick-child parents are about twice as large as in Table 3.4 and highly significant. In contrast, the life satisfaction of healthy-child parents is not affected by ozone.

Moreover, the literature provides evidence that high-income children are better able to cope with the adverse consequences of chronic conditions (Case, Lubotsky and Paxson, 2002; Reinhold and Jürges, 2012), which would imply smaller well-being decreases among high-income parents with a sick child being exposed to ozone. To investigate this, we split the samples of low- and high-income parents

[17] Table B.5 lists descriptives on both subsamples of parents. Both groups are similar in terms of life and health satisfaction, age, and number of kids, but parents of children with a respiratory disease are more frequently employed and have a higher income. We investigate heterogeneous effects by income groups in Tables 3.7 and B.6.

[18] Note that the sample size decreases because health outcomes are only surveyed for children younger than eleven years. Hence, we discard parents of older children due to a lack of data. Since older children are less susceptible to pollution exposure, the estimated well-being effects in Table 3.6 likely represent upper bounds.

Table 3.6: Effect of ozone on life and health satisfaction of parents, by child health

Dependent Variables:	*Life satisfaction*		*Health satisfaction*	
Ozone average	Respiratory	Healthy	Respiratory	Healthy
Weekly	-0.0038*	-0.0013	0.0020	0.0005
	(0.0015)	(0.0012)	(0.0019)	(0.0014)
Monthly	-0.0071***	-0.0005	-0.0037	-0.0008
	(0.0021)	(0.0017)	(0.0027)	(0.0021)
Quarterly	-0.0107***	-0.0030	-0.0066	0.0006
	(0.0032)	(0.0028)	(0.0043)	(0.0032)
Individuals	1,477	3,488	1,477	3,488
Observations	9,896	18,212	9,896	18,212

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure among parents with at least one child with doctor-diagnosed respiratory disease and parents with healthy children. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

by health status of their children. Table 3.7 presents suggestive evidence that low-income parents of children with respiratory illness experience stronger decreases in well-being due to ozone exposure at the weekly and monthly frequency, relative to their high-income counterparts. This is in line with the idea that high-income parents are better at managing the health problems of their children, e.g., by diligently following treatment regimes or modifying the child's environment to avoid pollution exposure. For longer-term exposures at the quarterly frequency, point estimates are very similar across income groups, but less precisely estimated for low-income parents. Notably, parents of healthy children are never significantly affected by ozone exposure.[19]

Taken together, these results suggest that the negative well-being effect of ozone is driven by parents whose child has developed a respiratory illness. The respiratory condition makes children more vulnerable to ozone exposure than healthy children, and their health status is more likely to deteriorate as a consequence of ozone exposure, which is reflected in lower life satisfaction of their parents.

[19] Table B.6 lists the corresponding results for health satisfaction, which is never significantly affected.

Table 3.7: Effect of ozone on life satisfaction of parents, by income group and by child health

	Low income		*High income*	
Ozone average	Respiratory	Healthy	Respiratory	Healthy
Weekly	-0.0059*	-0.0013	-0.0021	-0.0015
	(0.0029)	(0.0019)	(0.0018)	(0.0016)
Monthly	-0.0109**	-0.0009	-0.0035	-0.0004
	(0.0039)	(0.0029)	(0.0025)	(0.0024)
Quarterly	-0.0093	-0.0019	-0.0097*	-0.0017
	(0.0062)	(0.0046)	(0.0039)	(0.0036)
Individuals	962	2,544	1,035	2,003
Observations	4,233	9,768	5,632	8,417

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on ozone exposure among above-median and below-median earning parents with sick vs. healthy children. The income subsamples are split into parents with at least one child with doctor-diagnosed respiratory disease and parents of healthy children. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

3.7 Robustness tests

3.7.1 Randomization of ozone exposure

This section runs two sets of placebo regressions to test whether our main results are an artifact of a defect in our research design. First, we randomize pollutants across space by randomizing exposure over individuals from different parts of the country in a given year. Second, we randomize across time by randomizing the exposure values of the same individual over different years. We then re-estimate our preferred specification. Table 3.8 contains the results of these additional estimations. Point estimates are mostly insignificant and very close to zero. Only two coefficients are close to statistical significance, amounting to a false positive rate of 6.25%. Since these point estimates occur in the childless group and have opposite directions, we are confident that our main results are not driven by spurious correlations.

3.7.2 Cardinalization of well-being measures

One caveat of this paper and others attempting to explain variation in subjective health and well-being is the cardinalization of ordinal data when running OLS type regressions (Bond and Lang, 2019; Levinson, 2012). When cardinalizing ordinal scales, we implicitly assume that the distance between values is the same along the scale, for example, the gap between zero and one is the same as between nine

Table 3.8: Spatial and temporal randomization of pollutants, by child status

	Life satisfaction		*Health satisfaction*	
Ozone average	Parents	Childless	Parents	Childless
Spatial randomization				
Weekly	0.0101	-0.0007	0.0046	0.0035
	(0.0076)	(0.0027)	(0.0055)	(0.0025)
Monthly	-0.0138	0.0064^{+}	-0.0090	0.0022
	(0.0087)	(0.0033)	(0.0072)	(0.0030)
Quarterly	-0.0042	-0.0048^{+}	-0.0119	0.0041
	(0.0106)	(0.0028)	(0.0083)	(0.0036)
Temporal randomization				
Weekly	0.0006	0.0002	-0.0001	0.0004
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Monthly	0.0005	-0.0000	-0.0002	0.0004
	(0.0004)	(0.0005)	(0.0005)	(0.0006)
Quarterly	-0.0000	0.0001	-0.0000	0.0003
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Individuals	9,467	6,731	9,467	6,731
Observations	48,036	38,008	48,036	38,008

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on randomized ozone exposure. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

and ten. The linearity assumption corresponds to a monotonic transformation of the ordinal scale. Such monotonic transformations may alter and even reverse regression results obtained by treating ordinal data as cardinal (Bond and Lang, 2019).

We run fixed-effects probit models to analyze if our results hold up when treating our subjective outcomes as ordinal.[20] We transform the health and life satisfaction scales into binary variables using a number of different cut-off points c_j for $j = (1, ..., 9)$. For example, consider the cut-off point 2: If an individual's life satisfaction is smaller than or equal to 2, we assign a value of zero; that is, the individual is deemed ”unhappy.” If life satisfaction is greater than 2, we assign a 1; that is, the individual is considered ”happy.” Therefore, low cut-offs place more people in the ”happy” group, while the reverse is true for high cut-off points. In this setting, identification is based on people who transition from the happy to the unhappy group, or vice versa. Note that the location of the cut-off is arbitrary. Without information on the underlying distribution of happiness, it isn't possible

[20] We use the unconditional bias-corrected probit algorithm developed by Stammann, Heiss and McFadden (2016). The algorithm uses the unconditional probit framework that corrects for the incidental parameters problem (Neyman and Scott, 1948) with the jackknife procedure developed in Hahn and Newey (2004).

to make precise assessments of the suitability of a cut-off. We thus consider our results to be robust if they hold for multiple cut-off points.

Table 3.9 contains the Probit estimations for the sample of parents in the preferred specification. Results show that point estimates for life satisfaction are always negative. We observe significant effects for multiple cut-off points in the middle and the upper end of the life satisfaction scale, where sample sizes are much larger than for lower cut-offs. As in our baseline analysis, there are no significant results for health. Moreover, the corresponding table for the sample of childless people yields no significant results for life satisfaction (Table B.7), also confirming the results from the baseline regressions.[21]

Table 3.9: Probit estimations of effect of ozone on life and health satisfaction of parents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ozone average	*Dependent variable: Life satisfaction*								
Weekly	-0.0098	-0.0005	-0.0053	-0.0065*	-0.0058**	-0.0025	-0.0029*	-0.0008	-0.0024+
	(0.0112)	(0.0072)	(0.0042)	(0.0027)	(0.0022)	(0.0016)	(0.0013)	(0.0011)	(0.0014)
Monthly	0.0003	-0.0172	-0.0141	-0.0074	-0.0033	-0.0081*	-0.0049	-0.0048+	-0.0064*
	(0.0322)	(0.0167)	(0.0096)	(0.0064)	(0.0051)	(0.0037)	(0.0031)	(0.0026)	(0.0031)
Quarterly	0.0006	-0.0178	-0.0142	-0.0077	-0.0033	-0.0081*	-0.0049	-0.0047+	-0.0062*
	(0.0322)	(0.0167)	(0.0096)	(0.0064)	(0.0051)	(0.0037)	(0.0031)	(0.0026)	(0.0031)
Individuals	78	173	437	909	1,440	2,722	3,672	4,851	3,767
Observations	434	1,036	2,628	5,501	8,692	16,213	21,924	29,199	22,461
Ozone average	*Dependent variable: Health satisfaction*								
Weekly	-0.0041	-0.0039	-0.0003	0.0012	0.0023	0.0012	0.0017	0.0007	0.0006
	(0.0063)	(0.0042)	(0.0029)	(0.0019)	(0.0016)	(0.0013)	(0.0012)	(0.0011)	(0.0013)
Monthly	-0.0094	-0.0087	-0.0008	0.0026	0.0014	0.0005	0.0009	-0.0016	-0.0033
	(0.0097)	(0.0060)	(0.0040)	(0.0027)	(0.0023)	(0.0019)	(0.0018)	(0.0016)	(0.0020)
Quarterly	-0.0100	-0.0157	-0.0113+	0.0014	0.0024	0.0022	0.0027	-0.0006	-0.0016
	(0.0172)	(0.0100)	(0.0062)	(0.0043)	(0.0036)	(0.0029)	(0.0027)	(0.0026)	(0.0029)
Individuals	215	420	879	1,714	2,452	3,639	4,327	4,919	3,901
Observations	1,289	2,633	5,412	10,744	15,179	22,149	26,363	29,790	22,928

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Fixed-effects probit regressions of life satisfaction and health satisfaction on ozone exposure of parents. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Each columm relates to a specific cut-off point between 1 and 9 used to transform the original 11-point scale into a happiness status of 0 or 1. The estimated specifications and cut-off points $c_j \in j = (1, ..., 9)$ are related as follows: $[(1) = c_1, ..., (9) = c_9]$. Robust standard errors clustered at the household level in parentheses.

3.8 Conclusion

This paper hypothesizes that air pollution may – in addition to a direct health effect – decrease adults' well-being through its impact on their children. The

[21] Table B.7 shows that health satisfaction of childless individuals decreases in the lower part of the distribution, but effects are not consistently significant across different exposure windows.

study tests this hypothesis for the case of ground-level ozone by analyzing whether ozone exposure affects parents and childless persons in different ways. We use a representative panel of German individuals, the Socio-Economic Panel (SOEP), to study the effect of exposure to ground-level ozone on two measures of subjective well-being, health and life satisfaction. Moreover, we provide direct evidence on the children's health channel to parents' life satisfaction by estimating separate effects for parents of sick and healthy children. Our analysis also evaluates heterogeneity in the well-being effect introduced by parents' income.

We exploit information on the precise date of the SOEP interview to identify the effect of ozone on individuals from short-term variation in ozone levels. To do so, we match pollution levels from measuring stations across Germany with geo-coded SOEP data between 2005 and 2018 and compute the individual level of exposure through inverse distance weighting techniques. The study estimates the effects of ozone on the health and life satisfaction of parents and non-parents using fixed effects regressions. In the preferred specification, we control for time and individual fixed effects and include a battery of individual-level covariates and weather controls to account for time-varying observable and time-invariant unobservable heterogeneity.

We find statistically and economically significant adverse effects of ozone on parents' life satisfaction while finding no impacts on childless people. In contrast to life satisfaction, our analysis finds no evidence of a direct effect of ozone on adults' health satisfaction. Examining the children's health mechanism to losses in parents' life satisfaction, we find that higher ozone exposure strongly affects the well-being of parents whose child suffers from a respiratory disease, whereas parents of healthy kids are not affected. In line with the literature on the negative relationship between children's health and parents' income, the well-being effect is concentrated among below-median earners. Our results suggest that ozone concentrations in Germany are not high enough to affect the subjective health of adults, but that they do have negative consequences for the health of vulnerable children, which in turn diminishes the well-being of their parents.

Based on our analysis, we recommend considering the indirect influence of ozone on parents for future research dealing with the cost-benefit analysis of ozone-related environmental policies. One limitation of this study is the lack of exogenous variation in ozone exposure. Although we account for self-selection by excluding movers, and control for time-invariant unobservables and differences in observables in our regression framework, we cannot rule out the possibility of time-varying confounders entirely.

Chapter 4

Fracking and Health-Related Absenteeism of Employees

4.1 Introduction

Labor is one of the primary inputs to production in any economy and, hence, a crucial component to sustain economic growth. A key determinant of the labor supply is human health, because individuals' health outcomes affect overall productivity of the labor force: Poor health outcomes can have negative short-run impacts by decreasing employees' labor supply due to illness-related absenteeism, but they can also assert detrimental long-run effects by limiting human capital formation (Graff Zivin and Neidell, 2013), which would impose economic costs on society and decrease social welfare (DeLeire and Manning, 2004). There is growing evidence that poor health outcomes are causally linked to negative environmental externalities, such as pollution (e.g., Lavaine and Neidell, 2017; Currie and Neidell, 2005; Chay and Greenstone, 2003), suggesting that those externalities might have considerable impact on the labor market through adverse health effects (e.g., Hanna and Oliva, 2015; Carson, Koundouri and Nauges, 2010).

Hydraulic fracturing, commonly referred to as fracking, is a potential source of localized environmental externalities. It is a technique to extract natural gas and oil from shale rock formations by injecting high volumes of water, sand and additional chemicals into the ground. While its positive labor market effects, such as increases in local employment and wages, have been investigated extensively (e.g., Komarek, 2016; Cosgrove et al., 2015, Paredes, Komarek and Loveridge, 2015), little is known about its potential detrimental impacts on individuals' labor supply.

In this paper, we assess the short-run impact of fracking on surrounding households' labor market outcomes in terms of health-related absenteeism of employees, measured by the number of sick leave days. If fracking exerts significant negative environmental externalities, we expect individuals living in close proximity to fracking sites to have poorer health outcomes than comparable individuals, resulting in a higher number of sick leave days for those individuals exposed to fracking.

Our results inform the ongoing debates about the expansion of shale exploration activities in the US, where the "shale revolution" has fueled discussions about the costs and benefits of fracking: The proponents embrace it as a technology bridging the transition to renewable energy and emphasize its economic and socio-political benefits, e.g., local economic growth, lower energy prices or increased energy security. The opponents, on the other hand, believe that the costs arising from exposure to negative environmental externalities and subsequent health effects outweigh the benefits of exploitation. Negative externalities of fracking include diminished local air quality, surface and groundwater contamination, community character impacts through additional noise and traffic and an increased potential for seismic activity. In order to mitigate these adverse environmental and public health impacts of fracking, some federal states in the US have banned shale exploration activities entirely, for example New York (Leff, 2015). While the benefits of fracking are mainly of economic nature and are generally acknowledged, the associated costs have been explored only incompletely. But in order to conduct comprehensive cost-benefit analyses and to assess the net welfare effects of shale exploration, the costs induced by adverse health effects need to be taken into account. Quantifying the degree to which fracking-induced illnesses affect the labor market outcomes of individuals, in the form of decreases in labor supply as measured by sick leave days, allows us to estimate the economic costs imposed on the labor market.

There is a growing body of literature on the environmental externalities of fracking, exploring many potential channels through which fracking affects individuals' health. Adverse health effects could arise, e.g., from air pollutants like volatile organic compounds that are emitted during development and operation of the site (e.g., McKenzie et al., 2012; Colborn et al., 2014; Colborn et al., 2011), or from ground water sources that are contaminated with methane, chemicals or toxic heavy metals from fracking waste water (e.g., Hill and Ma, 2017; Fontenot et al., 2013; Jackson et al., 2013; Osborn et al., 2011).The numerous pollutants are related through complex interactions and accounting for all of them simultaneously is crucial to assess the net health effect of exposure to fracking sites. By looking at the number of sick leave days of individual employees, we capture several potential channels through which fracking impacts human health in the short run, allowing us to quantify a net health effect on labor market outcomes.

Empirical evidence on human health effects from exposure to fracking focuses either on very specific health outcomes, such as dermal and respiratory conditions (Rabinowitz et al., 2014; Rasmussen et al., 2016), on measures of infant health (Casey et al., 2016; Currie, Greenstone and Meckel, 2017; Hill, 2018), or on extreme health outcomes that lead to hospitalization of individuals (Jemielita et al., 2015; Willis et al., 2018). We contribute to this literature by assessing the effect of fracking on sick leave days. This outcome measure captures more subtle changes in health outcomes than hospitalization rates and can serve as a basis to approximate the economic costs imposed by fracking on the labor market. We provide first evidence of an ambiguous labor market effect of fracking, i.e. a decrease in labor supply due to short-term illness, which has not yet been explored in the literature.

To assess the localized health effects in terms of labor market outcomes, we use individual- and household-level data from the Panel Study of Income Dynamics (PSID), which contains our dependent variable, i.e. the number of sick leave days, locational identifiers as well as various socio-economic control variables. We combine the PSID data with a panel data set on oil and gas wells from the Pennsylvania Department of Environmental Protection (PA DEP), covering the years from 2000 to 2014, which are characterized by enhanced shale exploration activity. To establish a causal link between fracking and labor market outcomes, we implement a differences-in-differences approach that exploits the intertemporal and geographical variation in construction dates and locations of fracking wells: To estimate the effect of living close to a fracking site on the number of sick leave days, we compare households located within a specific radius from the fracking well (treatment group) to similar households located further away (control group). To ensure comparability, we use propensity-score matching on socio-economic characteristics of households. Our differences-in-differences specification controls for time-varying confounders on the individual- and household-level, for time-invariant unobserved heterogeneity by including individual fixed effects, and for time fixed effects. Our results suggest that living in proximity to a fracking site increases absenteeism by two to three days per year per employee. The magnitude of the effect is comparable to literature estimates on the impacts of having a chronic illness, e.g., diabetes or obesity (Asay et al., 2016; Finkelstein, Fiebelkorn and Wang, 2005).

The next section describes the process of hydraulic fracturing and discusses the costs and benefits of shale exploration. Section 4.2 provides details on the data used. Section 4.4 outlines the research design and explains the identification strategy employed. Section 4.5 presents results. Section 4.6 discusses the advantages and limitations of the research design. Section 4.7 concludes.

4.2 Background and related literature

4.2.1 Technical background

The recent "shale revolution" observed in the US has been fueled by technological advancements that made it economically viable to extract unconventional resources of natural oil and gas trapped in geological formations of low permeability, such as shale rock and tight sandstone. The techniques to exploit these unconventional resources rely on horizontal drilling and hydraulic fracturing of the rock formations.[1]

The first step of shale exploration activities consists of constructing the necessary production infrastructure. This includes building access roads, compressor stations, and pipeline networks as well as clearing and leveling the well pad, which requires typically between 12,000 and 20,000 m^2 of land. A new well is spudded[2] when the process of drilling begins: Horizontal drilling can take place several kilometers underground and spread over horizontal distances of two kilometers and more. After drilling and casing activities have been completed, fracking is used to stimulate oil and gas production of the well: The rock formations are cracked through high-pressure injection of large volumes of water, sand and additional chemicals, which creates fractures that enable the oil and gas to flow through the well to the surface, such that the well enters its production phase (Jackson et al., 2014).

The average production lifetime of an unconventional well varies with the shale play in which the well is located. E.g., in the Marcellus shale located in the North-East of the US, an average well produces 97 percent of its Estimated Ultimate Recoverable (EUR) gas quantity of 3.16 billion cubic feet within the first 7 years of production (Moeller and Murphy, 2016). When the well's oil and gas production is no longer economic, the well should be permanently plugged in order to prevent well safety issues in the future. Plugging entails removal of the pumping equipment and sealing with cement and other materials to prevent leaks. It is generally the operator's responsibility. However, because fracking regulations vary widely across the US federal states, the number of unplugged, abandoned wells on US territory is uncertain due to a lack of reporting standards (Townsend-Small et al., 2016).

4.2.2 Benefits of fracking

The proponents of fracking argue that it brings socio-political, environmental and economic benefits. The availability of fracking techniques made the extraction

[1] The main distinction between conventional and unconventional wells lies in the geological formation they are tapping: To exploit the conventional sedimentary formations, vertical well bores are typically sufficient and the stimulation of conventional wells generally does not require the volume of fluids typically required for unconventional wells, since the natural pressure in conventional sources is sufficient to pump the resources to the surface. Moreover, conventional wells typically have less drilling depth, smaller well pads, lower well head pressure and less equipment needs in terms of trucks, roads and pipeline systems (PA DEP, 2012).

[2] Spudding is an industry-specific term describing the process of beginning to drill an oil or gas well.

of unconventional resources economically viable, which increased the accessible energy reserves. This supply abundance increased energy security and decreased natural gas prices, leading in turn to an increase in energy affordability (Sovacool, 2014). The technology might also contribute to lowering greenhouse gas emissions if the natural gas from unconventional sources replaces other fossil fuels, such as oil and coal. If fracking led to a higher share of natural gas in the energy mix, e.g. in electricity generation, this could facilitate the achievement of climate goals, since the carbon content of natural gas is much lower than in most other fossil fuels (Jenner and Lamadrid, 2013).

The most apparent benefits of fracking are of economic nature: The oil and gas industry can foster local economic growth, thus creating additional jobs and tax revenues for the local communities. The positive labor market effects of fracking have been investigated extensively. For example, Paredes, Komarek and Loveridge (2015) explore the employment and income effects on the county level using propensity score matching and fixed effects regressions. The estimated average employment effects range from 71 to 181 total jobs for counties in which fracking takes place. Cosgrove et al. (2015) use county- and zip-code level data from 2001 to 2013 to study the regional economic impact of shale exploration in terms of wages and employment. They exploit the fracking moratorium that was passed by the federal government of New York in 2008 and implement a differences-in-differences approach that compares counties at the border between Pennsylvania and New York. Their results suggest that shale gas development increases employment and wages in the mining and construction sectors, while it might reduce employment levels in the manufacturing industries due to a crowding out effect. They find no evidence for an aggregate increase in employment levels or wages at the county level. In a similar vein, Komarek (2016) compares counties with fracking activity in Pennsylvania, Ohio and West Virginia to counties in New York, based on data from 2001 to 2013. The panel regressions indicate that fracking activity increases total employment by 3 to 6 percent and total wages by 8 to 12 percent. Bartik et al. (2019) confirm these findings on total employment and additionally show that household income, consisting of wages and royalty payments, increases by up to 6 percent.

4.2.3 Costs of fracking

The opponents of the technology emphasize that the environmental costs of fracking are likely to outweigh its benefits. Fracking is associated with a variety of environmental externalities that arise at all stages of shale exploration activity:

Prior to well spudding, during the process of drilling and fracturing the well, during the actual production phase and, if the well is not properly plugged, after its productive life. For example, the construction of the production infrastructure requires trucks and construction machines, resulting in noise pollution and additional traffic that impact the local communities. During development and operation of the well, air pollutants like volatile organic compounds are emitted, which contributes to diminishing local air quality (e.g., McKenzie et al., 2012; Colborn et al., 2014; Colborn et al., 2011; Vinciguerra et al., 2015). Furthermore, the exploitation of shale resources requires large amounts of water, for example, drilling and fracking of a single well in the Marcellus shale uses on average 15 million liters of water (NETL, 2009). The produced waste water, which is often highly saline and contaminated with barium, arsenic and radioactive radium, can contaminate water sources by diffusing into surface and groundwater bodies (e.g., Fontenot et al., 2013; Jackson et al., 2013; Osborn et al., 2011). For example, Hill and Ma (2017) show that fracking wells in the proximity of groundwater source intakes of community water system increase the concentration of shale gas-related contaminants in the municipal drinking water supply, even after treatment of raw waters. Moreover, air and water pollution can be aggravated by failures in well integrity, where damaged casing cannot prevent leakage of fracking fluids and gases, or from the improper handling of waste water, including surface leaks from open ponds and inadequate treatment before discharge (Jackson et al., 2014). Similarly, wells that have been abandoned or plugged incorrectly pose a long-term risk to the environment, e.g., by continuously emitting the greenhouse gas methane (e.g., Kang et al., 2014; Townsend-Small et al., 2016).

These environmental externalities translate into risks for human health. Since fracking is associated with a vast number of potentially harmful pollutants that interact with each other in complex ways, it is very challenging to disentangle the health effects of one single pollutant. Instead, the existing empirical studies focus on the effect of being exposed to fracking on specific health outcomes. Rabinowitz et al. (2014) assess the effect of household proximity to natural gas wells on reported health symptoms by means of a survey of 492 individuals living in households with ground-fed drinking wells in Washington County, Pennsylvania. They find that proximity of natural gas wells may be associated with the prevalence of several health symptoms, including dermal and respiratory conditions. Currie, Greenstone and Meckel (2017) study the impact of fracking on infant health using birth records. They combine data on 1.1 million birth certificates issued from 2004 to 2015 in Pennsylvania, including information on infant health and maternal addresses, with official oil and gas well data. The results of their differences-in-differences design reveal significant negative effects on infant health for mothers living within 1 km of a fracking site, whereas there is little evidence of health effects at distances further than 3 km away. Using similar data from 2003 to 2010, Hill (2018) compares birth outcomes of mothers next to an active fracking well and outcomes of mothers living close to a permitted but not-yet-drilled well. She finds that drilling activity increases the likelihood of low birthweight and premature birth among mothers living within 2.5 km of a well. Jemielita et al. (2015) investigate the relationship between fracking wells and healthcare utilization rates on the zip code level, using data from 2007 to 2011. They discover that an increasing number of wells is related to increases in cardiology and neurology inpatient prevalence rates. Using similar data, Willis et al. (2018) show that drilling activity increases pediatric asthma hospitalizations, especially among children between the age of two and six.[3] We contribute to this literature by assessing the effect of fracking on sick leave days, which captures more subtle changes in health outcomes than, for example, hospitalization or mortality rates. Furthermore, we are the first to assess these health impacts in terms of illness-related employee absenteeism, which allows us to approximate the economic costs imposed by fracking on the labor market. This provides first evidence of ambiguous labor market effects of fracking, i.e. a decrease in labor supply due to short-term illness, which has not yet been explored in the literature.

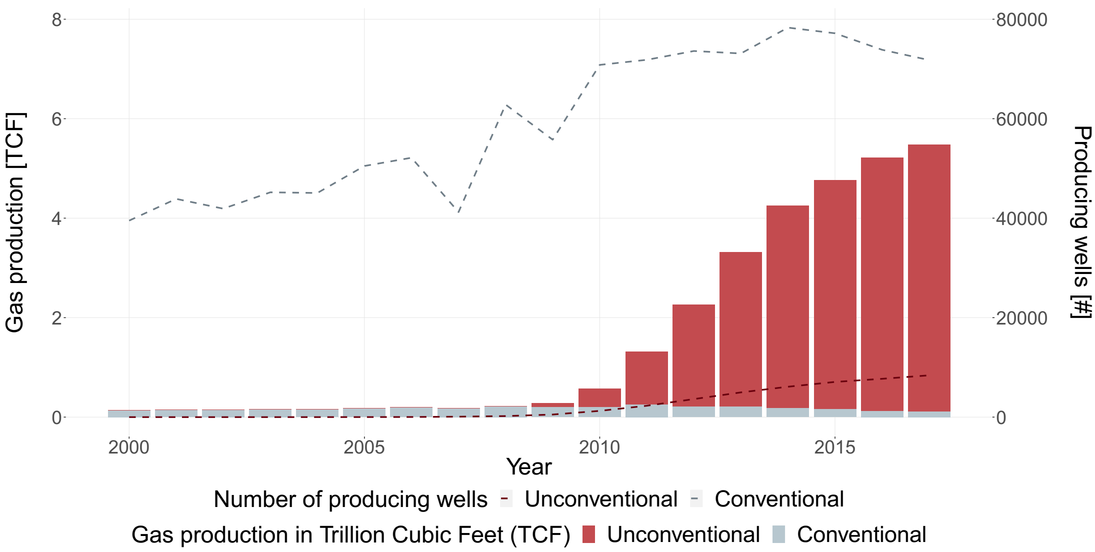
4.3 Data

4.3.1 Data on oil and gas wells

Our analysis focuses on the federal state of Pennsylvania (PA) for two reasons: First, PA is located above the Marcellus shale play and has the largest proven shale gas reserves among all federal states, adding up to 89.5 trillion cubic feet (TCF) out of a US total of 307.9 TCF in 2017 (EIA, 2018). Also, PA is one of the leading states in shale gas production, with 5.3 TCF of shale gas produced in 2017 (see Figure 4.1). Second, the official oil and gas data provided by the PA Department of Environmental Protection (DEP) is well documented, regularly updated and provides information on a sufficiently detailed level, e.g. information on the exact spud and plug dates of wells.

[3] Health effects may not only arise due to exposure to pollution, but also due to psychosocial factors. Hirsch et al. (2018) review the available literature and conclude that individuals from fracking communities may experience worry, anxiety and depression about lifestyle and health.

Figure 4.1: Gas production in PA (2000-2017)



Source: PA DEP *Oil and Gas Production Reports*, retrieved from `http://www.depreportingservices.state.pa.us`, accessed on May 31, 2022, own illustration.

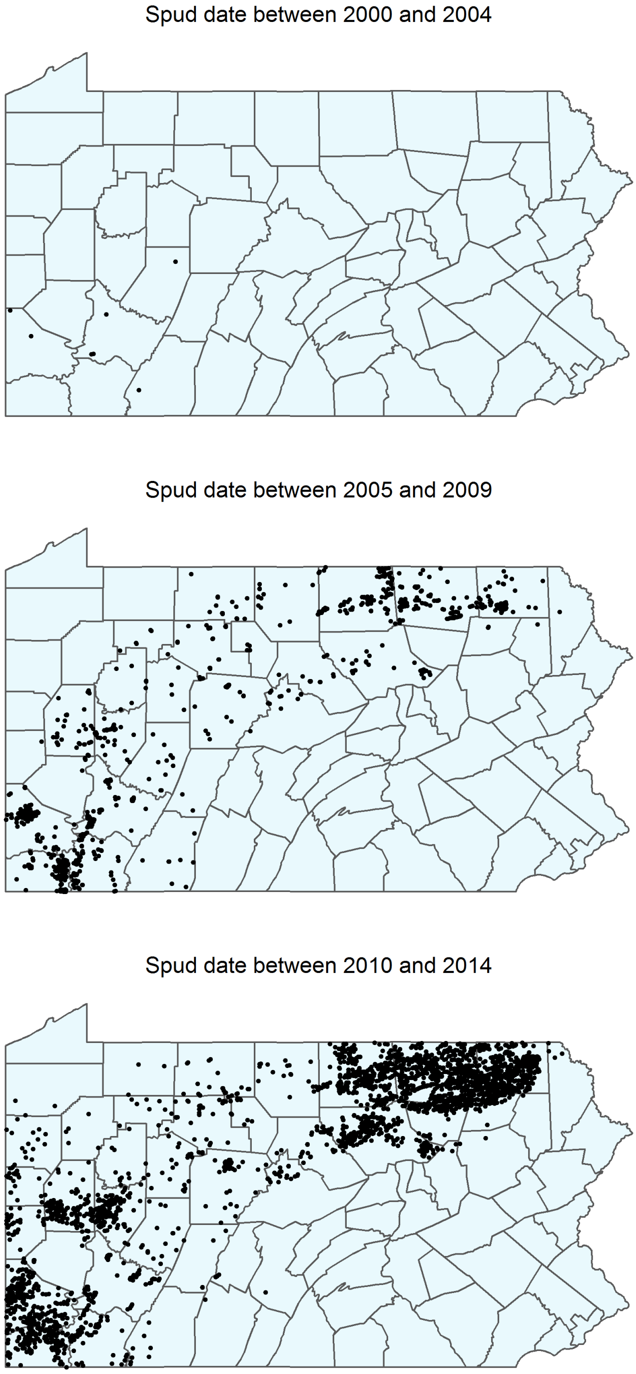
We use two data sets from the PA DEP covering oil and gas wells with construction dates ranging from 2000 to 2017: We combine the *Oil and Gas Operator Well Inventory*, containing information on well identifiers, exact geo locations, types of wells, spud and plug dates, permit issue and expiration dates of all oil and gas wells ever drilled or proposed, with the *Oil and Gas Production Reports*, comprising information on the annual production quantities and the number of production days of each oil and gas well.[4]

The PA DEP data covers conventional as well as unconventional oil and gas wells. Since we want to assess the health effects of shale gas production activities, we exclude all conventional wells. Furthermore, we consider all shale gas wells that have been spudded, regardless of whether they are in the process of drilling, actively producing or have been plugged or abandoned. Hence, we assume that the negative externalities from fracking arise not only during the processes of drilling and producing, but can also occur at a later point in time, e.g., due to casing damages resulting in waste water leakage into the ground, even after the well has been plugged.

The locations of fracking wells exhibits considerable variation across space and time: Figure 4.2 depicts the locations of wells that have been drilled during different time periods. Prior to 2005, there were less than ten fracking wells in

[4] See Table C.1 for descriptive statistics on the data sets.

Figure 4.2: Locations of unconventional wells in PA (2000-2014)



Source: PA DEP *Oil and Gas Operator Well Inventory*, retrieved from `http://data-padep-1.opendata.arcgis.com`, accessed on May 31, 2022, own illustration.

PA, but their number increased drastically since 2005. At the end of 2014, there were over 12,000 unconventional wells drilled in the Marcellus shale with more than half of them actively producing. This yields a large degree of intertemporal variation to exploit in our differences-in-differences approach.

4.3.2 Data on individuals and households

We use individual- and household-level data from the Panel Study of Income Dynamics (PSID), which is a longitudinal household survey in the US. The survey covers a broad range of socio-economic characteristics, such as employment, income, wealth, expenditures, health, childbearing, education and numerous other topics. The PSID is a biennial survey, i.e. interviews are conducted every other year.[5] Some core economic measures are surveyed for the two years prior to the survey year, but most variables refer only to the previous period, such as our dependent variable, the number of sick leave days,[6] which leaves us effectively with eight time periods between 2000 and 2014 to analyze. Besides our dependent variable and various sociodemographic controls, the PSID contains information on the location of each household on the census block level, which is the smallest geographic unit used by the US Census Bureau. The locational data is subject to stringent privacy regulations and reporting of results is restricted to cell sizes of more than ten observations.[7]

Since we are interested in adverse health-related labor market effects, we exclude individuals that are not employed. We consider only individuals that have been employed in all eight time periods and did not move out of the state PA, which yields a sample of 92 individuals with 736 observations. Consequently, we focus on a specific subpopulation of middle-aged employees, excluding students, unemployed and retired people.

4.4 Research design

4.4.1 Defining the treatment status

Since we do not know the exact coordinates of households in the PSID but only their census blocks, we have to make an identifying assumption on the location of each household within the census block to obtain exact coordinates: We assume

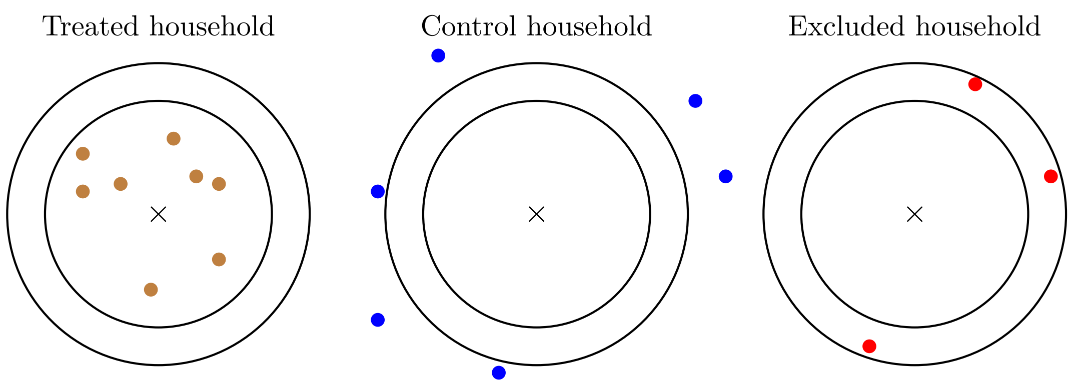
[5] The interviews were conducted in 2001, 2003, 2005, ..., 2015.

[6] The specific wording of the PSID questionnaire is "We're interested in time you spent away from work last year, during [YEAR]. Did you miss any work because you/someone else were/was sick?". Answers can be given in days, weeks or months. Note that we pool two questions (you or someone else in the household) to capture sick leave times of parents whose children become ill.

[7] The restricted PSID is remotely accessible and exporting results requires approval from PSID.

that households are located in the centroid of their respective census blocks, which allows us to draw a treatment radius around each household to define its treatment status. A household is considered as treated if a fracking well is located within the pre-defined radius. To achieve a clear distinction between treatment and control group, we set up a ban radius around the treatment radius: Households with a fracking well within the ban radius, but not the treatment radius, do neither enter the control nor the treatment group, but are discarded. The control group consists of households that are not affected by any wells within the ban radius. Figure 4.3 illustrates the method graphically. Our baseline specification considers a treatment radius of 10 km with a ban radius of 5 km. Under this specification, we obtain 35 individuals that have been treated in any year between 2006 and 2014.[8]

Figure 4.3: Treatment radius approach



Alternatively, we could define the treatment on the census block level, i.e. consider a household as treated if there is at least one fracking well located in its census block. The average area of a census block in PA is less than one square kilometer (see Table C.2), so the distances between households and fracking sites in treated census blocks are less than one kilometer, in most cases. However, although census blocks are generally small in area, their sizes can differ substantially. For example, census blocks in metropolitan areas are often rectangular city blocks bounded by streets from all sides, while census blocks in rural areas are typically much larger and their shapes are highly irregular since the blocks might be bounded by various features, such as roads, rivers or transmission lines. Hence, the distances between fracking wells and treated households are likely to vary across census blocks under this alternative approach, such that the households in our treatment group would exhibit varying levels of exposure to the externalities

[8] We would like to impose smaller radii, but with smaller distances the treatment group gets too small to obtain any meaningful results.

arising from fracking.[9] In contrast, the treatment radius approach allows us to consider radii that exceed the boundaries of the census blocks.

4.4.2 Identification strategy

In order to ensure causality of the relationship between proximity to fracking sites and labor market outcomes, we have to make the assumption that, in the absence of treatment, treatment and control groups' outcomes would have followed a common trend over time. This common trend assumption is not testable empirically because we cannot observe the counterfactual, i.e. the outcomes of the treatment group in the absence of treatment. To ensure comparability between treatment and control group, we apply propensity score (PS) matching on individual- and household level variables, which is described in more detail in the next subsection. We also include time-varying confounders in our differences-in-differences regression to account for any remaining differences in observables.

Moreover, we have to assume that our treatment is exogenous, i.e. the construction of fracking sites must be independent of the outcome variable, conditional on the observed covariates. Endogenous treatment could either arise due to residential sorting or due to endogenous construction. In the case of residential sorting, the affected population changes over time such that the outcome is systematically altered, for example, wealthier households with a better health status move away after a fracking well was constructed in their neighborhood. To account for residential sorting during the observation period, we exclude households that moved into and out of treatment. Excluding movers does not account for the possibility that fracking wells could be build close to poorer households that were already present at this location, but we account for this possibility by including individual-level fixed effects.

Additionally, construction of the fracking sites could be endogenous: For example, residents who own large areas of land might lease their property to mining companies to build fracking sites and receive royalties from the companies. To reduce the potential for endogenous construction, we exclude self-employed farmers, since they are more likely to lease land to oil and gas well operators. Moreover, we cannot account for any avoidance behavior besides mobility, for example, individuals spending less time outside during episodes of high pollution or households installing water filtration systems to protect against water contamination. Therefore, our approach measures the intention-to-treat and our estimates

[9] Implicitly, this approach assumes that fracking exerts its influence only within the census block of its location, which seems quite arbitrary given the varying sizes of blocks.

are interpretable as lower bounds based on individuals who do not move out of treatment.

4.4.3 Propensity score matching

Shale exploration in PA typically takes place in rural areas, therefore, individuals from the treatment group might not necessarily be comparable to individuals from the control group. Indeed, there are statistically significant differences between our treatment group and the unmatched control group, e.g., the treatment group is characterized by a higher share of people living in rural areas, a lower share of self-employed people and significantly lower health care expenditures, labor incomes, and house values.[10] Our treatment group consists, on average, of less wealthy individuals with poorer health outcomes, so we need to make both groups comparable.

To increase comparability of both groups and plausibility of the common trend assumption, we implement PS matching in the form of one-to-one nearest neighbor matching without replacement on the following household-level characteristics: Location in rural or urban area, the type of housing, the house value, the number of births per household, as well as household health care expenditure. These covariates are chosen based on their potential to influence treatment status and outcome simultaneously, and statistical significance levels in the binary outcome regressions. We match on the type of locations because rural households are more likely to be located close to a fracking well and, at the same time, potentially exhibit different patterns in sick leave absence. A similar argument applies to the type of housing and the house value, where apartments in more expensive areas have a lower likelihood of being treated. We also match on health care expenditure as a proxy for individual's health status, and the number of births as a predictor for work absences. PS matching is conducted on pre-treatment values of the covariates to rule out that they have been affected by the fracking activity. We present results for two different matching specifications: First, we match on values from 2000, since extensive shale exploration activity started only in 2005 and the first treated individuals in our sample are observed in 2006. Second, we match on average pre-treatment values from 2000 to 2004 of the continuous household-level variables and on 2002 values of the categorical characteristics.

[10] Table C.5 lists descriptive statistics on continuous and binary covariates for the unmatched sample, including t-tests on mean equivalence for treatment and control groups. Table C.7 lists descriptives for the categorical covariates for the unmatched sample, including Pearson's χ^2 tests on equal distributions in treatment and control groups.

Table 4.1: Descriptives on matched sample (PS matching on 2000 values)

Variable	Mean: Control	Mean: Treated	Mean difference	Normalized difference
Individual-level variables				
Number of sick leave days	3.5107	5.1214	1.6107*	0.0988
Age in years	45.4821	44.2464	-1.2357	-0.0893
Education in years	13.7750	13.4929	-0.2821	-0.0948
Is male	0.4571	0.4857	0.0286	0.0404
Is self-employed	0.0536	0.0964	0.0429*	0.1152
Is government employee[b]	0.2643	0.1818	-0.0825*	-0.1405
Labor income[ac]	53.5309	48.0010	-5.5298*	-0.1272
Health status	2.0893	2.4107	0.3214*	0.2663
Number of nights in hospital	0.1500	0.1250	-0.0250	-0.0194
Ever had heart attack	0.0357	0.0179	-0.0179	-0.0782
Ever had heart disease	0.0607	0.0393	-0.0214	-0.0695
Ever had hypertension	0.2821	0.3071	0.0250	0.0387
Ever had asthma	0.1464	0.1000	-0.0464*	-0.1000
Ever had lung disease	0.0071	0.0000	-0.0071	-0.0847
Ever had diabetes	0.0786	0.1179	0.0393	0.0934
Ever had cancer	0.0500	0.0321	-0.0179	-0.0636
Ever had psychological problems	0.0500	0.0643	0.0143	0.0435
Household-level variables				
Number of children	1.0214	0.9500	-0.0714	-0.0439
Age of youngest child	4.5214	3.4893	-1.0321*	-0.1375
Number of births [c]	0.0179	0.0286	0.0107	0.0503
Household member plus 60	0.1000	0.0964	-0.0036	-0.0085
Is home owner	0.8393	0.8357	-0.0036	-0.0068
House value [ac]	152.8057	130.0429	-22.7629*	-0.1432
Health care expenditure[ac]	2.9209	2.3995	-0.5214*	-0.1132
Expenditure for doctors visits etc.[a]	0.6593	0.3886	-0.2707*	-0.2105
Expenditure for prescriptions etc.[a]	0.4041	0.3180	-0.0861	-0.0906
Number of observations	280	280		
Number of individuals	35	35		

[a] In thousand dollars.

[b] This covariate exhibits missings: it is based on 280 observations in the control and 264 observations in the treatment group.

[c] These are the covariates used for PS matching.

Note: The fourth column reports the mean differences between treatment and control group, including significance levels of t-tests on mean equality: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The last column lists the normalized mean difference, calculated as $(\bar{x}_1 - \bar{x}_0)/\sqrt{\sigma_1^2 + \sigma_0^2}$, where $\bar{x}_1$ and $\bar{x}_0$ are the means in treatment and control group, respectively, and σ_1^2 and σ_0^2 are the respective variances.

Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table 4.1 lists descriptive statistics for the PS matching on 2000 values.[11] Our matching approach improves covariate balance relative to the unmatched sample, as indicated by decreasing mean differences in, e.g., labor incomes by 40 percent (from -8,459 to -5,529 dollars), house values by 60 percent (from -57,194 to -22,763 dollars) and health care expenditures by 60 percent (from -1,284 to -521 dollars). However, there are still remaining mean differences that are borderline statistically significant at the ten percent level. For example, the share of asthmatics is by 4.6 percentage points lower in the treatment group than in the control group. With respect to all other chronic illnesses, such as diabetes, both groups are quite balanced. We also report the normalized mean difference for each covariate, which is – in contrast to a t-test – insensitive to sample size. According to Imbens and Wooldridge (2009), linear regressions tend to be sensitive to specification if values of the normalized mean difference are larger than 0.25. This threshold is exceeded by only one of our covariates, namely the self-reported subjective health status: This variable is assessed on a five-point Likert scale, where 1 represents excellent and 5 indicates poor health status. Individuals in our treatment group have, on average, worse subjective health relative to the control group, although this is not mirrored through differences in objective health outcomes. Nevertheless, this suggests that we cannot rule out selection bias completely, and we should interpret our estimates as upper bounds, given that less healthy individuals are generally more vulnerable to pollution exposure.

Figure 4.4 depicts average outcomes over time in the treated and control groups. The first individuals are treated in 2006, so prior to this year, time trends should evolve in parallel for both groups. Since the error bars of the mean values in treatment and control group are overlapping in each period prior to 2006, the difference in means is not statistically significant. Hence, we cannot reject the parallel trend assumption after matching on pre-treatment values.

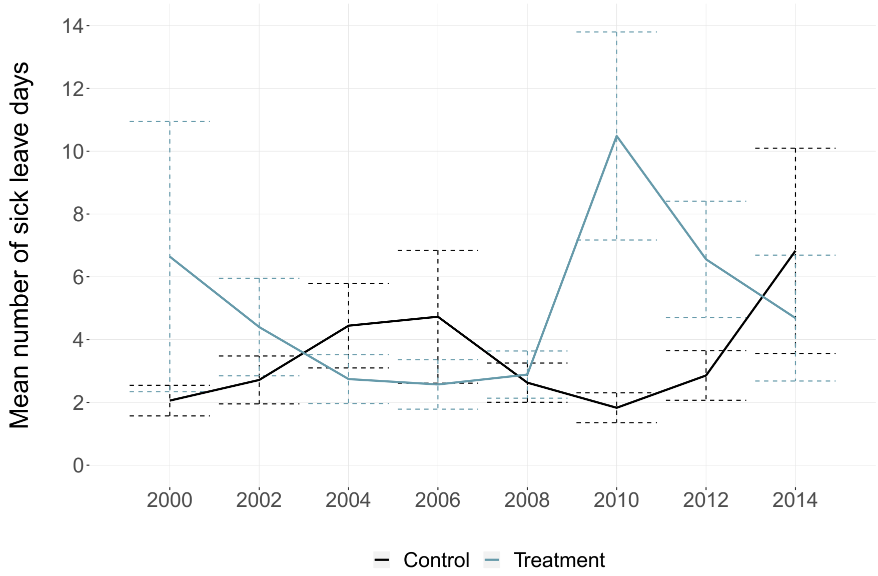
4.4.4 Differences-in-differences specification

We implement a differences-in-differences design that exploits the intertemporal and geographical variation in construction dates and locations of fracking wells.

$$y_{it} = \alpha_i + \rho D_{it} + \beta X_{it} + \lambda_t + \epsilon_{it} \tag{4.1}$$

[11] The results for PS matching on average pre-treatment values are largely similar; they are listed in Table C.6.

Figure 4.4: Time trend in treatment and matched control group (PS matching on 2000 values)



Note: This figure depicts the average number of sick leave days per year in treatment ($N_1 = 35$) and matched control ($N_0 = 35$) group. The control group is based on PS matching on pre-treatment values from 2000. The error bars depict standard errors for each group and year. *Source:* Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

In Equation 4.1, we regress the number of sick leave days of individual i in year t, y_{it}, on the treatment indicator, D_{it}, which is equal to one if individual i has a fracking well within its treatment radius in year t, and zero otherwise. We include a set of potential individual-level and household-specific confounders, X_{it}, such as the number of children and the age of youngest child in the household, individual's labor income, and health-related covariates, e.g., the annual number of nights spend in a hospital or the subjective health status. We also control for time-invariant unobserved heterogeneity by including individual fixed effects, α_i. Time fixed effects, λ_t, are included to account for unobservables that commonly affect all individuals in the same period.

4.5 Results

Tables 4.2 and 4.3 list the regression results for the samples matched on 2000 values and on average values from 2000 to 2004, respectively. All specifications include individual and year fixed effects.

Table 4.2: Regression results (PS matching on 2000 values)

Dependent variable: Number of sick leave days						
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment indicator	3.204*	2.980*	3.351*	3.258*	2.474	2.419
	(1.769)	(1.772)	(1.763)	(1.772)	(1.684)	(1.686)
Age of youngest child		-0.104				-0.054
		(0.122)				(0.117)
Number of births		10.245***				8.447***
		(3.323)				(3.172)
Number of children		0.289				0.526
		(0.794)				(0.759)
Labor income			-0.045			-0.032
			(0.036)			(0.034)
Health care expenditure				0.226		0.144
				(0.227)		(0.216)
Expenditure for doctors visits etc.				0.503		0.551
				(0.762)		(0.727)
Expenditure for prescriptions etc.				-0.767		-0.434
				(1.052)		(0.994)
Health status					-0.653	-0.584
					(0.865)	(0.866)
Number of nights in hospital					3.822***	3.780***
					(0.522)	(0.523)
Observations	560	560	560	560	560	560
Adjusted R^2	0.007	0.029	0.019	0.012	0.107	0.141
F Statistic	3.281*	3.605***	3.154**	1.431	19.086***	7.022***

Note: All regressions include individual and year fixed effects. Robust standard errors are clustered at the individual level in parentheses. Significance levels of the coefficient estimates are denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own calculations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

The first column depicts the baseline regression model including the binary treatment indicator as well as individual and time fixed effects. For both matching specifications, the baseline estimates suggest a positive treatment effect of about three additional sick leave days, significant at the ten percent level. This provides evidence of a significant negative effect of the fracking externalities on human health, resulting in a higher number of sick leave days for individuals living in close proximity to fracking sites. The magnitude of the effect appears substantial relative to other estimates from the literature: Having diabetes is associated with two additional sick leave days per year (Asay et al., 2016), and obesity increases employee absenteeism by two days (Finkelstein, Fiebelkorn and Wang, 2005).

The second column contains our preferred specification. It includes time-varying controls related to children living in the household, since our dependent

Table 4.3: Regression results (PS matching on average values from 2000 to 2004)

Dependent variable: Number of sick leave days						
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment indicator	2.939*	2.966*	3.308**	3.021*	2.444	2.916*
	(1.667)	(1.663)	(1.662)	(1.667)	(1.654)	(1.652)
Age of youngest child		-0.119				-0.086
		(0.114)				(0.113)
Number of births		7.641***				6.968**
		(2.759)				(2.735)
Number of children		0.099				0.182
		(0.703)				(0.709)
Labor income			-0.032			-0.030
			(0.024)			(0.024)
Health care expenditure				0.148		0.062
				(0.219)		(0.217)
Expenditure for doctors visits etc.				0.855		0.940
				(0.674)		(0.662)
Expenditure for prescriptions etc.				-0.672		-0.492
				(0.964)		(0.944)
Health status					-0.135	0.048
					(0.844)	(0.842)
Number of nights in hospital					2.206***	2.043***
					(0.606)	(0.606)
Observations	560	560	560	560	560	560
Adjusted R^2	0.006	0.026	0.026	0.013	0.033	0.075
F Statistic	3.109*	3.247**	4.299***	1.632	5.530***	3.462***

Note: All regressions include individual and year fixed effects. Robust standard errors are clustered at the individual level in parentheses. Significance levels of the coefficient estimates are denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own calculations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

variable captures absence days due to own illness and due illness of other household members. Specifically, we control for the number and the average age of children living in a household, since parents whose children fall ill might have to take sick leave days, especially when the children are young. Moreover, we include the number of births per household in a given year to account for sick leave days after childbirth. The estimated treatment effect is of similar magnitude as in the baseline specification and remains statistically significant at the ten percent level. The highly significant coefficient on the number of births implies that one additional birth per year in the household increases employee absenteeism on average by roughly eight to ten days.

The third column adds a potentially endogenous covariate, namely an individual's labor income. The estimated treatment effect increases to 3.3 in both matching specifications, most likely due to endogeneity bias. Income is an established determinant of an individual's health status in the sense that higher income is associated with better health outcomes (e.g., Lynch et al., 2000; Kawachi and Kennedy, 1999; Ettner, 1996). So labor income could credibly affect health status, but the labor income itself can be affected by shale exploration activities: If the treated individuals are more likely to work in sectors that benefit from the employment and wage effects of fracking, such as mining or construction, their labor income would increase as a consequence of treatment. In this case, we cannot disentangle the direct effect of proximity to a fracking well on sick leave days from the indirect effect of increased income.[12] The estimated coefficients in Tables 4.2 and 4.3 have the expected negative sign, but they are not statistically significant.

In column four, we add several controls for medical expenditures on the household level, but none of them asserts any significant effect on the number of sick leave days. This is also confirmed by the insignificant F-tests that occur under both matching strategies in this specification. Column five considers the self-reported health status and the number of nights spend in a hospital during a year. Only the latter is significant with positive coefficient estimates, indicating that one additional hospital night increases the number of sick leave days by 3.8 in the first matching specification and by 2.2 in the second specification. This result makes sense intuitively and the number of hospital nights seem to explain a large degree of variation in the number of sick leave days, since including them makes our estimated treatment effect insignificant. Nevertheless, this specification might suffer from endogeneity bias, since exposure to fracking has been shown to increase hospitalization rates (Jemielita et al., 2015; Willis et al., 2018).[13] The last column includes a full model specification with all time-varying covariates. Notably the estimated treatment effect remains significant for the matching specification based on average-pre-treatment values in Table 4.3, despite potential endogeneity bias.

4.6 Discussion

The general framework presented here limits the scope of the analysis: We focus only on one particular aspect related to health and labor market outcomes, namely the number of sick leave days, and our differences-in-differences specification does

[12] Results are robust against excluding individuals working in the mining and construction sector and are available upon request.

[13] We do not observe any statistically significant effects of fracking exposure on the number of nights spend in a hospital, most likely due to our small sample size.

not allow for a full cost-benefit analysis. For example, our analysis does not directly assess the positive labor market effects of fracking. Neither do we provide an estimate of the employment effects of shale exploration, since we only consider employed individuals to look at their number of sick leave days, nor do we directly estimate any wage effects. However, these positive labor market effects in terms of employment and wages are generally acknowledged and a vast body of empirical research aims at quantifying them.

Furthermore, pollution-induced illnesses can result in a variety of economic costs for society. Deteriorating public health as a consequence of shale gas exploration does not only impose costs on the labor market, but a significant share of costs arises in the health care system due to medical therapy and treatment of illnesses. Estimating these costs is outside the scope of this analysis; a comprehensive cost-benefit analysis would be necessary to assess them. Note that fracking also affects the health status of unemployed people, retired persons and people in education, but due to the nature of our research question, we can only quantify the effect on employees. Furthermore, we cannot account for long-term impacts that limit the process of human capital formation, which might arise through indirect channels, e.g., education. Young children, for example, are more severely affected by environmental externalities; their illness might not only force one or both of their parents to temporarily stay at home, causing short-term employee absenteeism, but it might also have long-term consequences for the child by impacting educational achievements.

Another feature of our approach is that the composite effects of fracking on human health cannot be disentangled. Negative health effects can arise, for example, from the various air and water pollutants that are emitted during exploration and operation of the site as well as from psychological effects. Due to the wide range of potentially harmful pollutants that are emitted simultaneously, and due to their complex interactions, it is very challenging to isolate the health effects arising from one particular channel. Therefore, we leave this task for future research and rather focus on estimating the net effect of fracking on health-related decreases in labor supply, i.e. we account for all potential externalities simultaneously. In doing so, we provide estimates of the adverse labor market impacts that can be readily used to approximate the economic costs imposed by fracking on the labor market.

4.7 Conclusion

Hydraulic fracturing, which has recently become an important process to extract fossil resources, is a source of localized negative environmental externalities that have the potential to adversely affect human health. Deteriorating public health due to fracking exposure does not only impose economic costs on the health care system, but also on the labor market in the form of short-term employee absenteeism, which have been ignored in the empirical literature so far. We assess the relationship between proximity to fracking sites and short-term labor market outcomes by asking whether exposure to fracking wells has any impact on the number of sick leave days of individuals living close-by. The answer to this question contributes to the ongoing debates about the expansion of fracking activities, since they can inform decision makers about the costs imposed by adverse health effects on the labor market.

We use individual- and household-level data from the PSID and combine it with oil and gas data from Pennsylvania covering the years from 2000 to 2014. We implement a differences-in-differences approach that exploits the intertemporal and geographical variation in construction dates and locations of fracking wells. To estimate a causal relationship, the treatment and control groups need to be comparable, hence we apply propensity-score matching techniques on household-level covariates. In addition, our regression equation controls for time-varying confounders, time-invariant unobserved heterogeneity by including household fixed effects and common time fixed effects. Our results indicate that employees who reside within ten kilometer distance to a fracking well take about two to three additional days of sick leave, providing first evidence on an adverse labor market effect of fracking. We show that exposure to fracking increases health-related absenteeism, which imposes short-term costs on the labor market.

These short-term costs imposed by employee absenteeism need to be considered when conducting comprehensive cost-benefit analyses of the technology. When it comes to the labor market effects of fracking, the focus has been on the apparent benefits of shale exploration activities, namely employment and wage increases in the local economy. But our results show that employees living close to fracking wells are affected by the pollution externalities, since these individuals are more likely to decrease their labor supply, because the employees themselves or another household member, like young children, fall ill. These adverse labor market effects need to be taken into account as well. When deciding on the expansion or contraction of fracking activities, decision makers and regulators need to carefully weigh the expected costs and benefits: In terms of labor market consequences, there is the potential for increased employment and wage growth, especially in the mining and construction sectors. But these benefits come at the cost of a short-term decrease in labor supply due to health-related absenteeism that potentially occurs in all sectors of the local economy. So it is crucial to quantify the population at risk, i.e. the number of individuals and households exposed to unconventional natural gas drilling, and to evaluate the potential costs and benefits of shale gas exploration.

We have quantified the net effect of fracking on health-related decreases in labor supply, since we accounted for all potential externalities simultaneously. This leaves room for future research to explore the potential channels through which fracking could affect human health, for example, water pollution: Individuals living in houses with ground-fed water supply are probably at a larger risk of drinking water contamination, relative to households that are connected to a piped water distribution network. Disentangling the potential channels would also allow for assessing potentially heterogeneous treatment effects.

Chapter 5

Organic Farming, Water Quality, and Drinking Water Supply Costs

5.1 Introduction

In the past half-century, the amount of nitrogen losses in the environment has increased significantly (Leach et al., 2012). Rockström et al. (2009) refer to the nitrogen cycle as one of the most perturbed geochemical cycles on earth, where excess nitrogen pollution has severe consequences on humans and the environment by fueling climate change, destroying habitats, driving species extinction, and threatening human health (Erisman et al., 2013; Townsend et al., 2003). Agriculture is one of the main sources of nitrogen pollution. In many high-income countries, the sector has overtaken contamination from settlements and industries (Parris, 2011).[1] With the application of mineral and organic fertilizers, nitrogen loads can reach surface and groundwater bodies through runoffs, diminishing surface and groundwater quality (Gomiero, Pimentel and Paoletti, 2011).[2] Increased nitrate levels threaten aquatic biodiversity via the eutrophication process, creating algal blooms and dead zones (Canfield, Glazer and Falkowski, 2010). Apart from impairing the ecosystem, nitrate-polluted drinking water can damage human health. Consumption of contaminated water causes methemoglobinemia among infants (blue baby syndrome) and is suspected of having carcinogenic effects on adults (Shukla and Saxena, 2019).

Reducing nitrate pollution to curb its considerable environmental and social costs represents a key priority for governments worldwide (Parris, 2011) and is high on the agenda of the European Commission (European Commission, 2021a). Despite a large body of legislation, e.g., the Nitrates Directive (EU, 1991), the Water Framework Directive (EU, 2000a), or the Reform of the Common Agricultural Policy (European Commission, 2010), excessive nitrogen emissions to water bodies are still occurring throughout Europe. Nitrate-polluted groundwater bodies are a particular concern since they serve as the primary source of drinking water, and pollution might become irreversible due to the prohibitive cost of remediation in groundwater bodies (Lall, Josset and Russo, 2020).

In this context, understanding the causes and consequences of groundwater nitrate pollution is necessary to quantify the associated economic costs and inform policymakers about effective mitigation strategies. This paper uses a

[1] For example, in the EU, 38 percent of water bodies are under significant pressure from agricultural water pollution. In the US, agriculture is the main source of pollution in rivers and streams. In China, agriculture is almost exclusively responsible for groundwater pollution by nitrogen (Evans et al., 2018).

[2] At the same time, nitrogen can also dissolve in the atmosphere, where it forms nitrous oxides and accelerates global warming. Nitrous oxide is a greenhouse gas hundreds of times more potent than carbon dioxide.

two-fold approach to provide empirical evidence on the causes and consequences of groundwater nitrate pollution: In the first stage, we analyze whether organic farming practices contribute to lowering groundwater nitrates. In a second stage, we investigate the economic consequences of nitrate pollution for a sector directly affected by groundwater quality, the drinking water supply sector. We empirically estimate the effect of groundwater nitrate pollution on firms' costs.

This paper makes three important contributions: First, we build a unique and extensive panel data set for Germany for the years 2008-2016 by merging seven administrative data sources which retain geo-referenced information on nitrate pollution, organic farming, mineral fertilizer application, land cover, settlement structure, weather, and firm-level data on drinking water supply firms. Second, the paper provides the first large-scale evidence of the negative association between organic farming and groundwater nitrates. Third, this paper presents robust empirical evidence on the increased cost of drinking water supply due to groundwater nitrate pollution based on administrative firm-level data.

Organic farming systems are crucial for the transformation towards sustainable agriculture, as recognized in the European Green Deal (European Parliament, 2021). Under the Farm-To-Fork Strategy, the EU seeks to expand its agricultural land under organic farming to 25 percent until 2030 (European Commission, 2020). Organic farming has to comply with higher standards for environmental protection and animal welfare than conventional farming. These standards include, among others, the prohibition of synthetic pesticides and mineral fertilizer application, a ban on landless livestock production, and reliance on multi-annual crop rotation and cultivation of nitrogen-fixing plants (EU, 2018). Consequently, organic farming can reduce some of the negative environmental impacts of agriculture, e.g., by increasing soil fertility and biodiversity, system stability, and erosion control, relative to conventional farming (Caporali, Mancinelli and Campiglia, 2003; Stolze et al., 2000). Moreover, several small-scale field studies suggest that organic farming can reduce nitrogen leaching by up to 64 percent (Schader, Stolze and Gattinger, 2012). Nevertheless, its impact on groundwater quality remains unclear due to a lack of empirical evidence.[3]

We build an econometric model to estimate the impact of organic farming on groundwater nitrate pollution. We hypothesize that organic farming in the vicinity of the groundwater sampling station reduces groundwater nitrate pollution, compared to agricultural land under conventional farming. We model

[3] Previous research mostly focused on the interrelations between land utilization and groundwater pollution (Bawa and Dwivedi, 2019; Gallagher and Gergel, 2017; Lawniczak et al., 2016; Mair and El-Kadi, 2013; Wick, Heumesser and Schmid, 2012).

annual nitrate levels as an auto-regressive process that depends on the share of organically farmed land, conditional on other factors affecting groundwater nitrate, such as mineral fertilizer application, land use, weather, and time-invariant hydro-geological characteristics. Estimating the marginal contribution of organic farmland to nitrate groundwater pollution using the system GMM estimator by Blundell and Bond (1998), we find that the share of organically farmed land decreases nitrate concentrations in surrounding groundwater bodies. Results suggest that an additional percentage point in the share of organically farmed land decreases nitrate concentrations in surrounding groundwater bodies by 0.3 mg/l on average.

Drinking water companies are directly affected by water pollution as they supply drinking water by abstracting raw water from ground and surface water sources. The European Drinking Water Directive limits the amount of nitrate in potable water by 50 mg/l (EU, 1998). If raw water nitrate surpasses the legal threshold, companies must take additional measures to secure its safety and purity. In the short run, water quality can influence factors such as chemical dosage, electricity use, and the need for extra personnel (Westling, Stromberg and Swain, 2020). Moreover, the companies might blend water sources, drill new wells, purchase water from nearby suppliers, or construct new treatment plants (Jensen et al., 2012; Jones, Hill and Brand, 2007; Oelmann, Czichy and Hormann, 2017). These measures give rise to additional costs that are passed through to water consumers through higher prices. However, the magnitude of cost increases is unknown since large-scale empirical evidence on the cost effects of groundwater nitrate pollution for water supply firms is lacking.[4]

To remove nitrate from raw water, water suppliers use different treatment processes and technologies that have varying impacts on operating and capital costs. We derive different econometric cost models to estimate the effect of groundwater nitrate pollution on firms' water treatment costs and total costs (including capital and labor costs). First, we hypothesize that raw water from catchment areas with higher nitrate concentrations requires additional treatment and, thus, is associated with higher treatment costs. We model treatment cost as a function of water quality, conditional on the quantity of water abstracted, the composition of source intake, and weather impacts. Estimates are obtained using a two-way fixed effects model that accounts for unobserved firm-level heterogeneity and common time effects. Our results suggest that higher groundwater nitrate

[4] The existing literature focuses on other forms of water pollution, mainly turbidity (Danelon, Augusto and Spolador, 2021; Lopes et al., 2019; Price and Heberling, 2018; Westling, Stromberg and Swain, 2020).

concentrations increase firms' treatment costs. More precisely, a one percent increase in groundwater nitrate is associated with an increase in treatment cost by about 0.04 to 0.05 percent. Second, we posit that water quality and the use of nitrate removal technologies do not only imply higher treatment costs but might also affect labor and capital costs. We estimate a total cost model to quantify the effect of groundwater nitrate on firms' total costs. Our findings reveal that groundwater nitrate pollution significantly increases total costs. The estimates show increases in total costs of 0.02 percent for an additional percentage point in groundwater nitrate pollution. These cost increases are likely to be passed through to consumers, who ultimately pay the price for water pollution stemming from the agricultural sector.

The structure of this paper is as follows: The next section provides background information on EU policies regulating water quality and organic farming practices and describes nitrate removal techniques used by water supply firms. Section 5.3 summarizes the relevant literature. Section 5.4 describes the data on water quality and the water supply firms. Section 5.5 outlines the empirical strategy. Section 5.6 presents results and Section 5.7 concludes.

5.2 Institutional background

5.2.1 Nitrate pollution and sustainable farming

Given its relevance for human, animal and plant life, and the economy, water protection is a central part of the EU's agenda on sustainability. Issued in 2000, the Water Framework Directive (WFD) represents the heart of the legal framework for European water regulation. Its main objective is to achieve a good environmental status for all EU waters. To do so, it establishes guidelines for the protection, management, and long-term sustainable use of inland surface waters, transitional waters, coastal waters, and groundwater bodies. It requires member states to develop and implement River Basin Management Plants[5] including specific measures to improve and uphold water quality (EU, 2000a).

The WFD is complemented by a set of specific directives, such as the Drinking Water Directive (DWD) (EU, 1998) and the Nitrates Directive (EU, 1991).[6] The DWD sets quality standards for water intended for human consumption.

[5] Management plans must be based on the natural geographical river basin, they are valid for six years, and a major tool to implement the WFD.

[6] Other examples are the Groundwater Directive, the Urban Waste Water Treatment Directive, the Environmental Quality Standards Directive and the Floods Directive.

Its purpose is to protect human health from any harm caused by contaminated water. The DWD applies to drinking water from distribution systems, tanks, and bottles, and those intended for the food processing industries. The policy mandates the monitoring of 48 microbiological, chemical, and other indicator parameters. The Nitrates Directive aims at protecting water bodies against nitrate pollution from agricultural sources. It imposes a maximum permissible level of 50 mg/l of nitrates in surface and groundwater bodies, mandates regular monitoring of nitrate pollution, and establishes nitrogen management requirements for farmers, including limitations on the amount and timing of fertilization. If the permissible level is frequently exceeded, member states are obliged to establish action programmes to reduce nitrate pollution.

Germany has a long history of exceeding the limit value of 50 mg/l in groundwater bodies. In 2018, the European Court of Justice pronounced Germany guilty of violating the Nitrates Directive by failing to implement sufficient countermeasures (European Court of Justice, 2018). Since then, the German Federal Government has reformed the German Fertilizer Law and Ordinance (Federal Ministry of Justice and Consumer Protection, 2009, 2017, 2020), which transpose the Nitrates Directive into national law. Despite legal efforts and repetitive reforms, agriculture remains the principal cause of water-related problems in Germany and Europe, and thus, farming practices have to become more sustainable (European Commission, 2021a).

The past two reforms of the EU's Common Agricultural Policy (CAP) aimed at contributing towards more sustainable agriculture but they fell short in delivery; important aspects such as the promotion of organic farming, water protection and soil quality were hardly addressed.[7] The next CAP (2023-2027) is supposed to be greener and fairer, such that it contributes to the goals of the European Green Deal and Farm-To-Fork Strategy. This includes the implementation of eco-schemes, where funding is re-allocated from direct payments, to provide stronger incentives for climate-and environmental-friendly farming practices and approaches (EU, 2021).

[7] The CAP comprises around 30 percent of the total EU budget. It is divided into two pillars. The first involves direct payments to farmers in the member states (70 percent), which are linked mainly to the area farmed and certain conditions. The second pillar includes subsidies that support rural communities in the modernization and establishment of a socially, ecologically and economically sustainable structural change (30 percent).

5.2.2 Nitrate removal from drinking water

In Germany, nitrate is removed from drinking water via separation processes and biological denitrification. Common separation processes are reverse osmosis and CARIX method. Reverse osmosis is pressure-driven and forces water molecules through a semi-permeable membrane. It takes place almost fully automatic and thus, has low personnel requirements. Nevertheless, the technology is associated with high operating costs due to membrane replacement and high energy demand (Malaeb and Ayoub, 2011). Without an energy recovery system in place, energy consumption ranges between six and eight kWh/m^3 (Khawaji, Kutubkhanah and Wie, 2008; Moch and Moch, 2002). Also, it involves the usage of chemicals to protect the membranes from deposit formation. The CARIX method is a special ion-exchange process with lower operating costs than reverse osmosis. It is a chemical-free process, uses less water, and requires less energy, with energy consumption ranging between 0.15 and 0.25 kWh/m^3 for modern plants (Veolia, 2021). However, investment costs are considerably higher.

Both separation processes generate (saline) wastewater as a by-product, the disposal of which can also increase the company's operating cost. Given permission by the local authorities, treatment companies are allowed to directly discharge their wastewater into surrounding surface waters free of charge. The approval practice is based on the Surface Water Ordinance and not granted easily, as high nutrient concentrations harm the ecosystem and impair surface water quality. Hence, water companies must often resort to one of the following two options: they can either discharge their wastewater to the sewerage system or wastewater treatment plant for considerable wastewater fees or treat the wastewater themselves before discharging it. The latter would lead to increases in capital and operating costs (Oelmann et al., 2017).

In contrast to separation processes, biological denitrification is a microbiological process that decomposes nitrate into gaseous nitrogen (N_2) rather than separating nitrate from drinking water. While post-treatment of water is required downstream of the bioreactors, the process virtually does not produce wastewater and only a small amount of sludge (Oelmann et al., 2017). In this way, biological denitrification is favorable over separation processes because it selectively eliminates nitrate and is more efficient in terms of resource recovery.[8] Disadvantageous is, however, the fact that this process does not simultaneously soften nor remove trace substances. In general, it is more complex and thus,

[8] Biological denitrification has a resource recovery rate of more than 95 percent, while separation processes' efficiency rate is at most 90 percent.

requires more personnel and maintenance. All in all, these removal technologies vary in their functioning and effectiveness, resource and disposal requirements, as well as capital and operating costs (Oelmann et al., 2017).

5.3 Related literature

Keiser and Shapiro (2019b) note that given the importance of water quality surprisingly little economic research analyses it. The few papers studying the effectiveness of water quality regulations focus on the impacts on surface water quality, e.g., Keiser and Shapiro (2019a) study the U.S. Clean Water Act, and Chabé-Ferret, Reynaud and Tène (2021) analyze the EU Nitrates Directive. Empirical evidence on the impact of these regulations on groundwater bodies is lacking, despite the growing importance of mitigating groundwater pollution. In contrast, the determinants of groundwater nitrate pollution have been studied frequently over the past two decades. We list the available evidence in the following subsection. Moreover, we review the empirical literature on the consequences of groundwater pollution for drinking water supply costs in subsection 5.3.2.

5.3.1 Groundwater nitrate pollution and land use

Table 5.1 lists an overview of the recent empirical contributions. These studies predominately focus on the implications of land use on nitrate and other groundwater pollutants, in particular agricultural crop production, grassland areas, urban or residential areas, and forest coverage (e.g., Bawa and Dwivedi (2019), Lawniczak et al. (2016)). Typically, these studies control for a range of other factors influencing groundwater nitrate, such as seasonality (Lawniczak et al., 2016), aquifer and soil characteristics (Mair and El-Kadi, 2013), weather conditions (Wick, Heumesser and Schmid, 2012), and groundwater table depth (Gallagher and Gergel, 2017). Most are ex-post evaluations based on large data sets. For example, Wick, Heumesser and Schmid (2012) study the factors influencing groundwater nitrate levels using a multivariate regression framework controlling for land use, soil type, and weather impacts. Based on a panel of 1200 Austrian municipalities from 1992 to 2008, they find that agricultural activity leads on average to higher nitrate levels in groundwater bodies. In contrast, grassland and forest decrease nitrate content.

While the positive relationship between agricultural cultivation and nitrate pollution is well established in the international empirical literature, only a few studies consider the impact of specific farming practices as an influencing factor.

Table 5.1: Empirical literature on land use and groundwater nitrate pollution

Authors	Region	Time period	Method	Dependent variable	Independent variable	Effect
Bawa and Dwivedi (2019)	Florida	2008-2018	Linear regression	Nitrate, Potassium	Land use	Agriculture (+)
Sun, Cheng and Chen (2018)	China	2010	Multivariate linear regression	Nitrate, phosphorus	Precipitation, land use	Cropland (+), forest (–), residential (+), grassland
Gallagher and Gergel (2017)	USA, Canada	2005-2016	Multivariate linear regression	Nitrate	Land use, water table height, depth below water	Cropland (+/-), forest (+/-), urban (+), bare (–)
Lawniczak et al. (2016)	Poland	2012	Multivariate analysis	Nitrate, phosphorus, ammonium	land use, season, fertilizer supply	Cropland (+), forest (–), residential area (–), spring (+), fertilizer (+)
Mair and El-Kadi (2013)	Hawaii	2000-2012	Logistic regression	Nitrate, fumigants, chlorinated solvents	Land use, water depth, soil, and aquifer media	Cropland (+)
Wick, Heumesser and Schmid (2012)	Austria	1992-2008	Pooled OLS, Fixed Effects	Nitrate	Land cover, precipitation, soil porosity, air temperature	Cropland (+), forest (–), city (–), grassland (–), precipitation (–), temperature (–)

Notes: The table provides an overview of the international empirical literature on the impact of land use on groundwater nitrate concentrations. The last column summarizes the results of each study, where + (–) represents a positive (negative) relationship between the dependent variable and the respective independent variable.

There are several agricultural field experiments from different countries and regions that support this hypothesis, see Kirchmann and Bergström (2001), Korsaeth and Eltun (2000), and Tuomisto et al. (2012).[9] Moreover, Wick, Heumesser and Schmid (2012) review the impact of conventional farming by crop cultivation types (oilseed and protein, forage, cereal and maize, row crops and vegetables, and grassland) on groundwater nitrate. Their results suggest that municipalities with a larger share of conventionally farmed areas record higher groundwater nitrate levels. Yet, to our knowledge, this is the first study to evaluate the effect of organic farming on nitrate groundwater pollution, conditional on mineral fertilizer supply, land use, and weather.

5.3.2 Water quality and drinking water supply costs

There are several international studies available that review the effect of surface water quality on treatment cost, in particular on the impact of turbidity, which is an indicator of the water's relative clarity.[10] Excessive values are a risk to human health, as turbidity is a proxy for the presence of pathogenic microorganisms, which can lead to waterborne disease outbreaks (WHO, 2017). Earlier studies have already found a positive correlation between turbidity and the treatment plant's chemical and filtration cost (Dearmont, McCarl and Tolman, 1998; Holmes, 1988), but these results are based on small samples. Over the past years, increased data availability has allowed researchers to move on to larger sample sizes and apply advanced empirical methods, such as panel approaches and spatial econometric models. Price and Heberling (2018) summarize 24 of these studies and derive cost elasticities where marginal improvements in turbidity result in gains in avoided treatment costs.

Recently, empirical studies started to look into measures of water quality beyond turbidity and the influence of natural ecosystem services on treatment cost. Table 5.2 lists an overview of the most recent empirical evidence. Westling, Stromberg and Swain (2020) estimate the marginal contribution of Escherichia coli (E.coli) levels in river water on chemical water treatment cost based on a panel of 76 Swedish water treatment plants. Danelon, Augusto and Spolador (2021) analyze a sample of 172 Brazilian water treatment companies that rely on surface water abstraction. The authors use fixed-effects panel models to estimate the

[9] Results confirm that the nitrogen input intensities are typically lower for organic farming systems, and in turn, is nitrate leaching per unit of area, but this effect does not necessarily hold for nitrogen leaching per product unit.

[10] There are different materials that turbid water, such as algae, plankton, and other microscopic organisms, clay and slit.

influence of total phosphorus, biochemical demand of oxygen, dissolved oxygen, E.coli, and turbidity levels on total costs. Both analyses do not find statistically significant relationships besides turbidity. In contrast, empirical evidence from Portugal, France, and Malaysia suggests that forest coverage can lower drinking water treatment costs by providing valuable ecosystem services such as water purification (Abildtrup, Garcia and Stenger, 2013; Lopes et al., 2019; Vincent et al., 2016). To our knowledge, we are the first to study the relationship between groundwater nitrate pollution and water treatment costs.

5.4 Data

We describe the data we use to investigate nitrate groundwater pollution, organic farming, and drinking water supply costs. In total, we use seven types of data. We first summarize the data we use to analyze the link between organic farming and nitrate groundwater pollution. We then move to the firm-level data to analyze drinking water supply costs with respect to water pollution.

Data on groundwater nitrate concentrations: Nitrate readings are provided by the German Environment Agency (UBA, 2019). The data contains nitrate concentrations measured from 2008 to 2016 at 1,350 groundwater sampling stations scattered across Germany. At most sampling stations, nitrate is measured once per year, but roughly 35 percent of sampling stations record several nitrate readings per year. Thus, we average over sub-annual readings at these sampling stations to obtain annual average nitrate levels, which yields 8,821 station-year observations.[11]

Data on organic farming: We collect data on organic farming at the district level from the Regional Statistics of the Statistical Offices of the Federation and the Länder. The data is available for 2007, 2010, and 2016; we interpolate missing years linearly. We derive the proportion of organic farmland relative to the utilized agricultural area for each district. We merge this information with nitrate readings based on the district where each nitrate station is located.

Data on mineral fertilizer: Likewise, we add data on the annual supply of mineral fertilizer measured at the district level for the years 2008 to 2016

[11] Figure D.1 depicts the locations of nitrate sampling sites in Germany.

Table 5.2: Empirical literature on groundwater quality and water treatment cost

Authors	Region	Time period	Method	Dependent variable	Independent variable	Effect
Danelon, Augusto and Spolador (2021)	Brasil	2003-2017	Fixed Effects	Total cost	Turbidity, total phosphorus, biochemical demand of oxygen, dissolved oxygen, E.coli, labor cost	Turbidity (+), labor cost (+), electricity cost (+), capacity (+)
Westling, Stromberg and Swain (2020)	Sweden	2000-2012	Generalized Method of Moments (GMM)	Chemical cost	Land use, water volume, precipitation	Turbidity (+), water volume (–), rainfall (+)
Lopes et al. (2019)	Portugal	2015	Two-stage least squares (2SLS)	Total variable cost	Forest area, volume, ownership, precipitation, groundwater intake, land cover, water quality, soil type, slope	Forest at the site and neighboring coverage (–)
Vincent et al. (2016)	Malaysia	1994-2007	Pooled OLS, Fixed Effects, IV	Operating cost	Forest, water volume, rainfall, rainfall squared	Forest (–), water volume (+), rainfall (+/-)
Abildtrup, Garcia and Stenger (2013)	France	2009	GMM with Instrumental Variables	Consumer price	Land use, number of municipalities served, water volume, ownership type, altitude, water intake source	Forest (–), private ownership (+)
Fiquepron, Garcia and Stenger (2013)	France	2002-2005	GMM	Consumer price	Pesticides, nitrate, land use, share of abstracted groundwater, population density, private delegation	Nitrate (+), population density (–), share underground water (–), private delegation (+), forest (–)

Notes: This table provides an overview of the international empirical literature on the impact of groundwater pollution on the cost of drinking water suppliers. The last column summarizes the results of each study, where + (–) represents a positive (negative) relationship between the dependent variable and the respective independent variable.

obtained from Häußermann et al. (2019).[12]

Data on land use: Data on land use is obtained from the Corine Land Cover (CLC) Database. For each nitrate sampling station, we calculate the share of various land use classes (farmland, wine growing, fruit cultivation, grassland, and forest) within a 500 meter radius around the sampling station.[13] The CLC is a grid-based land use database with a 25ha resolution in 2000 and 5ha in 2012, 2015, and 2018. We implement the radius approach for each available year, and afterward linearly interpolate between years at each sampling station to impute the data in missing years.

Weather data: Lastly, weather data is provided by the German Weather Agency (Deutscher Wetterdienst, DWD). The data consists of daily weather measurements between 2008 and 2016 from 612 monitors. We impute daily weather values at the nitrate sampling site's locations using an inverse distance-weighting approach and average daily to annual mean values. Specifically, we calculate weighted daily weather measurements for each nitrate sampling station based on all weather monitors within a 100 km radius of its location using the following formula:

$$W(Y_{jt}) = \frac{\sum_i^N \omega_{ij} \cdot Y_{it}}{\sum_i^N \omega_{ij}} \text{ with } \omega_{ij} = \frac{1}{distance(m_i, m_j)^p}$$

where, $W(Y_{jt})$ is the weighted value of weather at nitrate sampling station j and time t, Y_{it} refers to the value of weather measured at monitor i at time t, and $distance(m_i, m_j)$ is the distance between nitrate sampling station j and weather monitor i. The weights ω_{ij} are based on the inverse distance, while the power factor p modifies the heaviness of the distance-based weight of each weather monitor. The higher p, the larger the weight of closer stations. We choose a weight of $p = 2$ and limit the maximum distance to 100 km.[14]

Table 5.3 lists descriptive statistics on all nitrate sampling sites in Germany.[15] The average nitrate concentration is about 28 mg/l, which is below the European

[12] Data was obtained via email request.

[13] Results based on a 1000-meter radius look very similar and are available upon request.

[14] Imputing weather values via inverse-distance weighting with $p = 2$ is a standard approach in the literature studying the economic impacts of air pollution. The choice of p does not affect the inverse-distance weighted weather or air pollution values to a large degree (Zalakeviciute et al., 2020).

[15] A full overview on all variables, their descriptions, and data sources is provided in Table D.1 in the Appendix.

allowable threshold of 50 mg/l. However, the distribution is positively skewed, with the maximum annual average exceeding the legal limit value by as much as over 700 percent. About 18 percent of nitrate readings in our sample exceed the legal limit value of 50 mg/l; roughly 14 percent of observation measures nitrate concentration below but close to the limit value. The average share of organically farmed agricultural area is relatively low in German districts, with the distribution showing a large degree of cross-sectional heterogeneity. A total of 75 districts do not have any organically farmed land, whereas eight districts farm more than 25 percent of their agricultural area organically. However, the total average of five percent is still well below the EU's 2030 target value of 25 percent (European Commission, 2020).

Table 5.3: Descriptives on groundwater sampling sites

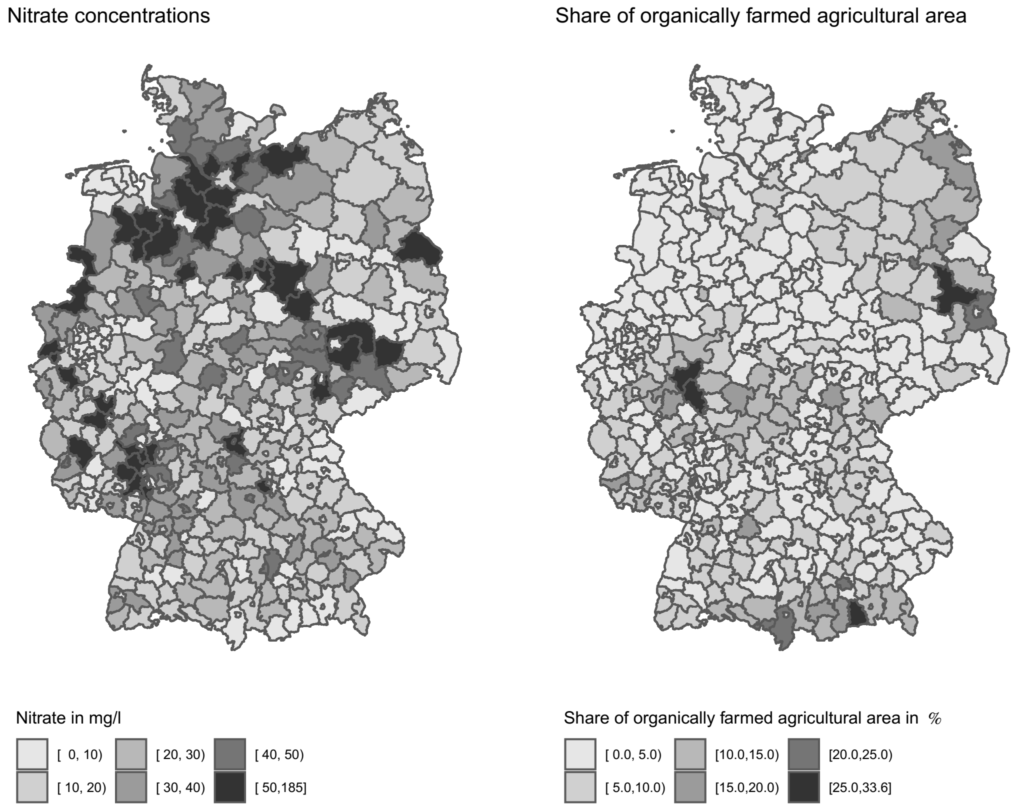
Variable	Mean	Median	SD	Min	Max
Nitrate [mg/l]	28.21	12.40	41.07	0.00	380.72
30 mg/l $<$ Nitrate $<$ 50 mg/l [%]	13.63	0.00	34.31	0.00	100.00
Nitrate $\geq$ 50 mg/l [%]	18.30	0.00	38.67	0.00	100.00
Organic farming [%]	6.29	4.78	5.42	0.00	36.32
Mineral fertilizer [kg/ha]	98.52	98.42	22.96	30.00	211.75
Mineral fertilzer $>$ 100 kg/ha [%]	47.22	0.00	49.93	0.00	100.00
Farmland [%]	36.90	33.72	32.71	0.00	99.95
Wine growing [%]	0.75	0.00	6.60	0.00	94.85
Fruit cultivation [%]	0.50	0.00	4.10	0.00	72.75
Grassland [%]	19.42	12.04	22.46	0.00	99.95
Forest [%]	27.57	11.48	33.20	0.00	99.95
Mean temperature [°C]	9.46	9.57	1.02	2.68	12.25
Mean precipitation [mm/day]	1.98	1.93	0.45	1.02	4.76
Sum precipitation [mm/year]	648.41	640.17	157.23	0.32	1588.68

Notes: This table lists descriptive statistics on 7,311 annual observations from 1,323 groundwater sampling sites for the years 2008 to 2016.

Figure 5.1 depicts the spatial distribution of nitrate and organic farming shares across Germany. The left panel shows average nitrate concentrations, with the darkest shade representing values above the legal limit of 50 mg/l. Nitrate pollution is particularly problematic in the north, east, and southwest of Germany. These areas typically have very low shares of organic farming between zero and five percent, as illustrated in the right panel of Figure 5.1. At the same time, a high share of organic farming appears to correlate with lower average nitrate readings.

Figure 5.2 shows the distribution of annual nitrate averages and shares of organically farmed area across time. Nitrate concentrations exhibit a slightly

Figure 5.1: Nitrate concentrations and share of organically farmed area per district in Germany



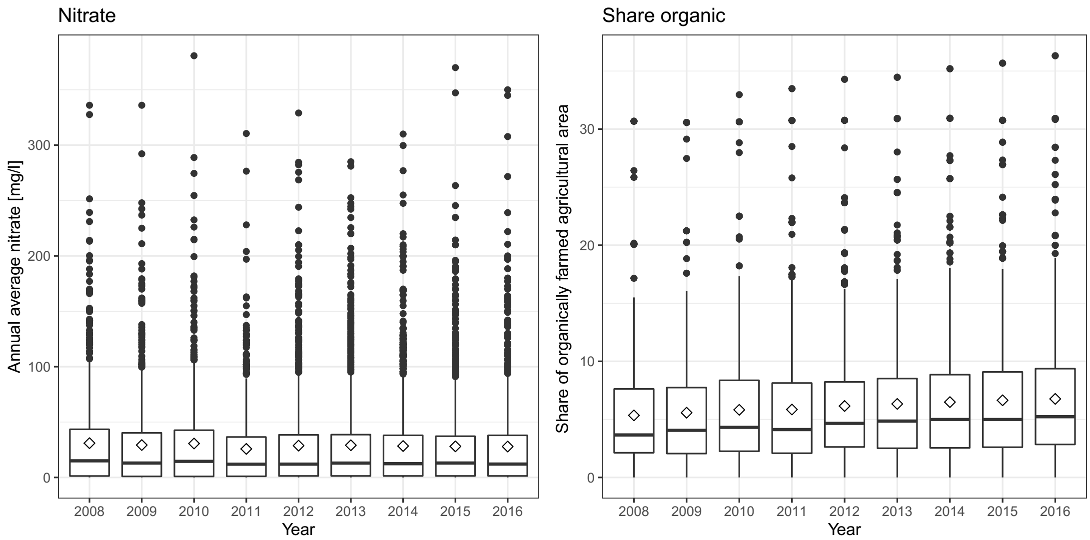
Notes: This figure depicts annual nitrate concentrations and shares of organically farmed land in German districts (*Landkreise*), averaged over the years 2008 to 2016.

decreasing trend, with annual median nitrate values decreasing from 15 mg/l in 2008 to 12.1 mg/l in 2016 (19 percent). The share of organically farmed agricultural land steadily increases over time, with median values increasing by about 43 percent from 2008 to 2016.

Data on drinking water companies: Company data comprises the public water supply survey (RDC, 2016) and the AFiD-panel of energy and water supply companies (RDC, 2017), both provided by the German Federal Statistical Office and Statistical Offices of the Federal States.[16] The public water supply survey covers the universe of water supply companies in Germany. It contains detailed information on the physical components of their production processes,

[16] Both surveys are subject to strict privacy regulations and can only be accessed on-site at the statistical offices' Research Data Centers (RDC). Exported results must be based on at least three observation units to prevent (re-)identification, implying that minima/maxima must not be reported.

Figure 5.2: Nitrate concentrations and share of organic farming across time



Notes: This figure depicts the annual distribution of nitrate concentrations and the share of organic farmland at the level of sampling stations using boxplots. The lower and upper edges of the boxes indicate the first and third quartile, respectively; the middle bar represents the median. The diamonds represent annual mean values. Whiskers depict the interquartile range multiplied by 1.5 and dots are individual observations outside the whisker's range.

e.g., the volume of abstracted ground- or surface water, the amount of distributed drinking water, and the number of customers served. We also observe the volumes and sources of water extracted at each single abstraction plant of a company. We focus on companies with at least one plant abstracting raw water from groundwater sources, which amounts to 70 percent of all German water suppliers.[17] To obtain information on the treatment cost of water suppliers, we merge the water survey with the AFiD-panel that provides information on various cost and revenue components at the firm level.[18] The AFiD-panel contains information on total costs and water treatment cost, as measured by expenditures for raw materials, energy and supplies. This includes the cost of chemicals applied in the water treatment process, which are potentially affected by changes in groundwater quality. Moreover, we observe physical labor input (number of hours worked), as well as expenses for labor, interest payments, and depreciation.[19] We deflate all cost components (€2015) using a price index for the German water supply sector (Destatis, 2020).

[17] The biochemical composition of the abstracted raw water is not surveyed.

[18] We use all firm-year combinations for which we have complete data in both surveys. This yields a panel of 2,369 firms with 17,802 annual observations.

[19] This allows us to calculate input prices for labor and capital at the company level. The labor price is the ratio between annual labor cost and total hours worked. The capital price is defined as the sum of annual depreciation and interest divided by the capital stock. Capital stocks are estimated as annual depreciation multiplied by the average economic lifetimes of buildings and equipment in the German water sector (Wagner, 2010).

To approximate water quality at the plant's location, we use information on the municipality where a plant is located, which is provided in the water supply survey. We merge the plant-level data with nitrate measurements from surrounding sampling sites by taking their spatial relationship into account: First, we obtain exact coordinates of plant locations by assuming that each plant is located at the geographic center of its municipality. Next, we calculate the distance between the plant's location and all nitrate sampling sites nearby. To determine water quality at the plant location, we calculate inverse-distance weighted averages of nitrate readings within a pre-specified distance.[20] We select a radius of four kilometers as our preferred specification,[21] which yields a sample of 512 water companies. We report results for varying radii around the plant location as a robustness check. Moreover, we account for the hydrogeological dependencies between the point of extraction and the underlying groundwater bodies by considering only nitrate monitors located in the same groundwater body as the municipality center.[22] Lastly, we aggregate these plant-level nitrate values to the company level by calculating a weighted average across all plants of a company, where weights are based on the amount of groundwater abstracted at the corresponding plant location.

Data on settlement structure: We add municipality-level data on population density from the Regional Statistics of the Statistical Offices of the Federation and the Länder. We merge this data with the firm-level data based on administrative shapefiles from the Federal Agency of Cartography and Geodesy.[23]

Table 5.4 lists descriptive statistics on the cost structure and the inputs and outputs for drinking water supply for our sample of water supply companies.[24] These companies abstract on average about 75 % of their raw water from groundwater sources; the remaining share consists of water purchased from other companies and abstraction from surface water resources. The water suppliers deliver about

[20] Alternatively, we could assume that groundwater bodies overlap with administrative units and assign nitrate values to water plants by averaging over all sampling sites within their municipality. However, this assumption is quite restrictive and disregards the spatial dimension of nitrate sampling sites. Our IDW approach incorporates the spatial dependencies by weighting nitrate readings by geographic proximity.

[21] The median size of German municipalities is about 50 km^2, which is represented by a radius of about four km around its center, assuming that municipalities are roughly circular in shape.

[22] Figure D.2 visualizes the approach.

[23] We add this measurement via company location, using the official municipality key *(Amtlicher Gemeindeschlüssel (AGS))*.

[24] Table D.1 provides an overview of variable definitions and data sources.

two-thirds of their treated water to end-users, such as residential and industrial customers. The rest of the water output is sold and distributed to other water suppliers in the form of bulk water.

Table 5.4: Descriptives on drinking water supply companies

Variable	Mean	Med	SD
Cost components			
Total cost [1000 €]	14701.92	4154.18	48489.24
Treatment cost [1000 €]	2064.64	325.73	13539.91
Physical inputs and outputs			
Total water abstraction [1000 m^3]	3032.33	1224.50	8532.12
Groundwater abstraction [1000 m^3]	2388.82	983.50	6132.05
Water purchase [1000 m^3]	623.34	12.17	2474.51
Total water delivered [1000 m^3]	3655.66	1447.33	9670.68
Water delivered to endusers [1000 m^3]	2453.46	1104.00	6932.04
Residential water delivered [1000 m^3]	1877.11	825.17	5079.21
Bulk water delivered [1000 m^3]	853.04	18.00	4375.44
Population served [number]	43837.87	18560.00	106026.49
Employees [number]	67.32	19.00	195.30
Abstraction plants [number]	10.02	4.00	16.33
Environmental variables			
Nitrate [mg/l]	28.74	17.47	35.24
$30 <$ Nitrate < 50 [%]	17.76	0.00	38.22
Nitrate ≥ 50 [%]	17.65	0.00	38.13
Mean precipitation [mm/day]	2.00	1.97	0.42
Sum precipitation [mm/year]	655.12	654.43	161.17
Mean temperature [° C]	9.57	9.65	1.01

Notes: This table lists descriptive statistics on the panel of drinking water supply companies that abstract groundwater resources within a four km radius of a nitrate groundwater sampling site. The panel consists 512 companies with 2,754 company-year observations between 2008 and 2016.
Source: RDC (2016) and RDC (2017), own calculations.

The average nitrate content in the groundwater bodies around the firms' abstraction plants amounts to 29 mg/l. More than 80 percent of our sample exhibit groundwater nitrate levels below the legal limit value of 50 mg/l, indicating that the majority of the raw water does not require additional processing for human consumption, at least with respect to its nitrate content. However, about 17 percent of our sample exhibit groundwater nitrate levels above the legal limit value. These water suppliers have to take additional measures to remove nitrate from their raw water, resulting in higher cost of producing drinking water. Indeed, water suppliers with limit exceeding nitrate levels not only have higher absolute treatment cost, but treatment cost also account for a larger share of total cost, as indicated by a series of mean equivalence tests in Table D.3. Moreover, unit treatment cost tend to be significantly higher when nitrate levels exceed the legal limit value.

Table D.4 lists descriptives on the subsample of firms we use to estimate the impact of nitrate pollution on total costs. To estimate the total cost model, we need additional information on physical labor inputs, i.e., the number of hours worked per year, and physical outputs, i.e., the population served with water deliveries. We discard all observations with missing values in these variables, leaving 1,846 observations on 342 companies to analyze.

5.5 Empirical strategy

5.5.1 Effect of organic farming on nitrate groundwater pollution

We model annual nitrate levels as an auto-regressive process that depends on the share of organically farmed land, conditional on other factors affecting groundwater nitrate, such as mineral fertilizer application, land use, and weather.[25] Equation 5.1 depicts the econometric model.

$$N_{it} = \alpha N_{it-1} + \beta O_{it} + \phi F_{it} + \gamma' L_{it} + \delta' W_{it} + \mu_i + \theta_t + \epsilon_{it} \tag{5.1}$$

In it, N_{it} represents the annual average nitrate concentration at groundwater monitor i in year t, which depends on its own past realizations from last year, $N_{i,t-1}$, to account for the high degree of persistence in annual nitrate readings. We include the share of organically farmed land relative to the utilized agricultural area, O_{it}, where β is the corresponding coefficient of interest that is expected to be negative according to our hypothesis.[26] We control for the supply of mineral fertilizer, F_{it}, a vector of land use shares, L_{it}, including farmland, wine growing, fruit cultivation, grassland, and forest coverage, and a vector of weather covariates, W_{it}, containing annual average temperature and precipitation and the sum of annual precipitation. We include station fixed effects, μ_i, to account for time-

[25] We base the selection of control variables on the international literature on land utilization and nitrate groundwater pollution outlined in Section 5.3.

[26] Organic farming shares are measured at the district level, while the analysis presented here is at the station level. This is problematic since there is no variation in organic farming shares at stations within the same district. Tables D.6 and D.7 in the Appendix confirm that all results also hold when aggregating to the district level.

invariant heterogeneity at the sampling site and year fixed effects, θ_t, to net out time trends common to all nitrate stations.

We estimate the model using the General Method of Moments (GMM) estimator initially developed by Arellano and Bond (1991). Specifically, we use Blundell and Bond (1998) (BB) type system-GMM estimators that account for the bias stemming from the inclusion of a highly persistent lagged dependent variable, N_{it-1}, and station fixed effects, μ_i. Inclusion of the lagged dependent variable, N_{it-1}, violates the assumption of strict exogeneity of regressors: N_{it-1} depends on past values of the error term, ϵ_{it}, which causes a correlation between the lagged dependent variable and the residuals of the (time-demeaned) model, essentially creating an endogeneity issue. Nickell (1981) proves that the Within estimator of a dynamic panel data model is biased and inconsistent in a framework with a small number of time periods T and a large number of sampling units N and that the asymptotic bias does not disappear with $N \rightarrow \infty$. Alvarez and Arellano (2003) demonstrate that the asymptotic bias disappears if $lim(\frac{N}{T}) = 0$. The analysis presented here cannot rely on those asymptotic properties with only nine years available. Hence, Within-estimates are expected to be biased for our panel dimensions, although consistency could be achieved, in theory, if a longer time span was available. Consequently, we rely on GMM to obtain consistent estimates.

The BB system-GMM consistently estimates the impact of the lagged dependent variable, even for high degrees of persistence of the dependent variable, by reformulating Equation 5.1 into a system of equations in levels and first differences. The equations in levels are instrumented by first-differenced lagged values, assuming that these first-differenced instruments are orthogonal to the unit-specific fixed effects. Similarly, the equations in first-differences are instrumented by lagged level values. Theoretically, the system GMM approach should yield more efficient estimates than the first-difference Arellano and Bond (1991) GMM approach since it uses more information. Our preferred BB system-GMM specification uses two lags of the instrumenting variables for the endogenous lagged nitrate levels.[27]

To ensure the validity of our GMM estimates, we check whether our instruments are exogenous by reporting p-values of Sargan and Hansen tests on over-identifying restrictions (Hansen, 1982; Sargan, 1958). In our system-GMM framework, the Hansen test is most appropriate since it is robust to heteroscedasticity and autocorrelation, though it might be weakened by too many instruments (Roodman, 2009a). Hence, all system GMM estimates rely on collapsed instruments to

[27] GMM results using different lag lengths of instruments are very similar, see Table D.5.

avoid the problem of too many instruments (Roodman, 2009b). All estimates report standard errors that are robust to within-station heteroscedasticity and autocorrelation and clustered at the level of sampling stations.

5.5.2 Effect of water pollution on firms' costs

As firms use different nitrate removal technologies that have distinct implications for operating and capital costs, we investigate different cost impacts. First, we consider the effect on treatment costs, covering the expenditures for chemicals, energy and other materials used in the removal process. Second, we look at total costs, consisting of treatment, labor and capital costs.

Effect on treatment costs

We model the firm's water treatment cost as a function of water quality and quantity, conditional on the total volume of water abstraction, the composition of source intake, weather impacts, and unobservable time-invariant characteristics at the firm level.[28] We account for non-linear cost functions by taking the natural logarithm of costs and covariates.

$$ln(C_{it}) = \alpha\ ln(N_{it}) + \beta\ ln(Q_{it}) + \delta\ ln(G_{it}) + \gamma' ln(W_{it}) + \mu_i + \theta_t + \epsilon_{it} \tag{5.2}$$

Equation 5.2 shows the econometric model, where C_{it} represents annual water treatment cost of firm i in year t. N_{it} represents nitrate groundwater content averaged across all abstraction sites of firm i in a given year t. Moreover, treatment costs depend on the total quantity of water abstracted, Q_{it}. We control for the share of abstracted groundwater, G_{it}, to capture differences in groundwater and surface water quality. Since weather can influence the availability of groundwater resources, we include a vector of weather covariates, W_{it}. Specifically, we control for annual average precipitation, the sum of annual precipitation, and the annual average temperature in close vicinity of the abstraction plants. We add year fixed effects, θ_t, to net out time trends common to all drinking water companies, and firm-level fixed effects, μ_i, to account for time-invariant heterogeneity across water companies, e.g., hydro-geological characteristics at the water abstraction sites. We

[28] We only include physical quantities and no input price data. We do not observe any input prices for the material inputs for nitrate removal. Implicitly, we assume that input prices are the same for all firms. The input price development is taken into account by deflating treatment costs. In fact, we conduct a cost driver analysis and do not estimate a real cost function from a theoretical point of view.

estimate the two-way fixed effects model via the Within estimator with standard errors clustered at the firm level.[29]

Effect on total costs

To assess whether nitrate pollution has also an effect on total costs, including labor and capital costs of the firm, we estimate a total cost function of water supply that depends on the nitrate levels in abstracted raw waters. We assume that water suppliers minimize the total cost of producing output, q, by choosing the optimal combination of inputs, x, given a vector of input prices, w, and production technology, T.

$$c(w,q) = \min_{x} \left[w'x : (q,x) \in T \right] \tag{5.3}$$

Equation 5.3 implies that firms choose a technically feasible combination of inputs, which minimizes the cost of producing the given output. Markets for inputs are assumed to be perfectly competitive, such that firms act as price takers.[30] To estimate the total cost function empirically we assume that the cost function is non-negative, non-decreasing in inputs and outputs, linearly homogeneous, and concave in input prices (Coelli et al., 2005). We specify the following Cobb-Douglas functional form:

$$ln(TC_{it}) = \beta_0 + \sum_{k=1}^{K} \beta_k ln(w_{kit}) + \sum_{m=1}^{M} \phi_m ln(q_{mit}) + \sum_{r=1}^{R} \delta_r ln(z_{rit}) + \mu_i + \theta_t + \epsilon_{it} \tag{5.4}$$

In Equation 5.4, TC_{it} represents total cost of firm i in year t, w_{kit} denotes prices for $k = 1, \ldots, K$ inputs, and q_{mit} represents quantities of $m = 1, \ldots, M$ outputs. We assume that the operating environment can impact total cost of a water supplier, hence we include several environmental factors, z_{rit}, e.g., nitrate pollution in groundwater bodies. To ensure that the cost function is non-decreasing, homogeneous, and concave in inputs, we assume that $\sum_{k=1}^{K} \beta_k = 1$ and substitute this constraint into Equation 5.4, which yields our final estimation equation 5.5.

[29] We assessed the appropriateness of a fixed-effects model relative to a random-effects model using a Hausman specification test, which suggests that the fixed effects specification is the preferred model since the error term and regressors are correlated.

[30] Again, we do not observe an input price for material inputs. Thus, our cost minimization problem includes only capital and labor prices. We implicitly assume that all firms face the same input prices for materials (like energy, chemicals etc.)

$$
\begin{aligned}
ln(TC_{it}/w_{Kit}) =& \beta_0 + \sum_{k=1}^{K-1} \beta_k ln(w_{kit}/w_{Kit}) + \sum_{m=1}^{M} \phi_m ln(q_{mit}) + \\
& \sum_{r=1}^{R} \delta_r ln(z_{rit}) + \mu_i + \theta_t + \epsilon_{it}
\end{aligned}
\tag{5.5}
$$

According to the international literature on water distribution (Filippini, Hrovatin and Zorić, 2008; Saal and Parker, 2000; Urakami and Parker, 2011), we estimate equation 5.5 with $R = 2$ outputs: the volume of water delivered as the main output of a water supply firm, and the number of customers served.We include $K = 2$ input prices for labor and capital. Labor prices are calculated as the sum of expenses for labor divided by the number of work hours. Capital prices are defined as the ratio between capital cost (sum of depreciation and interest) and estimated capital stock.[31] We also include $R = 4$ environmental variables, among them groundwater nitrate pollution as a proxy for water quality. We also control for the share of households served, defined as water delivered to residential customers relative to total water delivered. Since residential customers typically have lower volumes of water delivered per connection than industrial customers, we expect an increasing effect on total cost due to decreased capacity utilization of the water network. We include the share of groundwater abstraction, defined as abstracted groundwater volumes relative to total water intake, to incorporate differences in the quality of water intake. Moreover, we account for the average population density of the municipalities supplied by each water firm. Firms serving more densely populated areas can benefit from higher capacity utilization rates within their network, hence we expect an inverse relationship between total cost and population density.

In addition to input prices, output quantities, and environmental conditions, we include fixed effects for firms and years in Equation 5.5 to exploit the panel dimension of our data. Estimates are obtained by Within estimation with firm-level clustering of standard errors.

[31] We follow the approach proposed by Wagner (2010) and estimate the capital stock of a firm based on annual depreciation and average economic lifetimes of buildings and equipment in the German water sector.

5.6 Results

5.6.1 Organic farming and groundwater nitrate pollution

We first consider the effect of organic farming on groundwater nitrate. Table 5.5 summarizes the GMM estimates of different model specifications. The first column includes only the lagged dependent variable and our variable of interest, the share of organic farming. The second column adds an indicator for excessive mineral fertilizer application (> 100 kg/ha) and land use shares within a 500m radius around the sampling site location. The third column adds weather controls and is our preferred specification, corresponding to the full Equation 5.1.

The point estimate on organic farming is statistically significant and negative across all model specifications. Our preferred specification indicates that a one percentage point increase in the share of organically farmed land in the district of a monitor decreases groundwater nitrate concentrations by 0.3 mg/l, which is roughly one percent relative to the overall sample average.[32] This effect is in line with previous literature showing that organic farming reduces nitrate leaching loads per area (Biernat et al., 2020), even after controlling for mineral fertilizer application. Our results suggest that organic farming can contribute to improved water quality in the long-run.

The highly significant positive coefficient on the lagged dependent variable confirms that groundwater nitrate concentrations are very persistent over time. This is typically a result of legacy storage, where dissolved nitrogen is retained in the ground and accumulates over time (Van Meter et al., 2016; Winter et al., 2021), and low water table dynamics limit the stream nitrate export (Molenat et al., 2008). The coefficient estimates on the other control variables have the expected direction, and many of them are statistically different from zero: Higher shares of farmland and wine-growing areas in the vicinity of a groundwater monitor increase nitrate readings, whereas grassland and forest coverage are associated with lower nitrate pollution. Temperature positively affects nitrate readings, possibly due to higher soil mineralization rates, as discussed in the literature (Schweigert, Pinter and Ploeg, 2004; Thomsen, Lægdsmand and Olesen, 2010).

[32] Tables D.6 and D.7 present results for the same analysis using district-level data. Point estimates are slightly lower but still confirm the negative impact of organic farming on nitrate levels.

Table 5.5: Regression results for groundwater nitrate pollution

DV: Nitrate	(1)	(2)	(3)
Lagged Nitrate	0.546^{***}	0.552^{***}	0.550^{***}
	(0.121)	(0.114)	(0.115)
Share organic	-0.684^{***}	-0.317^{***}	-0.298^{***}
	(0.182)	(0.101)	(0.096)
Mineral fertilizer dummy		1.419^{*}	1.598^{*}
		(0.812)	(0.820)
Share farmland		0.133^{***}	0.134^{***}
		(0.040)	(0.041)
Share wine		0.423^{**}	0.411^{**}
		(0.181)	(0.180)
Share fruit		0.059	0.049
		(0.111)	(0.111)
Share grassland		-0.045^{*}	-0.041^{*}
		(0.024)	(0.024)
Share forest		-0.061^{***}	-0.058^{***}
		(0.021)	(0.020)
Mean temperature			1.086^{*}
			(0.609)
Sum precipitation			0.001
			(0.003)
Mean precipitation			0.563
			(1.121)
Year FEs	Yes	Yes	Yes
Station FEs	Yes	Yes	Yes
Nobs	7311	7311	7311
N [stations]	1323	1323	1323
% explained	0.838	0.857	0.857
sarganp	0.807	0.775	0.789
hansenp	0.974	0.972	0.975
No. instruments	12	18	21

Notes: This table shows BB system-GMM regression results for the impact of the share of organically farmed land on groundwater nitrate concentrations. Control variables include lagged nitrate levels, a dummy for mineral fertilizer use $\geq$ 100kg/ha, shares of land use within a 500m radius around nitrate monitor locations (farmland, wine growing, fruit cultivation, grassland, and forest), and inverse-distance weighted weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). We also include year and station fixed effects. We treat lagged nitrate levels as endogenous and instrument it with two lags in the levels- and first-differenced equations using collapsed instruments. All other controls are treated as exogenous. Reported model statistics are the p-value of the Hansen test of overidentifying restrictions (hansenp), the p-value of the Sargan test of overidentifying restrictions (sarganp), and % is the percent of variation in the dependent variable explained by factors other than time dummies, measured as one minus the mean squared error of the respective regression divided by the mean squared error of a regression on the time dummies alone. Standard errors are clustered at the level of nitrate sampling sites. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

5.6.2 Groundwater nitrate pollution and firms' costs

Effect on treatment costs

Next, we analyze the effect of groundwater nitrate on treatment costs. Table 5.6 lists OLS estimates for different model specifications including firm-level and year fixed effects. The first column includes only groundwater nitrate, the second column adds the volume of abstracted water as a proxy for firms' size, and the third column augments the model with the share of water abstracted from groundwater sources relative to the sum of total water abstraction and water purchases. The last three columns control for weather: The fourth column includes linear weather variables and corresponds to Equation 5.2. The fifth column adds quadratic weather terms, and the last column flexibly controls for non-linear weather effects by adding firm-specific quintile dummies.

Table 5.6: Regression results for treatment costs

DV: ln(Treatment cost)	(1)	(2)	(3)	(4)	(5)	(6)
ln(Nitrate)	0.046**	0.043**	0.043**	0.044**	0.044**	0.042**
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
ln(Water abstracted)		0.838*	0.807	0.732	0.716	0.777
		(0.488)	(0.496)	(0.482)	(0.483)	(0.500)
ln(Share groundwater)			0.150	0.152	0.154	0.144
			(0.096)	(0.096)	(0.095)	(0.098)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	Linear	Quadratic	Quintiles
Nobs	2754	2754	2754	2754	2754	2754
N	512	512	512	512	512	512
Adj.R2	0.890	0.891	0.891	0.891	0.891	0.891

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on treatment costs of water suppliers. Nitrate is measured as a volume-weighted average of nitrate measurements within a four kilometer radius around the plant location. Control variables include the volume of water abstracted, the share of abstracted groundwater relative to total abstraction, and different specifications of weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

The point estimate for groundwater nitrate is highly significant and relatively stable across model specifications, indicating that a one percent increase in groundwater nitrate is associated with an increase in treatment cost by about 0.04 to 0.05 percent. This aligns with the literature arguing that water companies affected by nitrate pollution take costly extra measures to reduce the nitrate load in potable water (Westling, Stromberg and Swain, 2020). Our point estimates are very close in magnitude to those obtained by Lopes et al. (2019), who estimate an elasticity of -0.04 between forest coverage and water treatment cost of groundwater abstracting water suppliers in Portugal. Moreover, we find that the volume of abstracted water has a positive impact on treatment cost across model specifications, also in line with Lopes et al. (2019). The coefficient on the share of groundwater abstraction is not significant buis nevertheless consistently positive. This could imply that raw water abstracted from groundwater bodies has lower quality than raw water from surface water or water purchased from other firms.

The results in Table 5.6 are based on a volume-weighted average of all nitrate measurements available within a four kilometer radius around the plant location. Concerning the pre-specified radius, we face a trade-off between sample size and spatial accuracy: A larger radius increases sample size but might introduce bias since the spatial relationship is incorrectly approximated. We check the robustness of our results using different radii in Table 5.7: The first three columns calculate the weighted nitrate averages using the same approach as before but allowing for varying distances. The last three columns introduce an additional restriction to account for hydro-geological dependencies of water abstraction. Here, weighted averages are based only on nitrate monitors that are located in the same groundwater body as the water abstraction plant.

Table 5.7: Regression results for treatment costs using different nitrate measures

DV: ln(Treatment cost) Nitrate radius	(1) 3km	(2) 4km	(3) 5km	(4) 3km restr.	(5) 4km restr.	(6) 5km restr.
ln(Nitrate)	0.033*	0.044**	0.045***	0.042**	0.063***	0.050**
	(0.019)	(0.020)	(0.015)	(0.020)	(0.024)	(0.020)
ln(Water abstracted)	0.280	0.716	0.721*	0.254	0.330	0.480
	(0.470)	(0.483)	(0.410)	(0.523)	(0.470)	(0.443)
ln(Share groundwater)	0.026	0.154	0.008	0.006	0.225**	0.060
	(0.090)	(0.095)	(0.082)	(0.122)	(0.114)	(0.096)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Nobs	1851	2754	3808	1523	2146	2857
N	354	512	696	290	401	527
Adj.R2	0.900	0.891	0.892	0.903	0.902	0.901

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on treatment costs of water suppliers. In the first three columns, nitrate is measured as a volume-weighted average of all available nitrate measurements within a pre-specified radius around the plant location. In the last three columns, volume-weighted nitrate averages are based on nitrate measurements from nitrate monitors in the same groundwater body as the water abstraction plant. Control variables include the volume of water abstracted, the share of abstracted groundwater relative to total abstraction, and quadratic weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

Results in Table 5.7 suggest a robust positive association between nitrate and treatment cost for different volume-weighted nitrate averages. Point estimates vary between .03 and .05 percentage points for the unrestricted averages. Imposing the restriction of groundwater bodies decreases the sample size, nevertheless point estimates become more pronounced in magnitude, most likely because the hydro-geological dependencies are depicted better in the restricted case.[33]

Lastly, we analyze heterogeneity in the relationship between groundwater nitrate and water supplier's treatment cost. In Table 5.8, we split our sample into water suppliers with groundwater abstraction shares below and above the sample median. The first column depicts regression results for firms with less than 90 percent of groundwater abstraction. The estimated coefficient on nitrate is indeed lower than in the full sample, since these firms rely to a larger extent on surface water abstraction and water purchases from other firms, where nitrate pollution is typically less of a problem. In contrast, treatment costs of firms with groundwater abstraction shares above 90 percent are more heavily affected by nitrate pollution, as indicated by the point estimates in the second column. The coefficient is about 50 percent larger than in the full sample, consistent with the idea that groundwater-dependent firms bear a larger share of cost increases due to nitrate pollution. These firms might have fewer possibilities to substitute polluted raw water from groundwater resources, e.g., by purchasing bulk water from other suppliers. Nevertheless, the difference between point estimates of both groups is not statistically significant, making it difficult to render a definite conclusion about the extent of heterogeneity in the relationship between groundwater nitrate and treatment cost.

[33] As another robustness check, we re-run the estimates for different subsamples of firms, e.g., restricted by duration of observation in the panel or share of abstracted groundwater. Results are listed in Table D.8, showing that point estimates are robust across subsamples.

Table 5.8: Heterogeneous effects on treatment cost

DV: ln(Treatment cost) Share groundwater	(1) Below median	(2) Above median
ln(Nitrate)	0.030	0.061*
	(0.020)	(0.033)
ln(Water abstracted)	1.099*	0.354
	(0.578)	(0.692)
ln(Share groundwater)	0.020	0.169*
	(1.322)	(0.093)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
Weather controls	Quadratic	Quadratic
Nobs	1383	1371
N	248	264
Adj.R2	0.900	0.881

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on treatment costs of water suppliers for two different samples: The first column is based on water suppliers with a share of groundwater abstraction that is lower than the median share, and the second column is based on water suppliers with above-median shares. Nitrate is measured as a volume-weighted average of nitrate measurements within a four kilometer radius around the plant location. Control variables include the volume of water abstracted, the share of abstracted groundwater relative to total abstraction, and quadratic weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

Effect on total costs

Table 5.9 depicts regression results for the total cost model. The first column uses only input prices and outputs on the right-hand side, the second column adds control variables. Both models include firm and year fixed effects.

The statistically significant and positive coefficient on nitrate suggests a 0.02 percent increase in total costs for each additional percent of groundwater nitrate. For an average firm, this would imply more than €335,000 in additional costs per year. The other coefficients have the expected direction and magnitude: Labor price increases raise total costs, and producing more output raises total costs. The sum of output coefficients is very close to one, pointing towards constant returns to scale in water supply. Results are robust to the inclusion of additional control variables; none of them is significantly related to total costs, presumably because we already explain a large share in variation through the fixed effects, prices, and output quantities.

Table D.9 in the Appendix presents results for an alternative definition of capital cost. Instead of considering only the depreciation expenses and interest payments, we define capital cost as the residual between total cost and labor

Table 5.9: Regression results for total costs

DV: ln(Total cost)	(1)	(2)
ln(Nitrate)	0.019*	0.018*
	(0.010)	(0.010)
ln(Labor price)	0.733***	0.733***
	(0.143)	(0.143)
ln(Water delivered)	0.884***	0.840***
	(0.159)	(0.163)
ln(Population served)	0.187	0.236
	(0.147)	(0.157)
ln(Share groundwater)		0.040
		(0.061)
ln(Share residential)		−0.024
		(0.098)
ln(Population density)		−0.058
		(0.086)
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
Nobs	1846	1846
N	342	342
Adj.R2	0.986	0.986

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on total costs of water suppliers. Nitrate is measured as a volume-weighted average of nitrate readings within a four kilometer radius around the plant location. We include the labor price and delivered water volumes and population served as outputs. Total cost and labor price are standardized by capital price. The capital price is defined as the sum of depreciation and interest payments divided by the capital stock. Control variables are the share of groundwater abstraction, the share of residential water deliveries, and the population density of the area served by the water company. All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

expenses. Point estimates and standard errors are very similar to those listed in Table 5.9.

Taken together, the results suggest that water supply companies incur substantial costs through groundwater nitrate pollution, both through increases in their treatment and total costs. Differential cost impacts can arise from different water treatment processes. For example, since reverse osmosis takes place almost fully automatic, no further labor costs are involved; instead, this technology is associated with high treatment costs through increased expenditures for energy and chemicals. In contrast, the CARIX method is more capital intensive, with lower operating costs relative to reverse osmosis.

5.7 Conclusion

Over the past decades, nitrate groundwater pollution has become a severe problem in many countries that has recently gained more attention from policymakers and researchers. In Germany, groundwater nitrate concentrations have been consistently high for many years. Currently, more than every fourth observed sampling site reports nitrate concentrations above the permissible value of 50 mg/l that must be attained in the EU. This potentially increases water prices for households, as treatment becomes more complex and elaborate, and consequently more costly.

This study provides the first large-scale evidence on the relationship between organic farming practices and water quality as proxied by groundwater nitrate pollution. Moreover, we quantify the consequences of groundwater pollution for drinking water supply firms by assessing the cost-driving effect of nitrate-polluted raw water on treatment and total cost. Our analysis is based on unique and novel panel data sets on groundwater nitrate pollution, agricultural indicators, and water companies in Germany, covering the years 2008 to 2016. Using geo-referenced micro-level data on nitrate monitors and water supply companies enables us to account for the spatial dependencies in groundwater abstraction in our analysis.

First, we analyze the determinants of nitrate concentrations using data on groundwater sampling sites. Our results suggest that organic farming in the vicinity of groundwater sampling stations is associated with lower groundwater nitrate levels relative to conventional agriculture. One additional percentage point in the share of organically farmed land corresponds to nitrate concentrations that are one percent lower, which implies an elasticity roughly equal to one. This relationship remains statistically significant even after controlling for mineral fertilizer use, suggesting that the positive impact of organic farming on water quality stems not only from mineral fertilizer applications being prohibited but also from other mechanisms. This implies that expanding organic farming activities could contribute to improving water quality.

Second, we estimate the impacts of groundwater nitrate pollution on the cost of drinking water supply using firm-level panel data. Our results indicate that treatment costs of water suppliers increase with higher levels of nitrate groundwater pollution, where a one percentage point increase in nitrate levels is associated with a 0.04 to 0.05 percentage point increase in treatment cost. The point estimates are robust to using different measures of groundwater nitrate pollution. Moreover, we find suggestive evidence that the negative relationship between nitrate pollution and treatment costs is more pronounced among water suppliers that rely to a large extent on groundwater abstraction. These firms might have fewer possibilities to substitute the raw water from groundwater resources by abstraction from other sources or water purchases. Estimating a total cost function, we further find that groundwater nitrate pollution also affects total costs (including capital and labor costs) and not only treatment costs. Our estimates point to a 0.02 percent increase in total costs for an additional percentage point in groundwater nitrate pollution. These cost increases will likely be passed through to water customers. Effective mitigation policies to improve groundwater quality could contribute to protecting water consumers from price increases stemming from agricultural nitrate pollution.

The analyses presented here suffer from several drawbacks related to data availability. First, data on organic farming practices and mineral fertilizer supply is only available at the district level. Detailed geo-referenced data on fertilizer application and the location and extent of organically farmed areas would certainly improve the accuracy of our estimates since the spatial dependencies between groundwater bodies, nitrate monitors, and organically farmed areas could be exactly represented. Second, we assume that water companies and their abstraction plants are located at the center of municipalities. Knowing the exact location of water abstraction would be beneficial to improve accuracy. These data limitations prevent us from further exploring relevant aspects of the agriculture-water quality nexus. For example, the question of why organic farming has benefits for water quality that go beyond reduced fertilizer application provides a promising avenue for future research. Detailed micro-level data on conventional and organic farming practices would be an essential prerequisite for identifying specific practices and mechanisms through which organic farming affects groundwater resources.

Bibliography

Abildtrup, J., Garcia, S. and Stenger, A. (2013). “The effect of forest land use on the cost of drinking water supply: A spatial econometric analysis”. *Ecological Economics* 92, pp. 126–136.

Aldy, J. E., Auffhammer, M., Cropper, M., Fraas, A. and Morgenstern, R. (2022). “Looking back at 50 years of the Clean Air Act”. *Journal of Economic Literature* 60 (1), pp. 179–232.

Alvarez, J. and Arellano, M. (2003). “The time series and cross-section asymptotics of dynamic panel data estimators”. *Econometrica* 71 (4), pp. 1121–1159.

Ambrey, C. L., Fleming, C. M. and Chan, A. Y.-C. (2014). “Estimating the cost of air pollution in South East Queensland: An application of the life satisfaction non-market valuation approach”. *Ecological Economics* 97, pp. 172–181.

Anderson, T. W. and Hsiao, C. (1982). “Formulation and estimation of dynamic models using panel data”. *Journal of Econometrics* 18 (1), pp. 47–82.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist’s companion*. Princeton, NJ: Princeton University Press.

Aragon, 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, pp. 295–309.

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, pp. 295–309.

Arellano, M. and Bond, S. (1991). “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations”. *The Review of Economic Studies* 58 (2), p. 277.

Asay, G. R. B., Roy, K., Lang, J. E., Payne, R. L. and Howard, D. H. (2016). “Absenteeism and employer costs associated with chronic diseases and health risk factors in the US workforce”. *Preventing Chronic Disease* 13 (E141), pp. 1–11.

Auffhammer, M., Bento, A. M. and Lowe, S. E. (2009). “Measuring the effects of the Clean Air Act Amendments on ambient PM_{10} concentrations: The critical importance of a spatially disaggregated analysis”. *Journal of Environmental Economics and Management* 58 (1), pp. 15–26.

Baetschmann, G. (2013). “Heterogeneity in the relationship between happiness and age: Evidence from the German Socio-Economic Panel”. *German Economic Review* 15 (3), pp. 393–410.

Bartik, A. W., Currie, J., Greenstone, M. and Knittel, C. R. (2019). “The local economic and welfare consequences of hydraulic fracturing”. *American Economic Journal: Applied Economics* 11 (4), pp. 105–55.

Barwick, P. J., Li, S., Rao, D. and Zahur, N. B. (2018). “The Morbidity Cost of Air Pollution: Evidence from Consumer Spending in China”. *NBER Working Paper No. 24688.*

Bates, D. V. (1995). “The effects of air pollution on children.” *Environmental Health Perspectives* 103 (Suppl 6), pp. 49–53.

Bawa, R. and Dwivedi, P. (2019). “Impact of land cover on groundwater quality in the Upper Floridan Aquifer in Florida, United States”. *Environmental Pollution* 252, pp. 1828–1840.

Beach, B., Ferrie, J., Saavedra, M. and Troesken, W. (2016). “Typhoid fever, water quality, and human capital formation”. *The Journal of Economic History* 76 (1), pp. 41–75.

Bell, M. L. and Davis, D. L. (2001). “Reassessment of the lethal London fog of 1952: Novel indicators of acute and chronic consequences of acute exposure to air pollution”. *Environmental Health Perspectives* 109 (Suppl 3), pp. 389–394.

Bennear, L. S. and Olmstead, S. M. (2008). “The impacts of the “right to know”: Information disclosure and the violation of drinking water standards”. *Journal of Environmental Economics and Management* 56 (2), pp. 117–130.

Biernat, L., Taube, F., Vogeler, I., Reinsch, T., Kluß, C. and Loges, R. (2020). “Is organic agriculture in line with the EU-Nitrate directive? On-farm nitrate leaching from organic and conventional arable crop rotations”. *Agriculture, Ecosystems & Environment* 298, p. 106964.

Block, M. L. and Calderón-Garcidueñas, L. (2009). “Air pollution: Mechanisms of neuroinflammation and CNS disease”. *Trends in Neurosciences* 32 (9), pp. 506–516.

Blundell, R. and Bond, S. (1998). “Initial conditions and moment restrictions in a dynamic panel data models”. *Journal of Econometrics* 87, pp. 115–143.

Bond, T. N. and Lang, K. (2019). “The Sad Truth About Happiness Scales: Empirical Results”. *Journal of Political Economy* 127 (4), pp. 1629–1640.

Brainerd, E. and Menon, N. (2014). “Seasonal effects of water quality: The hidden costs of the Green Revolution to infant and child health in India”. *Journal of Development Economics* 107, pp. 49–64.

Brunekreef, B. and Holgate, S. T. (2002). “Air pollution and health”. *The Lancet* 360 (9341), pp. 1233–1242.

Brunel, C. and Johnson, E. P. (2019). “Two birds, one stone? Local pollution regulation and greenhouse gas emissions”. *Energy Economics* 78, pp. 1–12.

Burnett, R. T., Smith-Doiron, M., Stieb, D., Raizenne, M. E., Brook, J. R., Dales, R. E., Leech, J. A., Cakmak, S. and Krewski, D. (2001). "Association between ozone and hospitalization for acute respiratory diseases in children less than 2 years of age". *American Journal of Epidemiology* 153 (5), pp. 444–452.

Caliendo, M. and Kopeinig, S. (2008). "Some practical guidance for the implementation of propensity score matching". *Journal of Economic Surveys* 22 (1), pp. 31–72.

Callaway, B. and Sant'Anna, P. H. (2021). "Difference-in-differences with multiple time periods". *Journal of Econometrics* 225 (2), pp. 200–230.

Canfield, D. E., Glazer, A. N. and Falkowski, P. G. (2010). "The evolution and future of earth's nitrogen cycle". *Science* 330, pp. 192–196.

Caporali, F., Mancinelli, R. and Campiglia, E. (2003). "Indicators of cropping system diversity in organic and conventional farms in Central Italy". *International Journal of Agricultural Sustainability* 1 (1), pp. 67–72.

Carson, R. T., Koundouri, P. and Nauges, C. (2010). "Arsenic mitigation in Bangladesh: A household labor market approach". *American Journal of Agricultural Economics* 93 (2), pp. 407–414.

Case, A., Lubotsky, D. and Paxson, C. (2002). "Economic status and health in childhood: The origins of the gradient". *American Economic Review* 92 (5), pp. 1308–1334.

Casey, J. A., Savitz, D. A., Rasmussen, S. G., Ogburn, E. L., Pollak, J., Mercer, D. G. and Schwartz, B. S. (2016). "Unconventional natural gas development and birth outcomes in Pennsylvania, USA". *Epidemiology* 27 (2), p. 163.

Chabé-Ferret, S., Reynaud, A. and Tène, E. (2021). *Water Quality, Policy Diffusion Effects and Farmers' Behavior*. TSE Working Paper 21-1229. Toulouse School of Economics. Available at: `https://www.tse-fr.eu/sites/default/files/TSE/documents/doc/wp/2021/wp_tse_1229.pdf`, accessed on May 31, 2022.

Chan, H. R., Chupp, B. A., Cropper, M. L. and Muller, N. Z. (2018). "The impact of trading on the costs and benefits of the Acid Rain Program". *Journal of Environmental Economics and Management* 88, pp. 180–209.

Chang, T., Graff Zivin, J. and Neidell, M. (2016). "Particulate pollution and the productivity of pear packers". *American Economic Journal: Economic Policy* 8 (3), pp. 141–69.

Chang, T. Y., 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 (1), pp. 151–72.

Chay, K. Y. and Greenstone, M. (2003). "The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession". *The Quarterly Journal of Economics* 118 (3), pp. 1121–1167.

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, pp. 465–497.

Chen, Y., Jin, G. Z., Kumar, N. and Shi, G. (2013). "The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality". *Journal of Environmental Economics and Management* 66 (3), pp. 424–443.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. and Battese, G. E. (2005). *An introduction to efficiency and productivity analysis.* 2nd ed. New York: Springer Science & Business Media.

Colborn, T., Kwiatkowski, C., Schultz, K. and Bachran, M. (2011). "Natural gas operations from a public health perspective". *Human and Ecological Risk Assessment: An International Journal* 17 (5), pp. 1039–1056.

Colborn, T., Schultz, K., Herrick, L. and Kwiatkowski, C. (2014). "An exploratory study of air quality near natural gas operations". *Human and Ecological Risk Assessment: An International Journal* 20 (1), pp. 86–105.

Collier, S. A., Deng, L., Adam, E. A., Benedict, K. M., Beshearse, E. M., Blackstock, A. J., Bruce, B. B., Derado, G., Edens, C., Fullerton, K. E., et al. (2021). "Estimate of burden and direct healthcare cost of infectious waterborne disease in the United States". *Emerging Infectious Diseases* 27 (1), p. 140.

Coneus, K. and Spiess, C. K. (2012). "Pollution exposure and child health: Evidence for infants and toddlers in Germany". *Journal of Health Economics* 31 (1), pp. 180–196.

Cosgrove, B. M., LaFave, D. R., Dissanayake, S. T. and Donihue, M. R. (2015). "The economic impact of shale gas development: A natural experiment along the New York/Pennsylvania border". *Agricultural and Resource Economics Review* 44 (2), pp. 20–39.

Cunado, J. and De Gracia, F. P. (2013). "Environment and happiness: New evidence for Spain". *Social Indicators Research* 112 (3), pp. 549–567.

Currie, J., Graff Zivin, J., Meckel, K., Neidell, M. and Schlenker, W. (2013). "Something in the water: Contaminated drinking water and infant health". *Canadian Journal of Economics* 46 (3), pp. 791–810.

Currie, J., Greenstone, M. and Meckel, K. (2017). "Hydraulic fracturing and infant health: New evidence from Pennsylvania". *Science Advances* 3 (12), e1603021.

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 (4), pp. 682–694.

Currie, J. and Lin, W. (2007). "Chipping away at health: more on the relationship between income and child health". *Health Affairs* 26 (2), pp. 331–344.

Currie, J. and Neidell, M. (2005). "Air pollution and infant health: What can we learn from California's recent experience?" *The Quarterly Journal of Economics* 120 (3), pp. 1003–1030.

Cutler, D. and Miller, G. (2005). "The role of public health improvements in health advances: The twentieth-century United States". *Demography* 42 (1), pp. 1–22.

Danelon, A. F., Augusto, F. G. and Spolador, H. F. S. (2021). "Water resource quality effects on water treatment costs: An analysis for the Brazilian case". *Ecological Economics* 188, p. 107134.

Davis, L. W. (2008). "The effect of driving restrictions on air quality in Mexico City". *Journal of Political Economy* 116 (1), pp. 38–81.

— (2017). "Saturday driving restrictions fail to improve air quality in Mexico City". *Scientific Reports* 7 (1), pp. 1–9.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). "Two-way fixed effects estimators with heterogeneous treatment effects". *American Economic Review* 110 (9), pp. 2964–96.

De Mesnard, L. (2013). "Pollution models and inverse distance weighting: Some critical remarks". *Computers & Geosciences* 52, pp. 459–469.

Dearmont, D., McCarl, B. A. and Tolman, D. A. (1998). "Costs of water treatment due to diminished water quality: A case study in Texas". *Water Resources Research* 34 (4), pp. 849–853.

DeLang, M. N., Becker, J. S., Chang, K.-L., Serre, M. L., Cooper, O. R., Schultz, M. G., Schröder, S., Lu, X., Zhang, L., Deushi, M., et al. (2021). "Mapping yearly fine resolution global surface ozone through the Bayesian Maximum Entropy data fusion of observations and model output for 1990–2017". *Environmental Science & Technology* 55 (8), pp. 4389–4398.

DeLeire, T. and Manning, W. (2004). "Labor market costs of illness: Prevalence matters". *Health Economics* 13 (3), pp. 239–250.

Destatis (2020). *Erzeugerpreisindex gewerblicher Produkte 5-Steller: GP09-36001*. Available at: `https://www-genesis.destatis.de/genesis/online`, accessed on May 31, 2022.

Devlin, R. B., McDonnell, W. F., Mann, R., Becker, S., House, D. E., Schreinemachers, D. and Koren, H. S. (1991). "Exposure of humans to ambient levels of ozone for 6.6 hours causes cellular and biochemical changes in the lung". *Am J Respir Cell Mol Biol* 4 (1), pp. 72–81.

Ellison, R. B., Greaves, S. P. and Hensher, D. A. (2013). "Five years of Londons low emission zone: Effects on vehicle fleet composition and air quality". *Transportation Research Part D: Transport and Environment* 23, pp. 25–33.

Energy, National Energy Technology Laboratory (NETL) (2009). *Modern shale gas development in the United States: A primer*. Report. US Department of Energy, Office of Fossil Energy. Available at: `https://www.energy.gov/sites/default/files/2013/03/f0/ShaleGasPrimer_Online_4-2009.pdf`, accessed on May 31, 2022.

Erisman, J. W., Galloway, J. N., Seitzinger, S., Bleeker, A., Dise, N. B., Petrescu, A. R., Leach, A. M. and Vries, W. de (2013). "Consequences of human modification of the global nitrogen cycle". *Philosophical Transactions of the Royal Society B: Biological Sciences* 368 (1621), p. 20130116.

Ettner, S. L. (1996). "New evidence on the relationship between income and health". *Journal of Health Economics* 15 (1), pp. 67–85.

EU (1991). "Council Directive 91/676/EEC of 12 December 1991 concerning the protection of waters against pollution caused by nitrates from agricultural sources". *Official Journal of the European Communities* L375, pp. 1–8.

— (1996). "Council Directive 96/62/EC of 27 September 1996 on ambient air quality assessment and management". *Official Journal of the European Communities* L296, pp. 55–63.

— (1998). "Council Directive 98/83/EC of 3 November 1998 on the quality of water intended for human consumption". *Official Journal of the European Communities* L330, pp. 32–54.

— (1999). "Directive 1999/30/EC of 22 April 1999 relating to limit values for sulphur dioxide, nitrogen dioxide and oxides of nitrogen, particulate matter and lead in ambient air". *Official Journal of the European Communities* L163, pp. 41–60.

— (2000a). "Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy". *Official Journal of the European Communities* L327, pp. 1–72.

— (2000b). "Directive 2000/69/EC of the European Parliament and of the Council of 16 November 2000 relating to limit values for benzene and carbon monoxide in ambient air". *Official Journal of the European Communities* L313, pp. 12–21.

— (2001). "Directive 2001/80/EC of the European Parliament and of the Council of 23 October 2001 on the limitation of emissions of certain pollutants into the air from large combustion plants". *Official Journal of the European Communities* L309, pp. 1–21.

— (2002). "Directive 2002/3/EC of the European Parliament and of the Council of 12 February 2002 relating to ozone in ambient air". *Official Journal of the European Communities* L67, pp. 14–30.

— (2003). "Directive 2003/17/EC of the European Parliament and of the Council of 3 March 2003 amending Directive 98/70/EC relating to the quality of petrol and diesel fuels". *Official Journal of the European Union* L76, pp. 10–19.

— (2008a). "Commission Regulation (EC) No 692/2008 of 18 July 2008 implementing and amending Regulation (EC) No 715/2007 of the European Parliament and of the Council on type-approval of motor vehicles with respect to emissions from light passenger and commercial vehicles (Euro 5 and Euro 6) and on access to vehicle repair and maintenance information". *Official Journal of the European Union* L199, pp. 1–136.

— (2008b). "Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe". *Official Journal of the European Union* L152, pp. 1–44.

EU (2009a). "Directive, 2009/125/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for the setting of ecodesign requirements for energy-related product". *Official Journal of the European Union* L285, pp. 10–35.

— (2009b). "Regulation (EC) No 595/2009 of the European Parliament and of the Council of 18 June 2009 on type-approval of motor vehicles and engines with respect to emissions from heavy duty vehicles (Euro VI) and on access to vehicle repair and maintenance information and amending Regulation (EC) No 715/2007 and Directive 2007/46/EC and repealing Directives 80/1269/EEC, 2005/55/EC and 2005/78/EC". *Official Journal of the European Union* L188, pp. 1–13.

— (2010). "Directive 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions (integrated pollution prevention and control)". *Official Journal of the European Union* L334, pp. 17–119.

— (2015). "Directive (EU) 2015/2193 of the European Parliament and of the Council of 25 November 2015 on the limitation of emissions of certain pollutants into the air from medium combustion plants". *Official Journal of the European Union* L313, pp. 1–19.

— (2016a). "Commission Regulation (EU) 2016/646 of 20 April 2016 amending Regulation (EC) No 692/2008 as regards emissions from light passenger and commercial vehicles (Euro 6)". *Official Journal of the European Union* L109, pp. 1–22.

— (2016b). "Directive (EU) 2016/802 of the European Parliament and of the Council of 11 May 2016 relating to a reduction in the sulphur content of certain liquid fuels". *Official Journal of the European Union* L132, pp. 58–78.

— (2018). "Regulation (EU) 2018/848 of the European Parliament and of the Council of 30 May 2018 on organic production and labelling of organic products and repealing Council Regulation (EC) No 834/2007". *Official Journal of the European Union* L189, pp. 41–60.

— (2021). "Regulation (EU) 2021/2115 of the European Parliament and of the Council of 2 December 2021 establishing rules on support for strategic plans to be drawn up by Member States under the common agricultural policy (CAP Strategic Plans) and financed by the European Agricultural Guarantee Fund (EAGF) and by the European Agricultural Fund for Rural Development (EAFRD) and repealing Regulations (EU) No 1305/2013 and (EU) No 1307/2013". *Official Journal of the European Union* L435, pp. 1–186.

European Commission (2010). "The CAP towards 2020: Meeting the food, natural resources and territorial challenges of the future". *COM(2010) 672 final*. Available at: `https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:0672:FIN:en:PDF`, accessed on May 31, 2022.

— (2020). "A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system". *COM(2020) 381 final*. Available at: `https://eur-`

lex.europa.eu/resource.html?uri=cellar:ea0f9f73-9ab2-11ea-9d2d-01aa75ed71a1.0001.02/DOC_1&format=PDF, accessed on May 31, 2022.

— (2021a). "Report from the Commission to the Council and the European Parliament on the implementation of Council Directive 91/676/EEC concerning the protection of waters against pollution caused by nitrates from agricultural sources based on Member State reports for the period 2016–2019". *COM(2021) 1000 final*. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021DC1000&from=EN, accessed on May 31, 2022.

— (2021b). "Report from the Commission to the Council and the European Parliament on the implementation of the Water Framework Directive (2000/60/EC), the Environmental Quality Standards Directive (2008/105/EC amended by Directive 2013/39/EU) and the Floods Directive (2007/60/EC)". *COM(2021) 381 final*. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021DC0970, accessed on May 31, 2022.

European Court of Justice (2018). "Judgment of the Court (Ninth Chamber) of 21 June 2018. European Commission v Federal Republic of Germany. Failure of a Member State to fulfil obligations of Directive 91/676/EEC". *Case C-543/16*. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A62016CJ0543, accessed on May 31, 2022.

European Environmental Agency (2018). *Europe's urban air quality – Re-assessing implementation challenges in cities*. Available at: https://www.eea.europa.eu/publications/europes-urban-air-quality/download, accessed on May 31, 2022.

— (2022). *Managing air quality in Europe*. Available at: https://www.eea.europa.eu/publications/managing-air-quality-in-europe, accessed on May 31, 2022.

European Parliament (2021). "European Parliament resolution of 15 January 2020 on the European Green Deal (2019/2956(RSP)". *C270*, pp. 2–20. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020IP0005&from=EN, accessed on May 31, 2022.

Evans, A. E., Mateo-Sagasta, J., Qadir, M., Boelee, E. and Ippolito, A. (2018). "Agricultural water pollution: Key knowledge gaps and research needs". *Current Opinion in Environmental Sustainability* 36, pp. 20–27.

Federal Ministry of Justice and Consumer Protection (2009). "Düngegesetz". *Bundesgesetzblatt* I (4), pp. 54–60.

— (2017). "Verordnung über die Anwendung von Düngemitteln, Bodenhilfsstoffen, Kultursubstraten und Pflanzenhilfsmitteln nach den Grundsätzen der guten fachlichen Praxis beim Düngen (Düngeverordnung - DüV)". *Bundesgesetzblatt* I (32), pp. 1305–1348.

— (2020). "Verordnung zur Änderung der Düngeverordnung und anderer Vorschriften". *Bundesgesetzblatt* I (20), pp. 846–861.

Ferreira, S., Akay, A., Brereton, F., Cuñado, J., Martinsson, P., Moro, M. and Ningal, T. F. (2013). "Life satisfaction and air quality in Europe". *Ecological Economics* 88, pp. 1–10.

Ferreira, S. and Moro, M. (2010). "On the use of subjective well-being data for environmental valuation". *Environmental and Resource Economics* 46 (3), pp. 249–273.

Filippini, M., Hrovatin, N. and Zorić, J. (2008). "Cost efficiency of Slovenian water distribution utilities: An application of stochastic frontier methods". *Journal of Productivity Analysis* 29 (2), pp. 169–182.

Finkelstein, E., Fiebelkorn, I. C. and Wang, G. (2005). "The costs of obesity among full-time employees". *American Journal of Health Promotion* 20 (1), pp. 45–51.

Fiquepron, J., Garcia, S. and Stenger, A. (2013). "Land use impact on water quality: Valuing forest services in terms of the water supply sector". *Journal of Environmental Management* 126 (15), pp. 113–121.

Fontenot, B. E., Hunt, L. R., Hildenbrand, Z. L., Carlton Jr, D. D., Oka, H., Walton, J. L., Hopkins, D., Osorio, A., Bjorndal, B., Hu, Q. H., et al. (2013). "An evaluation of water quality in private drinking water wells near natural gas extraction sites in the Barnett Shale Formation". *Environmental Science & Technology* 47 (17), pp. 10032–10040.

Fowler, D., Brimblecombe, P., Burrows, J., Heal, M. R., Grennfelt, P., Stevenson, D. S., Jowett, A., Nemitz, E., Coyle, M., Liu, X., et al. (2020). "A chronology of global air quality". *Philosophical Transactions of the Royal Society A* 378 (2183), p. 20190314.

Freeman III, A. M., Herriges, J. A. and Kling, C. L. (2014). *The measurement of environmental and resource values: Theory and methods*. 2nd ed. New York, US: Routledge.

Friedman, M. S., Powell, K. E., Hutwagner, L., Graham, L. M. and Teague, W. G. (2001). "Impact of changes in transportation and commuting behaviors during the 1996 Summer Olympic Games in Atlanta on air quality and childhood asthma". *Journal of the American Medical Association* 285 (7), pp. 897–905.

Frijters, P., Haisken-DeNew, J. P. and Shields, M. A. (2004). "Investigating the patterns and determinants of life satisfaction in Germany following reunification". *Journal of Human Resources* 39 (3), pp. 649–674.

Gallagher, T. L. and Gergel, S. E. (2017). "Landscape indicators of groundwater nitrate concentrations: An approach for trans-border aquifer monitoring". *Ecosphere* 8 (12), e02047.

Gallego, F., Montero, J.-P. and Salas, C. (2013). "The effect of transport policies on car use: Evidence from Latin American cities". *Journal of Public Economics* 107, pp. 47–62.

Gehrsitz, M. (2017). “The effect of low emission zones on air pollution and infant health”. *Journal of Environmental Economics and Management* 83, pp. 121–144.

Gent, J. F., Triche, E. W., Holford, T. R., Belanger, K., Bracken, M. B., Beckett, W. S. and Leaderer, B. P. (2003). “Association of low-level ozone and fine particles with respiratory symptoms in children with asthma”. *Journal of the American Medical Association* 290 (14), pp. 1859–1867.

Gomiero, T., Pimentel, D. and Paoletti, M. G. (2011). “Environmental impact of different agricultural management practices: Conventional vs. organic agriculture”. *Critical Reviews in Plant Sciences* 30 (1-2), pp. 95–124.

Goodman-Bacon, A. (2021). “Difference-in-differences with variation in treatment timing”. *Journal of Econometrics* 225 (2), pp. 254–277.

Graff Zivin, J. and Neidell, M. (2013). “Environment, health, and human capital”. *Journal of Economic Literature* 51 (3), pp. 689–730.

Grande, G., Ljungman, P. L., Eneroth, K., Bellander, T. and Rizzuto, D. (2020). “Association between cardiovascular disease and long-term exposure to air pollution with the risk of dementia”. *JAMA Neurology* 77 (7), pp. 801–809.

Greenstone, M. (2004). “Did the Clean Air Act Cause the remarkable decline in sulfur dioxide concentrations?” *Journal of Environmental Economics and Management* 47 (3), pp. 585–611.

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M. C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N. and Noble, I. (2013). “Sustainable development goals for people and planet”. *Nature* 495 (7441), pp. 305–307.

Gryparis, A., Forsberg, B., Katsouyanni, K., Analitis, A., Touloumi, G., Schwartz, J., Samoli, E., Medina, S., Anderson, H. R., Niciu, E. M., et al. (2004). “Acute effects of ozone on mortality from the air pollution and health: a European approach project”. *American journal of respiratory and critical care medicine* 170 (10), pp. 1080–1087.

Hahn, J. and Newey, W. (2004). “Jackknife and analytical bias reduction for nonlinear panel models”. *Econometrica* 72 (4), pp. 1295–1319.

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, pp. 68–79.

Hansen, L. P. (1982). “Large sample properties of generalized method of moments estimators”. *Econometrica* 50 (4), pp. 1029–10554.

Hardy, K., Buckley, S., Collins, M. J., Estalrrich, A., Brothwell, D., Copeland, L., Garcıa-Tabernero, A., Garcıa-Vargas, S., De La Rasilla, M., Lalueza-Fox, C., et al. (2012). “Neanderthal medics? Evidence for food, cooking, and medicinal plants entrapped in dental calculus”. *Naturwissenschaften* 99 (8), pp. 617–626.

Häußermann, U., Bach, M., Klement, L. and Breuer, L. (2019). *Stickstoff-Flächenbilanzen für Deutschland mit Regionalgliederung Bundesländer und Kreise - Jahre 19995 bis 2017. Methodik, Ergebnisse und Minderungsmaßnahmen.*

Texte 131/2019. Dessau - Roßlau: Umeltbundesamt. Available at: https://www.umweltbundesamt.de/sites/default/files/medien/1410/publikationen/2019-10-28_texte_131-2019_stickstoffflaechenbilanz.pdf, accessed on May 31, 2022.

Henderson, J. V. (1996). "Effects of air quality regulation". *The American Economic Review* 86 (4), pp. 789–813.

Hill, E. and Ma, L. (2017). "Shale gas development and drinking water quality". *American Economic Review: Papers & Proceedings* 107 (5), pp. 522–25.

Hill, E. L. (2018). "Shale gas development and infant health: Evidence from Pennsylvania". *Journal of Health Economics* 61, pp. 134–150.

Hirsch, J. K., Smalley, K. B., Selby-Nelson, E. M., Hamel-Lambert, J. M., Rosmann, M. R., Barnes, T. A., Abrahamson, D., Meit, S. S., GreyWolf, I., Beckmann, S., et al. (2018). "Psychosocial impact of fracking: A review of the literature on the mental health consequences of hydraulic fracturing". *International Journal of Mental Health and Addiction* 16 (1), pp. 1–15.

Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B. and Kaufman, J. D. (2013). "Long-term air pollution exposure and cardio-respiratory mortality: A review". *Environmental Health* 12 (1), pp. 1–16.

Holmes, T. P. (1988). "The offsite impact of soil erosion on the water treatment industry". *Land Economics* 64 (4), pp. 356–366.

Hov, Ö., Hesstvedt, E. and Isaksen, I. S. (1978). "Long-range transport of tropospheric ozone". *Nature* 273 (5661), pp. 341–344.

Imbens, G. W. and Wooldridge, J. M. (2009). "Recent Developments in the Econometrics of Program Evaluation". *Journal of Economic Literature* 47 (1), pp. 5–86.

Iskandar, A., Andersen, Z. J., Bønnelykke, K., Ellermann, T., Andersen, K. K. and Bisgaard, H. (2012). "Coarse and fine particles but not ultrafine particles in urban air trigger hospital admission for asthma in children". *Thorax* 67 (3), pp. 252–257.

Jackson, R. B., Vengosh, A., Carey, J. W., Davies, R. J., Darrah, T. H., O'Sullivan, F. and Pétron, G. (2014). "The environmental costs and benefits of fracking". *Annual Review of Environment and Resources* 39, pp. 327–362.

Jackson, R. B., Vengosh, A., Darrah, T. H., Warner, N. R., Down, A., Poreda, R. J., Osborn, S. G., Zhao, K. and Karr, J. D. (2013). "Increased stray gas abundance in a subset of drinking water wells near Marcellus shale gas extraction". *Proceedings of the National Academy of Sciences* 110 (28), pp. 11250–11255.

Jayachandran, S. (2009). "Air quality and early-life mortality evidence from Indonesia's wildfires". *Journal of Human Resources* 44 (4), pp. 916–954.

Jemielita, T., Gerton, G. L., Neidell, M., Chillrud, S., Yan, B., Stute, M., Howarth, M., Saberi, P., Fausti, N., Penning, T. M., et al. (2015). "Unconventional gas and oil drilling is associated with increased hospital utilization rates". *PLOS one* 10 (7), e0131093.

Jenner, S. and Lamadrid, A. J. (2013). “Shale gas vs. coal: Policy implications from environmental impact comparisons of shale gas, conventional gas, and coal on air, water, and land in the United States”. *Energy Policy* 53, pp. 442–453.

Jensen, V. B., Darby, J. L., Seidel, C. and Gorman, C. (2012). “Drinking water treatment for nitrate. Technical report 6”. In: *Addressing Nitrate in California’s Drinking Water with a Focus on Tulare Lake Basin and Salinas Valley Groundwater. Report for the State Water Resources Control Board Report to the Legislature.* Center for Watershed Sciences, University of California, Davis. Available at: `https://groundwaternitrate.ucdavis.edu/files/139107.pdf`, accessed on May 31, 2022.

Jones, C. S., Hill, D. and Brand, G. (2007). “Use a multifaceted approach to manage high source-water nitrate”. *Opflow* 33 (6), pp. 20–22.

Kampa, M. and Castanas, E. (2008). “Human health effects of air pollution”. *Environmental Pollution* 151 (2), pp. 362–367.

Kang, M., Kanno, C. M., Reid, M. C., Zhang, X., Mauzerall, D. L., Celia, M. A., Chen, Y. and Onstott, T. C. (2014). “Direct measurements of methane emissions from abandoned oil and gas wells in Pennsylvania”. *Proceedings of the National Academy of Sciences* 111 (51), pp. 18173–18177.

Kassenboehmer, S. C. and Haisken-DeNew, J. P. (2009). “You’re Fired! The Causal Negative Effect of Entry Unemployment on Life Satisfaction”. *The Economic Journal* 119 (536), pp. 448–462.

Kawachi, I. and Kennedy, B. P. (1999). “Income inequality and health: Pathways and mechanisms”. *Health Services Research* 34 (1), p. 215.

Keiser, D. A. and Shapiro, J. S. (2019a). “Consequences of the Clean Water Act and the demand for water quality”. *The Quarterly Journal of Economics* 134 (1), pp. 349–396.

— (2019b). “US water pollution regulation over the past half century: Burning waters to Crystal Springs?” *Journal of Economic Perspectives* 33 (4), pp. 51–75.

Khawaji, A. D., Kutubkhanah, I. K. and Wie, J.-M. (2008). “Advances in seawater desalination technologies”. *Desalination* 221 (1-3), pp. 47–69.

Kim, K. J., Shin, J. and Choi, J. (2018). “Cancer risk from exposure to particulate matter and ozone according to obesity and health-related behaviors: A nationwide population-based cross-sectional study”. *Cancer Epidemiology, Biomarkers & Prevention.*

Kirchmann, H. and Bergström, L. (2001). “Do organic farming practices reduce nitrate leaching?” *Communications in Soil Science and Plant Analysis* 32 (7-8), pp. 997–1028.

Knittel, C. R., Miller, D. L. and Sanders, N. J. (2016). “Caution, drivers! Children present: Traffic, pollution, and infant health”. *Review of Economics and Statistics* 98 (2), pp. 350–366.

Koken, P. J., Piver, W. T., Ye, F., Elixhauser, A., Olsen, L. M. and Portier, C. J. (2003). “Temperature, air pollution, and hospitalization for cardiovascular diseases among elderly people in Denver". *Environmental Health Perspectives* 111 (10), p. 1312.

Komarek, T. M. (2016). "Labor market dynamics and the unconventional natural gas boom: Evidence from the Marcellus region". *Resource and Energy Economics* 45, pp. 1–17.

Komisarow, S. and Pakhtigian, E. L. (2022). "Are power plant closures a breath of fresh air? Local air quality and school absences". *Journal of Environmental Economics and Management* 112, p. 102569.

Korsaeth, A. and Eltun, R. (2000). "Nitrogen mass balances in conventional, integrated and ecological cropping systems and the relationship between balance calculations and nitrogen runoff in an 8-year field experiment in Norway". *Agriculture, Ecosystems & Environment* 79 (2-3), pp. 199–214.

Kurt, O. K., Zhang, J. and Pinkerton, K. E. (2016). "Pulmonary health effects of air pollution". *Current Opinion in Pulmonary Medicine* 22 (2), pp. 138–143.

Lall, U., Josset, L. and Russo, T. (2020). "A snapshot of the world's groundwater challenges". *Annual Review of Environment and Resources* 45, pp. 171–194.

Lavaine, E. and Neidell, M. (2017). "Energy production and health externalities: Evidence from oil refinery strikes in France". *Journal of the Association of Environmental and Resource Economists* 4 (2), pp. 447–477.

Lawniczak, A. E., Zbierska, J., Nowak, B., Achtenberg, K., Grześkowiak, A. and Kanas, K. (2016). "Impact of agriculture and land use on nitrate contamination in groundwater and running waters in central-west Poland". *Environmental Monitoring and Assessment* 188 (3), p. 172.

Leach, A. M., Galloway, J. N., Bleeker, A., Erisman, J. W., Kohn, R. and Kitzes, J. (2012). "A nitrogen footprint model to help consumers understand their role in nitrogen losses to the environment". *Environmental Development* 1 (1), pp. 40–66.

Lee, J.-T., Kim, H., Song, H., Hong, Y.-C., Cho, Y.-S., Shin, S.-Y., Hyun, Y.-J. and Kim, Y.-S. (2002). "Air pollution and asthma among children in Seoul, Korea". *Epidemiology* 13 (4), pp. 481–484.

Leff, E. J. (2015). *Final supplemental generic environmental impact statement on the oil, gas and solution mining regulatory program: Regulatory program for horizontal drilling and high-volume hydraulic fracturing to develop the Marcellus Shale and other low-permeability gas reservoirs*. Findings Statement. New York State Department of Environmental Conservation (NYSDEC). Available at: `https://www.dec.ny.gov/docs/materials_minerals_pdf/findingstatehvhf62015.pdf`, accessed on May 31, 2022.

Levinson, A. (2012). "Valuing public goods using happiness data: The case of air quality". *Journal of Public Economics* 96 (9-10), pp. 869–880.

Li, Y., Shang, J., Zhang, C., Zhang, W., Niu, L., Wang, L. and Zhang, H. (2021). "The role of freshwater eutrophication in greenhouse gas emissions: A review". *Science of The Total Environment* 768, p. 144582.

Lleras-Muney, A. (2010). “The needs of the army using compulsory relocation in the military to estimate the effect of air pollutants on children’s health”. *Journal of Human Resources* 45 (3), pp. 549–590.

Lopes, A. F., Macdonald, J. L., Quinteiro, P., Arroja, L., Carvalho-Santos, C., Cunha-e-Sá, M. A. and Dias, A. C. (2019). “Surface vs. groundwater: The effect of forest cover on the costs of drinking water”. *Water Resources and Economics* 28, p. 100123.

Luby, S. P., Halder, A. K., Huda, T. M., Unicomb, L., Islam, M. S., Arnold, B. F. and Johnston, R. B. (2015). “Microbiological contamination of drinking water associated with subsequent child diarrhea”. *The American Journal of Tropical Medicine and Hygiene* 93 (5), pp. 904–911.

Luechinger, S. (2009). “Valuing air quality using the life satisfaction approach”. *The Economic Journal* 119 (536), pp. 482–515.

Lynch, J. W., Smith, G. D., Kaplan, G. A. and House, J. S. (2000). “Income inequality and mortality: Importance to health of individual income, psychosocial environment, or material conditions”. *British Medical Journal* 320 (7243), pp. 1200–1204.

Mair, A. and El-Kadi, A. I. (2013). “Logistic regression modeling to assess groundwater vulnerability to contamination in Hawaii, USA”. *Journal of Contaminant Hydrology* 153, pp. 1–23.

Malaeb, L. and Ayoub, G. M. (2011). “Reverse osmosis technology for water treatment: State of the art review”. *Desalination* 267 (1), pp. 1–8.

Malina, C. and Scheffler, F. (2015). “The impact of low emission zones on particulate matter concentration and public health”. *Transportation Research Part A: Policy and Practice* 77, pp. 372–385.

Margaryan, S. (2021). “Low emission zones and population health”. *Journal of Health Economics* 76, p. 102402.

Marshall, A. (1916). *Principles of Economics*. 7th ed. London, UK: Macmillan.

McKenzie, L. M., Witter, R. Z., Newman, L. S. and Adgate, J. L. (2012). “Human health risk assessment of air emissions from development of unconventional natural gas resources”. *Science of the Total Environment* 424, pp. 79–87.

Meleux, F., Solmon, F. and Giorgi, F. (2007). “Increase in summer European ozone amounts due to climate change”. *Atmospheric Environment* 41 (35), pp. 7577–7587.

Moch, I. and Moch, J. (2002). “A 21st century study of global seawater reverse osmosis operating and capital costs”. In: *Proceedings of the IDA World Congress on Desalination and Water Reuse* (Manama, Bahrain, March 8–13, 2002). International Desalination Association.

Moeller, D. and Murphy, D. (2016). “Net energy analysis of gas production from the Marcellus Shale”. *BioPhysical Economics and Resource Quality* 1 (1), p. 5.

Molenat, J., Gascuel-Odoux, C., Ruiz, L. and Gruau, G. (2008). “Role of water table dynamics on stream nitrate export and concentration in agricultural headwater catchment (France)”. *Journal of Hydrology* 348 (3-4), pp. 363–378.

Monks, P. S., Archibald, A., Colette, A., Cooper, O., Coyle, M., Derwent, R., Fowler, D., Granier, C., Law, K. S., Mills, G., et al. (2015). “Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer”. *Atmospheric Chemistry and Physics* 15 (15), pp. 8889–8973.

Moretti, E. and Neidell, M. (2011). “Pollution, health, and avoidance behavior evidence from the ports of Los Angeles”. *Journal of Human Resources* 46 (1), pp. 154–175.

Murazaki, K. and Hess, P. (2006). “How does climate change contribute to surface ozone change over the United States?” *Journal of Geophysical Research: Atmospheres* 111 (D05301).

Neyman, J. and Scott, E. L. (1948). “Consistent estimates based on partially consistent observations”. *Econometrica* 16 (1), pp. 1–32.

Nickell, S. (1981). “Biases in dynamic models with fixed effects”. *Econometrica* 49 (6), pp. 1417–1426.

Oelmann, M., Czichy, C. and Hormann, L. (2017). *Gutachten zur Berechnung der Kosten der Nitratbelastung in Wasserkörpern für die Wasserwirtschaft.* BDEW Gutachten. Bundesverband der Energie- und Wasserwirtschaft e.V. (BDEW). Available at: `https://www.bdew.de/media/documents/20170113_BDEW_Gutachten_Nitrat_final.pdf`, accessed on May 31, 2022.

Oelmann, M., Czichy, C., Scheele, U., Zaun, S., Dördelmann, O., Harms, E., Penning, M., Kaupe, M., Bergmann, A. and Steenpaß, C. (2017). *Quantifizierung der landwirtschaftlich verursachten Kosten zur Sicherung der Trinkwasserbereitstellung.* Texte 43/2017. Dessau-Roßlau: Umweltbundesamt (UBA). Available at: `https://www.umweltbundesamt.de/sites/default/files/medien/1410/publikationen/2017-05-24_texte-43-2017_kosten-trinkwasserversorgung.pdf`, accessed on May 31, 2022.

Osborn, S. G., Vengosh, A., Warner, N. R. and Jackson, R. B. (2011). “Methane contamination of drinking water accompanying gas-well drilling and hydraulic fracturing”. *Proceedings of the National Academy of Sciences* 108 (20), pp. 8172–8176.

Ostro, B., Lipsett, M., Mann, J., Braxton-Owens, H. and White, M. (2001). “Air pollution and exacerbation of asthma in African-American children in Los Angeles”. *Epidemiology*, pp. 200–208.

Pandey, P. K., Kass, P. H., Soupir, M. L., Biswas, S. and Singh, V. P. (2014). “Contamination of water resources by pathogenic bacteria”. *AMB Express* 4 (1), pp. 1–16.

Paredes, D., Komarek, T. and Loveridge, S. (2015). "Income and employment effects of shale gas extraction windfalls: Evidence from the Marcellus region". *Energy Economics* 47, pp. 112–120.

Parris, K. (2011). "Impact of agriculture on water pollution in OECD countries: Recent trends and future prospects". *International Journal of Water Resources Development* 27, pp. 33–52.

Pennsylvania Department of Environmental Protection (2012). *ACT 13 Frequently Asked Questions*. Available at: `http://files.dep.state.pa.us/OilGas/OilGasLandingPageFiles/Act13/Act_13_FAQ.pdf`, accessed on May 31, 2022.

Pestel, N. and Wozny, F. (2021). "Health effects of Low Emission Zones: Evidence from German hospitals". *Journal of Environmental Economics and Management* 109, p. 102512.

Pigou, A. C. (1920). *The Economics of Welfare*. 4th ed. London, UK: MacMillan & Co., limited.

Price, J. I. and Heberling, M. T. (2018). "The effects of source water quality on drinking water treatment costs: A review and synthesis of empirical literature". *Ecological Economics* 151, pp. 195–209.

Rabinowitz, P. M., Slizovskiy, I. B., Lamers, V., Trufan, S. J., Holford, T. R., Dziura, J. D., Peduzzi, P. N., Kane, M. J., Reif, J. S., Weiss, T. R., et al. (2014). "Proximity to natural gas wells and reported health status: Results of a household survey in Washington County, Pennsylvania". *Environmental Health Perspectives* 123 (1), pp. 21–26.

Rajagopalan, S., Al-Kindi, S. G. and Brook, R. D. (2018). "Air pollution and cardiovascular disease: JACC state-of-the-art review". *Journal of the American College of Cardiology* 72 (17), pp. 2054–2070.

Rasmussen, S. G., Ogburn, E. L., McCormack, M., Casey, J. A., Bandeen-Roche, K., Mercer, D. G. and Schwartz, B. S. (2016). "Association between unconventional natural gas development in the Marcellus Shale and asthma exacerbations". *JAMA Internal Medicine* 176 (9), pp. 1334–1343.

Rehdanz, K. and Maddison, D. (2008). "Local environmental quality and life-satisfaction in Germany". *Ecological Economics* 64 (4), pp. 787–797.

Reinhold, S. and Jürges, H. (2012). "Parental income and child health in Germany". *Health Economics* 21 (5), pp. 562–579.

Research Data Center (RDC) of the Federal Statistical Office and Statistical Offices of the Federal States (2016). "Erhebung über die öffentliche Wasserversorgung (EVAS 32211) der Statistischen Ämter des Bundes und der Länder, 2007, 2010, 2013, 2016". DOI: `10.21242/32211.2013.00.00.1.1.0`. Available at: `https://www.forschungsdatenzentrum.de/de/umwelt/wasserversorgung`, accessed on May 31, 2022.

— (2017). "AFiD-Panel Energieunternehmen (EVAS 43221), 2008-2016". DOI: `10.21242/43221.2017.00.01.1.1.0`. Available at: `https://www.`

forschungsdatenzentrum.de/de/energie/afid-panel-energieunternehmen, accessed on May 31, 2022.

Richter, D., Metzing, M., Weinhardt, M. and Schupp, J. (2013). “SOEP Scales Manual”. *SOEP Survey Papers 138: Series C - Data Documentations.*

Rivera, N. (2021). “Air quality warnings and temporary driving bans: Evidence from air pollution, car trips, and mass-transit ridership in Santiago”. *Journal of Environmental Economics and Management* 108, p. 102454.

Rocks, N., Vanwinge, C., Gilles, C., Gerard, C., Blacher, S., Noel, A. and Cataldo, D. (2017). “A role for ozone pollution in lung cancer progression”. *American Journal of Respiratory and Critical Care Medicine.*

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., Wit, C. A. de, Hughes, T., Leeuw, S. van der, Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R. W., Fabry, V. J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P. and Foley, J. A. (2009). “A safe operating space for humanity”. *Nature* 461 (7263), pp. 472–475.

Rohlf, A., Holub, F., Koch, N. and Ritter, N. (2020). “The effect of clean air on pharmaceutical expenditures”. *Economics Letters* 192, p. 109221.

Roodman, D. (2009a). “A note on the theme of too many instruments”. *Oxford Bulletin of Economics and statistics* 71 (1), pp. 135–158.

— (2009b). “How to do xtabond2: An introduction to difference and system GMM in Stata”. *The Stata Journal* 9 (1), pp. 86–136.

Rosenzweig, C., Civerolo, K., Ku, J. and Kinney, P. (2004). “Assessing ozone-related health impacts under a changing climate”. *Environmental Health Perspectives* 112 (15), pp. 1557–1563.

Rubin, D. B. (1974). “Estimating causal effects of treatments in randomized and nonrandomized studies”. *Journal of Educational Psychology* 66 (5), pp. 688–701.

Saal, D. S. and Parker, D. (2000). “The impact of privatization and regulation on the water and sewerage industry in England and Wales: A translog cost function model”. *Managerial and Decision Economics* 21 (6), pp. 253–268.

Sargan, J. D. (1958). “The estimation of economic relationships using instrumental variables”. *Econometrica* 26 (3), pp. 393–415.

Sarmiento, L. (2022). “Air pollution and the productivity of high-skill labor: Evidence from court hearings”. *The Scandinavian Journal of Economics* 124 (1), pp. 301–332.

Sarmiento, L., Wägner, N. and Zaklan, A. (2021). “The Air Quality and Well-Being Effects of Low Emission Zones”. *DIW Discussion Paper 1947.*

Schader, C., Stolze, M. and Gattinger, A. (2012). “Environmental performance of organic farming”. In: *Green technologies in food production and processing*. Springer, pp. 183–210.

Schwarzenbach, R. P., Egli, T., Hofstetter, T. B., Von Gunten, U. and Wehrli, B. (2010). “Global water pollution and human health”. *Annual Review of Environment and Resources* 35, pp. 109–136.

Schweigert, P., Pinter, N. and Ploeg, R. R. van der (2004). “Regression analyses of weather effects on the annual concentrations of nitrate in soil and groundwater”. *Journal of Plant Nutrition and Soil Science* 167 (3), pp. 309–318.

Schwela, D. (2000). “Air pollution and health in urban areas”. *Reviews on Environmental Health* 15 (1-2), pp. 13–42.

Seigneur, C. (2019). “Emissions of air pollutants and emission control technologies”. *Air Pollution: Concepts, Theory, and Applications*, pp. 6–32.

Selin, N. E., Wu, S., Nam, K.-M., Reilly, J. M., Paltsev, S., Prinn, R. G. and Webster, M. D. (2009). “Global health and economic impacts of future ozone pollution”. *Environmental Research Letters* 4 (4), p. 044014.

Shukla, S. and Saxena, A. (2019). “Global status of nitrate contamination in groundwater: Its occurrence, health impacts, and mitigation measures”. In: *Handbook of Environmental Materials Management*. Ed. by Hussain, C. M. Cham, Switzerland: Springer International Publishing, pp. 869–888.

Shumaker, B. and Sinnott, R. (1984). “Astronomical computing: 1. Computing under the open sky. 2. Virtues of the haversine”. *Sky and Telescope* 68, pp. 158–159.

Simeonova, E., Currie, J., Nilsson, P. and Walker, R. (2021). “Congestion pricing, air pollution, and children’s health”. *Journal of Human Resources* 56 (4), pp. 971–996.

Singh, B. and Craswell, E. (2021). “Fertilizers and nitrate pollution of surface and ground water: An increasingly pervasive global problem”. *SN Applied Sciences* 3 (4), pp. 1–24.

Smith, V. H. and Schindler, D. W. (2009). “Eutrophication science: Where do we go from here?” *Trends in Ecology & Evolution* 24 (4), pp. 201–207.

Snow, J. (1855). *On the mode of communication of cholera*. London: John Churchill.

Sovacool, B. K. (2014). “Cornucopia or curse? Reviewing the costs and benefits of shale gas hydraulic fracturing (fracking)”. *Renewable and Sustainable Energy Reviews* 37, pp. 249–264.

Stammann, A., Heiss, F. and McFadden, D. (2016). “Estimating fixed effects logit models with large panel data”. In: *Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel* (Augsburg, September 5–8, 2016).

Stolze, M., Piorr, A., Häring, A. M. and Dabbert, S. (2000). *Environmental impacts of organic farming in Europe*. Organic Farming in Europe: Economics and Policy, Volume 6. Universität Hohenheim, Stuttgart-Hohenheim.

Suarez-Bertoa, R. and Astorga, C. (2018). "Impact of cold temperature on Euro 6 passenger car emissions". *Environmental Pollution* 234, pp. 318–329.

Sun, R., Cheng, X. and Chen, L. (2018). "A precipitation-weighted landscape structure model to predict potential pollution contributions at watershed scales". *Landscape Ecology* 33 (9), pp. 1603–1616.

Thomsen, I. K., Lægdsmand, M. and Olesen, J. E. (2010). "Crop growth and nitrogen turnover under increased temperatures and low autumn and winter light intensity". *Agriculture, Ecosystems & Environment* 139 (1-2), pp. 187–194.

Thurston, G. D., Lippmann, M., Scott, M. B. and Fine, J. M. (1997). "Summertime haze air pollution and children with asthma." *American Journal of Respiratory and Critical Care Medicine* 155 (2), pp. 654–660.

Tolbert, P. E., Mulholland, J. A., Macintosh, D. L., Xu, F., Daniels, D., Devine, O. J., Carlin, B. P., Klein, M., Butler, A. J., Nordenberg, D. F., et al. (2000). "Air quality and pediatric emergency room visits for asthma and Atlanta, Georgia". *American Journal of Epidemiology* 151 (8), pp. 798–810.

Townsend, A. R., Howarth, R. W., Bazzaz, F. A., Booth, M. S., Cleveland, C. C., Collinge, S. K., Dobson, A. P., Epstein, P. R., Holland, E. A., Keeney, D. R., et al. (2003). "Human health effects of a changing global nitrogen cycle". *Frontiers in Ecology and the Environment* 1 (5), pp. 240–246.

Townsend-Small, A., Ferrara, T. W., Lyon, D. R., Fries, A. E. and Lamb, B. K. (2016). "Emissions of coalbed and natural gas methane from abandoned oil and gas wells in the United States". *Geophysical Research Letters* 43 (5), pp. 2283–2290.

Troeger, C., Blacker, B. F., Khalil, I. A., Rao, P. C., Cao, S., Zimsen, S. R., Albertson, S. B., Stanaway, J. D., Deshpande, A., Abebe, Z., et al. (2018). "Estimates of the global, regional, and national morbidity, mortality, and aetiologies of diarrhoea in 195 countries: A systematic analysis for the Global Burden of Disease Study 2016". *The Lancet Infectious Diseases* 18 (11), pp. 1211–1228.

Tuomisto, H. L., Hodge, I., Riordan, P. and Macdonald, D. W. (2012). "Does organic farming reduce environmental impacts? A meta-analysis of European research". *Journal of Environmental Management* 112, pp. 309–320.

U.S. Energy Information Administration (2018). *U.S. crude oil and natural gas proved reserves, year-end 2017*. Independent Statistics & Analysis. Energy Information Administration (EIA), US Department of Energy. Available at: `https://www.eia.gov/naturalgas/crudeoilreserves/archive/2017/pdf/usreserves.pdf`, accessed on May 31, 2022.

U.S. Environmental Protection Agency (EPA) (2016). *Ozone and Your Patients' Health - Online Course for Medical Professionals*. Available at: `https://www.epa.gov/ozone-pollution-and-your-patients-health`, accessed on May 31, 2022.

— (2018). *Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI)*. EPA 454/B-18-007. Air Quality Assessment Division; Office of Air Quality Planning and Standards. Available at: `%5Curl%7Bhttps://www.airnow.gov/sites/default/files/2020-05/aqi-technical-assistance-document-sept2018.pdf%7D`, accessed on May 31, 2022.

UK Ministry of Health (1954). *Mortality and morbidity during the London fog of December 1952*. Reports on Public Health and Medical Subjects 95.

Umweltbundesamt (2019). *Official nitrate readings from the EEA-Groundwater Monitoring Network*. Dessau-Roßlau, Germany: Department for Water & Soil.

United Nations (2010). *Resolution adopted by the General Assembly on 28 July 2010*. Available at: `https://documents-dds-ny.un.org/doc/UNDOC/GEN/N09/479/35/PDF/N0947935.pdf`.

Urakami, T. and Parker, D. (2011). "The effects of consolidation amongst Japanese water utilities: A hedonic cost function analysis". *Urban Studies* 48 (13), pp. 2805–2825.

Van Meter, K. J., Basu, N. B., Veenstra, J. J. and Burras, C. L. (2016). "The nitrogen legacy: Emerging evidence of nitrogen accumulation in anthropogenic landscapes". *Environmental Research Letters* 11 (3), p. 035014.

Velthof, G. L., Lesschen, J., Webb, J., Pietrzak, S., Miatkowski, Z., Pinto, M., Kros, J. and Oenema, O. (2014). "The impact of the Nitrates Directive on nitrogen emissions from agriculture in the EU-27 during 2000–2008". *Science of the Total Environment* 468-469, pp. 1225–1233.

Veolia (2021). *Trinkwasseraufbereitung mit Kohlendioxid-Reduktion - Das CARIX Verfahren*. Available at: `https://www.veoliawatertechnologies.de/watertechnews/trinkwasseraufbereitung-mit-kohlendioxid-reduktion-carix-verfahren`, accessed on May 31, 2022.

Viard, V. B. and Fu, S. (2015). "The effect of Beijing's driving restrictions on pollution and economic activity". *Journal of Public Economics* 125, pp. 98–115.

Vincent, J. R., Ahmad, I., Adnan, N., Burwell, W. B., Pattanayak, S. K., Tan-Soo, J.-S. and Thomas, K. (2016). "Valuing water purification by forests: An analysis of Malaysian panel data". *Environmental and Resource Economics* 64 (1), pp. 59–80.

Vinciguerra, T., Yao, S., Dadzie, J., Chittams, A., Deskins, T., Ehrman, S. and Dickerson, R. R. (2015). "Regional air quality impacts of hydraulic fracturing and shale natural gas activity: Evidence from ambient VOC observations". *Atmospheric Environment* 110, pp. 144–150.

Vohra, K., Vodonos, A., Schwartz, J., Marais, E. A., Sulprizio, M. P. and Mickley, L. J. (2021). "Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem". *Environmental Research* 195, p. 110754.

Von Sperling, M. (2007). *Wastewater characteristics, treatment and disposal.* London, UK: IWA publishing.

Wagner, J. (2010). *Estimated capital stock values for German manufacturing enterprises covered by the cost structure surveys.* Working Paper Series in Economics 171. University of Lüneburg.

Wang, L., Xu, J. and Qin, P. (2014). "Will a driving restriction policy reduce car trips? The case study of Beijing, China". *Transportation Research Part A: Policy and Practice* 67, pp. 279–290.

Westling, N., Stromberg, P. M. and Swain, R. B. (2020). "Can upstream ecosystems ensure safe drinking water: Insights from Sweden". *Ecological Economics* 169, p. 106552.

Wick, K., Heumesser, C. and Schmid, E. (2012). "Groundwater nitrate contamination: Factors and indicators". *Journal of Environmental Management* 111, pp. 178–186.

Willis, M. D., Jusko, T. A., Halterman, J. S. and Hill, E. L. (2018). "Unconventional natural gas development and pediatric asthma hospitalizations in Pennsylvania". *Environmental Research* 166, pp. 402–408.

Winter, C., Lutz, S. R., Musolff, A., Kumar, R., Weber, M. and Fleckenstein, J. H. (2021). "Disentangling the impact of catchment heterogeneity on nitrate export dynamics from event to long-term time scales". *Water Resources Research* 57 (1), e2020WR027992.

Wolf, J., Prüss-Ustün, A., Cumming, O., Bartram, J., Bonjour, S., Cairncross, S., Clasen, T., Colford Jr, J. M., Curtis, V., De France, J., et al. (2014). "Systematic review: Assessing the impact of drinking water and sanitation on diarrhoeal disease in low-and middle-income settings: Systematic review and meta-regression". *Tropical Medicine & International Health* 19 (8), pp. 928–942.

Wolff, H. (2014). "Keep your clunker in the suburb: Low-emission zones and adoption of green vehicles". *The Economic Journal* 124 (578), F481–F512.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* Cambridge, MA: MIT press.

World Bank (2022). *The global health cost of PM2.5 air pollution: A case for action beyond 2021.* Washington, DC. Available at: `https://openknowledge.worldbank.org/bitstream/handle/10986/36501/9781464818165.pdf`, accessed on May 31, 2022.

World Health Organization (2017). "Water quality and health - Review of turbidity: Information for regulators and water suppliers". *Technical brief.* Available at: `https://www.who.int/publications/i/item/WHO-FWC-WSH-17.01`, accessed on May 31, 2022.

— (2019). *Ten threats to global health in 2019.* Available at: `%5Curl%7Bhttps://www.who.int/news-room/spotlight/ten-threats-to-global-health-in-2019%7D`, accessed on May 31, 2022.

World Health Organization and the United Nations Children's Fund (2021). *Progress on household drinking water, sanitation and hygiene 2000-2020: Five years into the SDGs*. Available at: `https://www.unwater.org/app/uploads/2021/07/jmp-2021-wash-households-LAUNCH-VERSION.pdf`, accessed on May 31, 2022.

Zalakeviciute, R., Bastidas, M., Buenaño, A. and Rybarczyk, Y. (2020). "A traffic-based method to predict and map urban air quality". *Applied Sciences* 10 (6), p. 2035.

Zhai, M. and Wolff, H. (2021). "Air pollution and urban road transport: evidence from the world's largest low-emission zone in London". *Environmental Economics and Policy Studies* 23, pp. 721–748.

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, pp. 81–94.

Zhong, N., Cao, J. and Wang, Y. (2017). "Traffic congestion, ambient air pollution, and health: Evidence from driving restrictions in Beijing". *Journal of the Association of Environmental and Resource Economists* 4 (3), pp. 821–856.

Zivin, J. G. and Neidell, M. (2012). "The impact of pollution on worker productivity". *The American Economic Review* 102 (7), pp. 3652–3673.

Appendix A to accompany Chapter 2

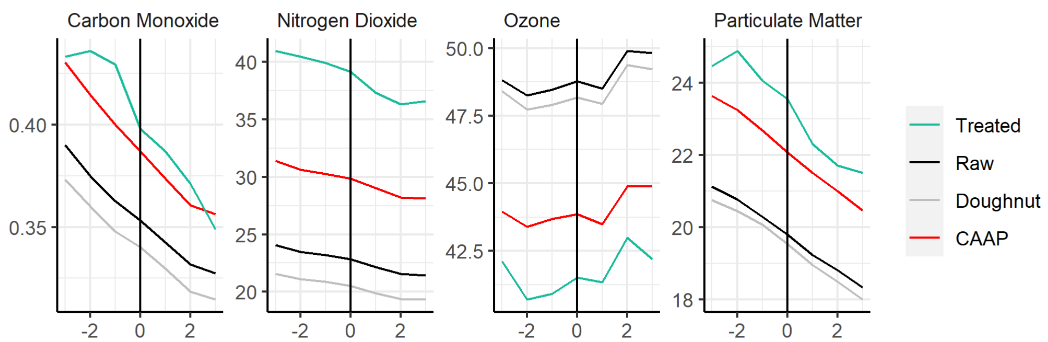
A.1 Why ground-level ozone is special

Ground-level ozone differs from the other criteria pollutants in that it is a secondary pollutant, i.e., it requires precursors as it is created through the interaction of solar radiation with nitrous oxides (NO_x) and volatile organic compounds (VOC), whose concentration in the air is much increased beyond natural levels by the combustion of fossil fuels. Road traffic is one of the major causes of this increase.

The relationship between the concentrations of ozone and its precursors is complex, as there are two sides to the interaction. On the one hand, the interaction of solar radiation with NO_x and VOC forms ozone. On the other, it also degrades it. The balance between the two sides leads to patterns in ozone concentrations that deviate from those of other criteria pollutants: In areas with high levels of precursor pollution, such as urban centers with dense vehicle traffic, ozone concentrations are lower than in suburban areas. The reason is that at high concentrations of precursor pollutants, ozone degrades faster than it is formed, whereas the formation process dominates at lower levels of precursors, e.g., in rural areas. This phenomenon is sometimes referred to as the "ozone paradox" (Monks et al., 2015).

A.2 Data

Figure A.1: Pre- and post-treatment averages in treatment and control groups



Notes: Inter-temporal comparison of the AQI between treated and control units. The vertical axis contains the average of each criteria pollutant and the horizontal axis the time to treatment, i.e., number of years to the introduction of a LEZ. Each data point corresponds to the average value of all possible event-time combinations across treatment and control groups.

Table A.1: Descriptive statistics on pollution levels

	Inside LEZ			Outside LEZ			
	Total	Before	After	Raw	Buffer	Doughnut	CAAP
CO	0.44	0.50	0.39	0.38	0.38	0.36	0.43
	(0.16)	(0.18)	(0.13)	(0.14)	(0.14)	(0.13)	(0.14)
NO_2	42.41	43.57	41.77	23.12	21.97	20.57	30.82
	(17.34)	(18.01)	(16.94)	(12.48)	(12.54)	(10.95)	(12.77)
O_3	40.84	40.51	41.06	49.16	50.32	48.69	44.91
	(5.87)	(5.13)	(6.32)	(10.38)	(9.98)	(8.51)	(8.61)
PM_{10}	24.51	26.65	23.27	20.31	20.00	19.86	22.76
	(5.72)	(6.09)	(5.11)	(5.27)	(5.24)	(5.24)	(4.89)
AQI	46.49	46.38	46.54	39.98	39.90	40.34	41.44
	(13.22)	(12.59)	(13.57)	(11.65)	(11.77)	(11.06)	(12.71)

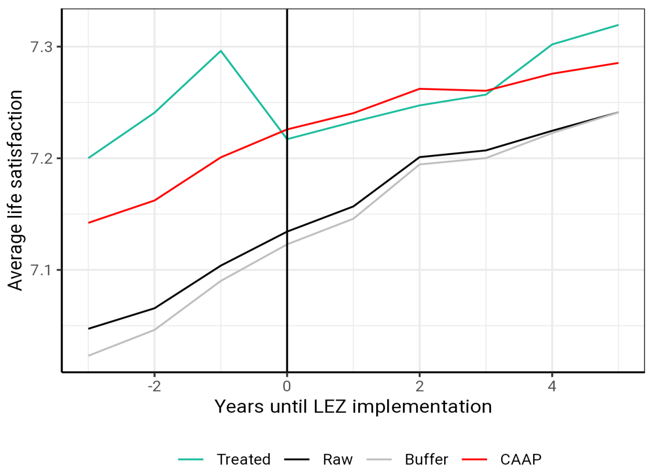
Notes: This table lists annual average pollution levels at monitors inside and outside LEZs, with standard deviations in parentheses. For monitors inside LEZs, overall averages from 2005 to 2018 and pre- and post-treatment averages are listed. For monitors outside LEZs, the first column lists overall averages from 2005 to 2018 using all monitors outside of LEZs, the second column excludes monitors within 25km distance to the nearest LEZ, the third column restricts the control group to monitors within 25 km to 75 km distance to a LEZ, and the fourth column includes only monitors located in cities with a CAAP but without LEZ. Ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$) and carbon monoxide (CO) in milligrams per cubic meter (mg/m^3). The AQI is defined on a scale from 0 to 500.

Table A.2: Descriptive statistics on SOEP individuals - all control groups

	Inside LEZ			Outside LEZ		
	Total	Before	After	Raw	Buffer	CAAP
Life satisfaction [0-10]	7.11	7.08	7.14	7.10	7.08	7.18
	(1.73)	(1.73)	(1.73)	(1.76)	(1.75)	(1.73)
Age [years]	54.47	52.86	55.65	54.11	54.09	55.36
	(16.64)	(16.04)	(16.98)	(17.04)	(17.06)	(17.61)
Is female [%]	0.53	0.53	0.53	0.52	0.52	0.53
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Is employed [%]	0.56	0.54	0.57	0.56	0.56	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Income [Thsd Euro]	44.99	43.90	45.79	42.20	39.23	41.45
	(35.11)	(34.61)	(35.45)	(33.81)	(29.96)	(34.57)
Education [years]	12.89	12.69	13.04	12.26	12.09	12.72
	(3.06)	(3.02)	(3.08)	(2.63)	(2.49)	(2.90)
Number children	0.44	0.51	0.39	0.48	0.48	0.40
	(0.90)	(0.93)	(0.87)	(0.92)	(0.90)	(0.81)
Owns motor vehicle [%]	0.81	0.83	0.80	0.90	0.90	0.82
	(0.39)	(0.38)	(0.40)	(0.30)	(0.30)	(0.38)
Number motor vehicles	1.26	1.28	1.26	1.58	1.57	1.23
	(0.95)	(0.91)	(0.97)	(1.06)	(1.06)	(0.92)
Owns diesel car [%]	0.32	0.33	0.31	0.33	0.32	0.27
	(0.47)	(0.47)	(0.46)	(0.47)	(0.47)	(0.44)
Number doctor visits	11.09	11.30	10.94	10.08	9.87	11.44
	(15.19)	(15.60)	(14.88)	(15.08)	(14.61)	(17.12)
Has hypertension [%]	0.31	0.32	0.31	0.32	0.34	0.34
	(0.46)	(0.47)	(0.46)	(0.47)	(0.47)	(0.47)
Has cancer [%]	0.06	0.06	0.06	0.06	0.06	0.09
	(0.24)	(0.23)	(0.25)	(0.24)	(0.23)	(0.28)
Number individuals	1436	1436	1436	19578	11130	1866
Number observations	12634	5348	7286	141411	81514	13167

Notes: This table shows the average characteristics of treated and control SOEP individuals. Treated persons reside within the LEZs area and control individuals outside. For the treated sample, we present overall, pre-treatment, and post-treatment averages. For control persons, the first column uses all individuals outside of LEZs, the second excludes persons living within 25 km to the nearest zone, and the third column includes only individuals living in cities with a CAAP but without LEZ.

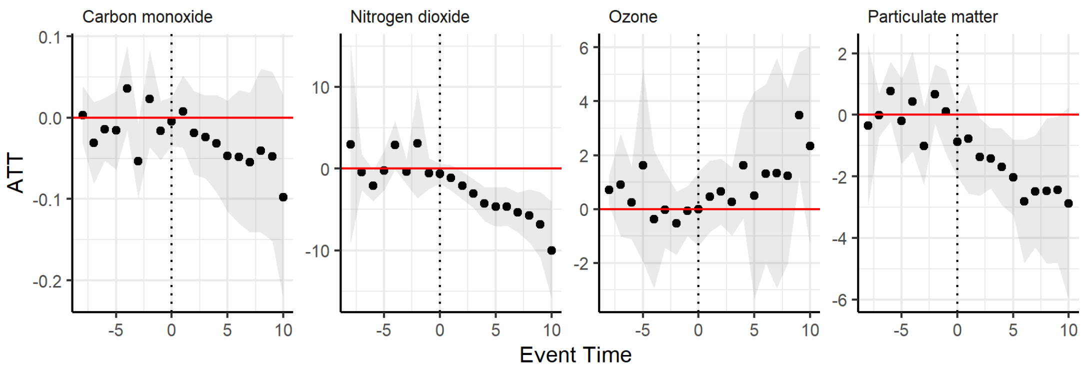
Figure A.2: Average well-being of treated and control individuals



Notes: This figure shows annual averages of life satisfaction between treated and control units. The vertical axis contains the average of each criteria pollutant, and the horizontal axis the time to treatment (τ). Each data point corresponds to the average value of all possible event-time combinations across treatment and control groups three years around policy adoption.

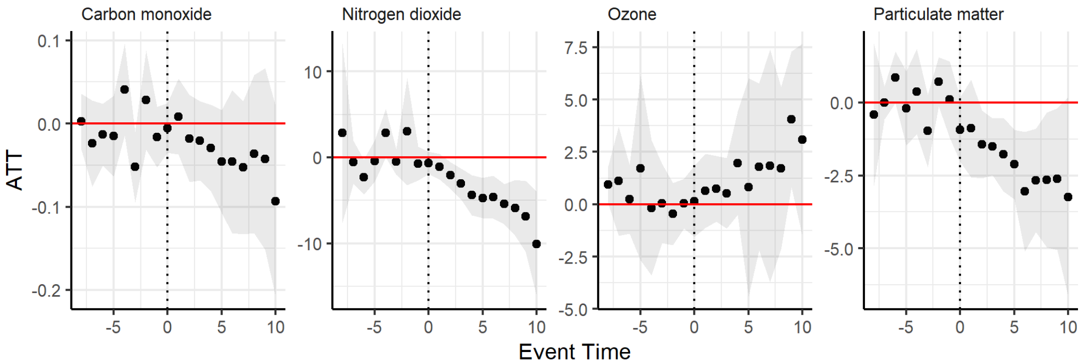
A.3 Difference-in-differences design robustness checks

Figure A.3: Event-time ATTs for the full control sample (raw specification)



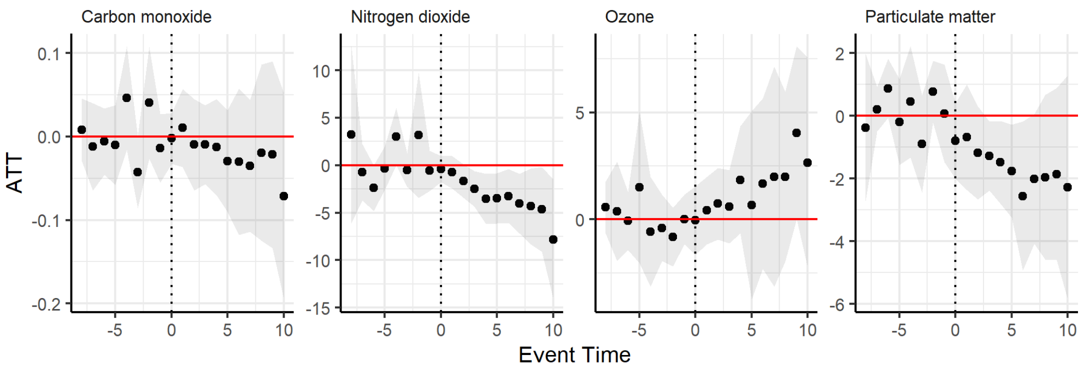
Notes: Event-time Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β_e) of the impact of LEZs on annual air pollutant concentrations for the raw design. Event time measured in years before/after LEZ introduction. Treated stations are all those stations inside a zone, and control stations all stations outside of a zone. The CS-DD model controls for station and year fixed effects. Grey ribbons represent 95% confidence intervals. Standard errors clustered at the municipality level. Effects on ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter (μg/m^3). For carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Figure A.4: Event-time ATTs for the buffer control sample



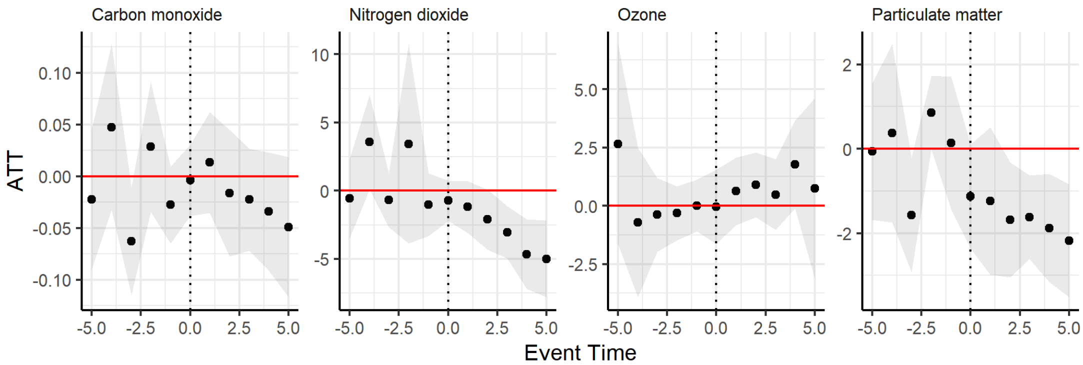
Notes: Event-time Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β_e) of the impact of LEZs on annual air pollutant concentrations for the buffer design. Event time measured in years before/after LEZ introduction. Treated stations are all those stations inside a zone, and control stations all stations outside of a zone. The CS-DD model controls for station and year fixed effects. Grey ribbons represent 95% confidence intervals. Standard errors clustered at the municipality level. Effects on ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$). For carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Figure A.5: Event-time ATTs for the buffer CAAP control sample



Notes: Event-time Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β_e) of the impact of LEZs on annual air pollutant concentrations for the CAAP design. Event time measured in years before/after LEZ introduction. Treated stations are all those stations inside a zone, and control stations all stations outside of a zone. The CS-DD model controls for station and year fixed effects. Grey ribbons represent 95% confidence intervals. Standard errors clustered at the municipality level. Effects on ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$). For carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Figure A.6: Event-time ATTs for the balanced doughnut specification



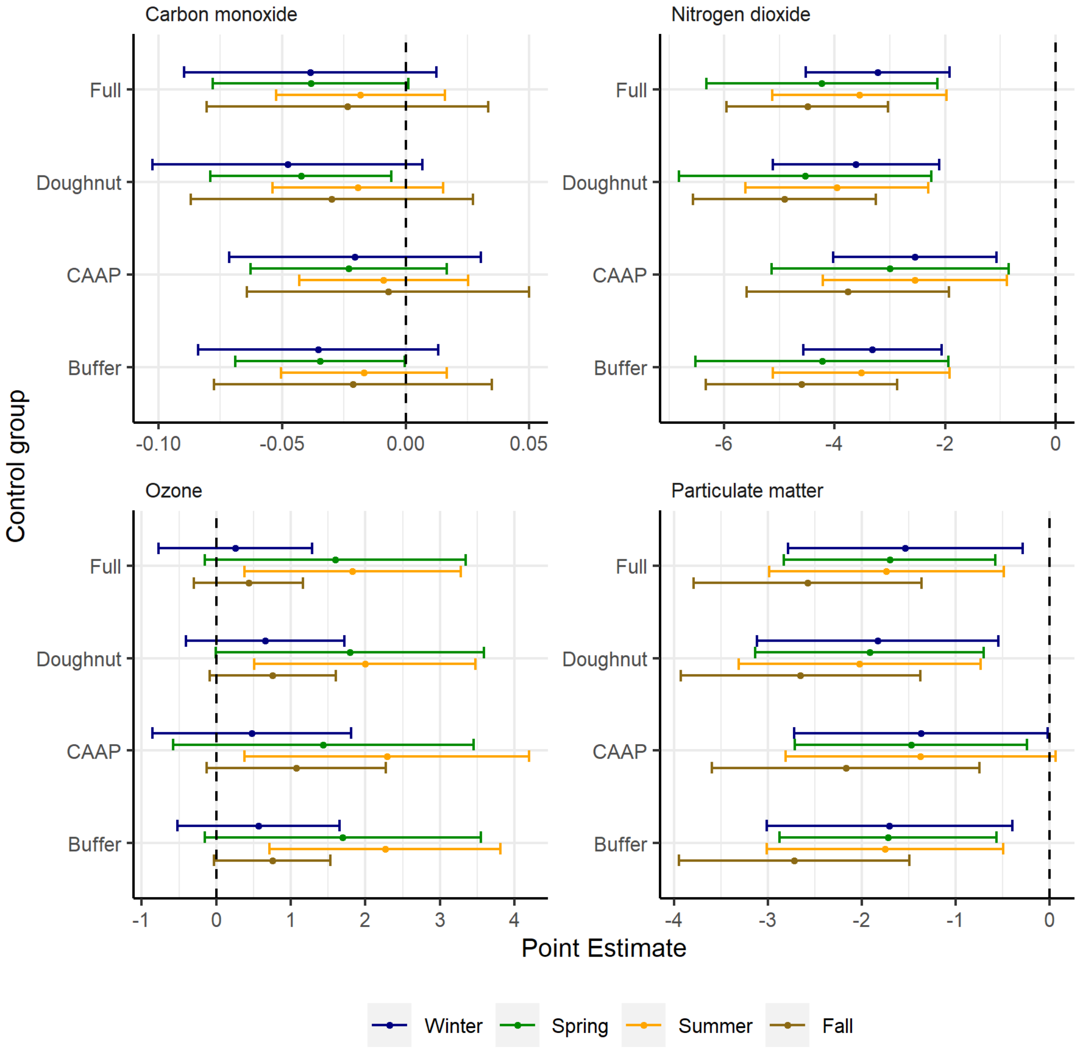
Notes: Event-time Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β_e) of the impact of LEZs on yearly air pollution levels for the doughnut design in a balanced panel for treated units at least for $e > 3$. Event time measured in years before/after LEZ introduction. Treated stations are all those stations inside the zone, and control stations all stations further away than 25 km from the zone's border and up until 75 km. The CS-DD model controls for station and year fixed effects. Grey ribbons represent 95% confidence intervals. Standard errors clustered at the municipality level. Effects on ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter (μg/m^3). For carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

Table A.3: Effect of LEZ introduction on the air quality index (AQI) across control groups

	Raw	Buffer	Dght	CAAP
	-4.58^{***}	-4.57^{***}	-5.17^{***}	-4.43^{***}
	(1.48)	(1.47)	(1.45)	(1.66)
N.Obs	6301	4887	2970	2719
N.Stations	589	451	277	251
N.Groups	8	8	8	8
N.Periods	14	14	14	14

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β) of the impact of LEZs on the yearly average of the AQI for six different specifications and air pollutants. Control units in the raw specification are stations outside the LEZs. In the buffer design, we restrict control units to stations beyond 25 km from the LEZs. The doughnut design further trims the control group by restricting its outer edge to 75 km. Next, the control groups in the CAAP specification contain only stations in cities with Clean Air Action Plans (CAAP) but without LEZ. The CS-DD model controls for station and year fixed effects. Standard errors are clustered at the municipality level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Figure A.7: Seasonal ATTs across different control samples



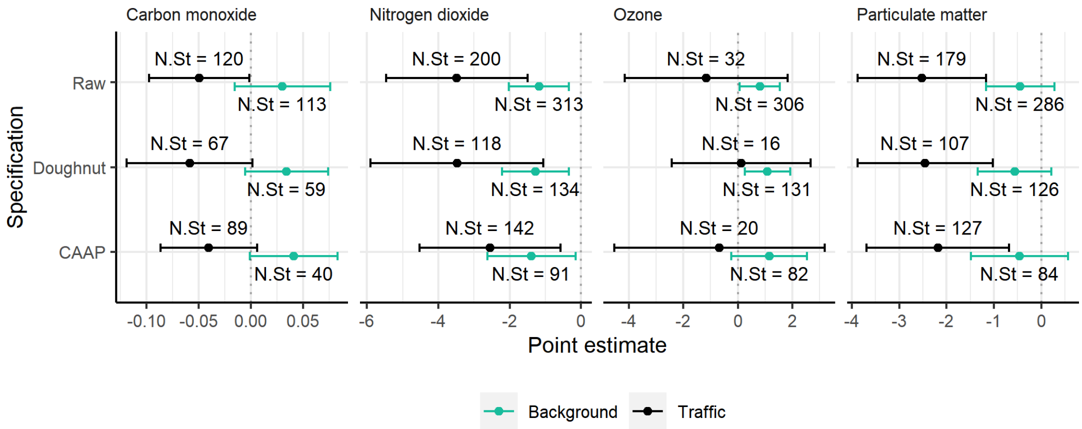
Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates (β) of the impact of LEZs on seasonal air pollution concentrations for four different specifications of the control group.In the buffer design, we restrict control units to stations beyond 25 km from the LEZs. The doughnut design further trims the control group by restricting its outer edge to 75 km. Next, the control groups in the CAAP specification contain only stations in cities with Clean Air Action Plans (CAAP) but without LEZ. The CS-DD model controls for station and year fixed effects. Standard errors are clustered at the municipality level; 95% confidence intervals depicted. Effects on ozone (O_3), nitrogen dioxide (NO_2), and coarse particulate matter (PM_{10}) reported in micrograms per cubic meter ($\mu g/m^3$), and for carbon monoxide (CO) in milligrams per cubic meter (mg/m^3).

A.4 Difference-in-differences design heterogeneity analysis

A.4.1 Analysis by the type of station

Although we find no evidence opposing the common trends assumption, it is still possible that treated pollution monitors are not comparable to control stations due to their local environments being inherently different. To address this concern, we separate the sample of stations into traffic and background stations.[1] Traffic stations are often placed next to major roads or traffic junctions, while background stations are located in residential areas further away from direct pollution sources.

Figure A.8: Heterogeneous effects by type of measuring station



Notes: CS-DD estimates for the impact of LEZs on traffic and background stations for different samples of control stations. The raw sample uses all stations outside LEZs. The doughnut specification only includes stations between 25 and 75 km from the zones border. And the CAAP design only considers stations in cities with CAAPs but no LEZs. "Traffic" implies that we only look at traffic stations. "Background" that we only look at background stations. The CS-DD model controls for station and year fixed effects. Standard errors clustered at the municipal level; 95% confidence intervals displayed.

Figure A.8 shows the ATT at traffic and background stations for the raw, doughnut and CAAP control groups. Across all control group specifications, traffic stations show significant reductions in CO, NO_2, and PM_{10} after LEZ implementation. This significant reduction across all traffic contaminants arises because traffic stations' inherent environment allows them to catch changes in transit emissions more easily than background stations. At background stations, on the other hand, we only uncover a decrease in NO_2 after policy adoption. Notably, background stations are the ones capturing the O_3 increase because of a larger share of measuring values and the spread-out nature of O_3 .

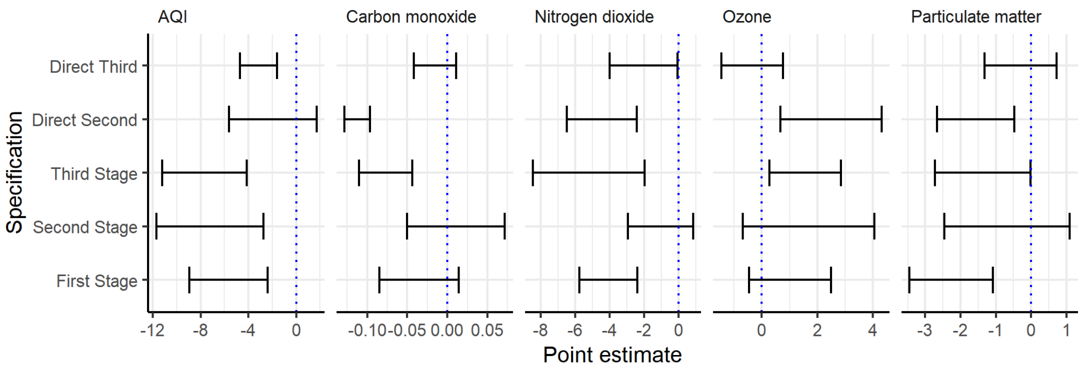
[1] UBA provides the classification. We do not look at industry stations separately since LEZs only cover seven industry stations (one percent of all stations in the raw sample).

A.4.2 Analysis by LEZ stages

Next, we look at the effects of stringency levels on our point estimates. Throughout the study, we have assigned treatment with a dichotomous variable indicating the presence of a LEZ, assuming that all LEZs are equally strict. However, LEZs can have three stringency levels. In the first stage, only gasoline vehicles with catalytic converters and diesel cars with Euro 2 (or Euro 1 with particle filter) can enter the LEZs. Stage 2 restricts diesel cars to Euro 3 (or Euro 2 with particle filter). And finally, stage three restrains diesel cars to Euro 4 (or Euro 3 with particle filter) and gasoline automobiles to Euro 1. The date on which each LEZ went through each stage is heterogeneous. Furthermore, some zones skipped stages by jumping straight to stage two, three, or missing two on their way to three.

To explore the effect of each stage, we run the CS-DD for five different samples of the Doughnut design. The ”First Stage” sample restricts the treatment group to LEZs shifting from no LEZ to the first stage. Moreover, we further limit the sample to the years before implementing any other step to reduce confounding effects. The ”Second Stage” sample measures the impact of moving from the first to the second stage; the control group corresponds to not yet treated stations still in the first stage and the treatment group to already treated stations before implementing the third stage. The ”Third Stage” sample is analogous to the ”Second Stage” and estimates the effect from jumping from the second to the third stage. Finally, the direct third and second samples assess the impact of jumping directly from no LEZ to the second or third stage by using the control group of never-treated stations vs. the treated group of zones skipping the first stage. Figure A.9 shows the point estimates of all of these comparisons.

Figure A.9: Heterogeneous treatment effects by policy stringency



Results show that the AQI has significant decreases in the First, Second, and Third stages as well as when the LEZ jumps straight to the third stage. There are significant reductions for CO for the Direct Second and Third Stage. For NO_2, we uncover statistically significant decreases for all samples except the shift from the first to the second stage. Concerning O_3, coefficients are positive and statistically different from zero in the Direct Second and Third Stage samples, borderline significant for the First and Second Stages, and not statistically different from zero in the Direct Third sample. Finally, point estimates for PM_{10} are all negative and statistically significant for the First Stage, Third Stage, and Direct Second samples.

A.5 Effect of LEZs on well-being and health outcomes, additional results and robustness checks

Table A.4: Effect of LEZ introduction on different threshold values of life satisfaction

	LS $\geq$ 2	LS $\geq$ 4	LS $\geq$ 6	LS $\geq$ 8
ATT	0.003	-0.012^{*}	-0.034^{**}	-0.060^{***}
	(0.003)	(0.006)	(0.012)	(0.016)
N.Obs	94248	94248	94248	94248
N.Individuals	12588	12588	12588	12588
N.Groups	9	9	9	9
N.Periods	14	14	14	14

Notes: CS-DD estimates of the impact of LEZs on threshold values of life satisfaction. Thresholds values are based on the ordinary scale from 0 to 10 and correspond to binary variables: LS $\geq$ 2 is equal to one if individuals rate their well-being to be at least 2 or higher, and zero otherwise, etc. ATTs are identified based on individuals switching between both categories of the binary well-being measure. The treatment group consists of all individuals inside a LEZ, the control group includes individuals living further away than 25km from LEZs. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

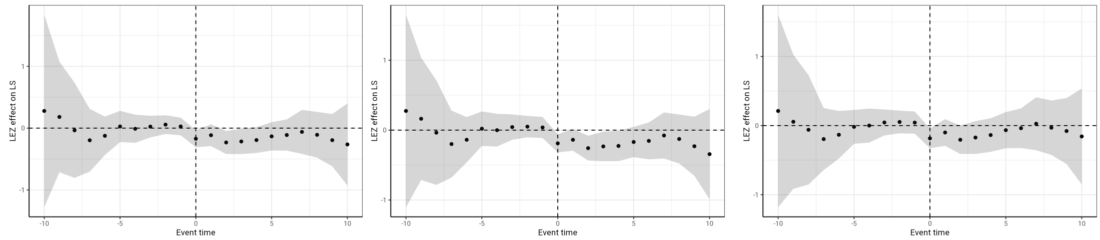
Table A.5: Effect of LEZ introduction on life satisfaction (including moving households)

	(1)	(2)	(3)
ATT	-0.112^{**}	-0.150^{***}	-0.122^{*}
	(0.042)	(0.042)	(0.051)
N.Obs	238711	144922	45379
N.Individuals	30953	19146	6190
N.Groups	9	9	9
N.Periods	14	14	14

Notes: CS-DD estimates of the impact of LEZs on life satisfaction. The first column lists results obtained on the full sample including moving households, the second restricts the control group to individuals living further away than 25km from LEZs, and the third further restricts the control group to persons living in cities with a CAAP but no LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

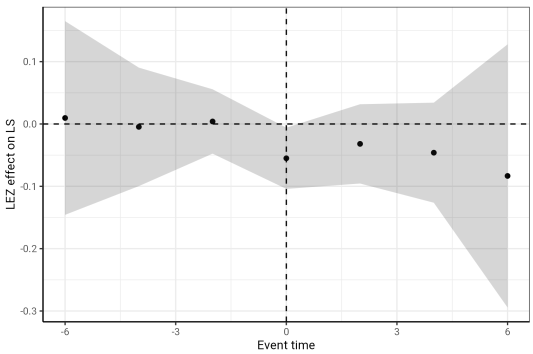
Figure A.10: Dynamic effects of LEZs on life satisfaction across samples

(a) Full sample (b) Buffer (c) CAAP



Notes: Dynamic CS-DD estimates (β_e) of the impact of LEZs on life satisfaction of individuals living inside the LEZs. We use three different control groups: First, all SOEP individuals outside LEZs, second, individuals further than 25km away from the nearest LEZ, and third, individuals in cities with a CAAP but without LEZ. Standard errors clustered at the household level; 95% confidence bands displayed.

Figure A.11: Dynamic LEZ effects on hypertension



Notes: Dynamic CS-DD estimates (β_e) of the impact of LEZs on the probability to develop hypertension of individuals living inside the LEZs. Dynamic effects refer to years before/after LEZ introduction.The sample of control individuals is restricted to residences further than 25km away from the nearest LEZ. Standard errors clustered at the household level.

Table A.6: Spatial spillovers in life satisfaction across different control groups

	(1)	(2)	(3)
ATT	-0.197^{***}	-0.195^{***}	-0.122^{**}
	(0.031)	(0.036)	(0.047)
N.Obs	141377	95966	60491
N.Individuals	19554	11717	6892
N.Groups	11	11	11
N.Periods	14	14	14

Notes: Group-time difference-in-differences (gtDD) estimates of the impact of LEZs on life satisfaction of individuals living within 25km distance to any LEZ. Point estimates represent the simple aggregation across all groups and time periods (β). The control group in the first column consists of all individuals residing further than 25km away from the nearest LEZ, the second column restricts the control group to individuals in residences between 25 and 75 km from the nearest LEZ, and the third column restricts the control group to individuals living in cities with a CAAP. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$.

A.6 Effect of LEZs on well-being and health outcomes, additional results using alternative control group

Table A.7: Heterogeneous LEZ effects on life satisfaction

(a) By MV ownership

	With MV	Without MV
ATT	−0.092	−0.153
	(0.070)	(0.185)
N.Obs	14547	3309
N.Individuals	1339	341
N.Groups	9	9
N.Periods	14	14

(b) By diesel car ownership

	Diesel	Other fuels
ATT	-0.301^{**}	-0.140^{+}
	(0.103)	(0.077)
N.Obs	11832	24740
N.Individuals	1152	2290
N.Groups	9	9
N.Periods	14	14

(c) By income quartiles

	Q1	Q2	Q3	Q4
ATT	−0.158	−0.190	−0.147	−0.134
	(0.165)	(0.125)	(0.141)	(0.088)
N.Obs	6286	6004	5428	8181
N.Individuals	899	810	676	956
N.Groups	9	9	9	9
N.Periods	14	14	14	14

(d) By age groups

	$\geq$ 65y	¡ 65y
ATT	0.001	-0.158^{*}
	(0.121)	(0.078)
N.Obs	8381	17520
N.Individuals	1113	2669
N.Groups	9	9
N.Periods	14	14

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction using subsets of individuals living inside the LEZs. The control sample of is restricted to individuals living in cities with CAAP but without LEZ. Subsamples are split based on motor vehicle ownership, diesel vehicle ownership, income quartiles and age groups. Point estimates represent the simple aggregation across all groups and time periods (β). Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$

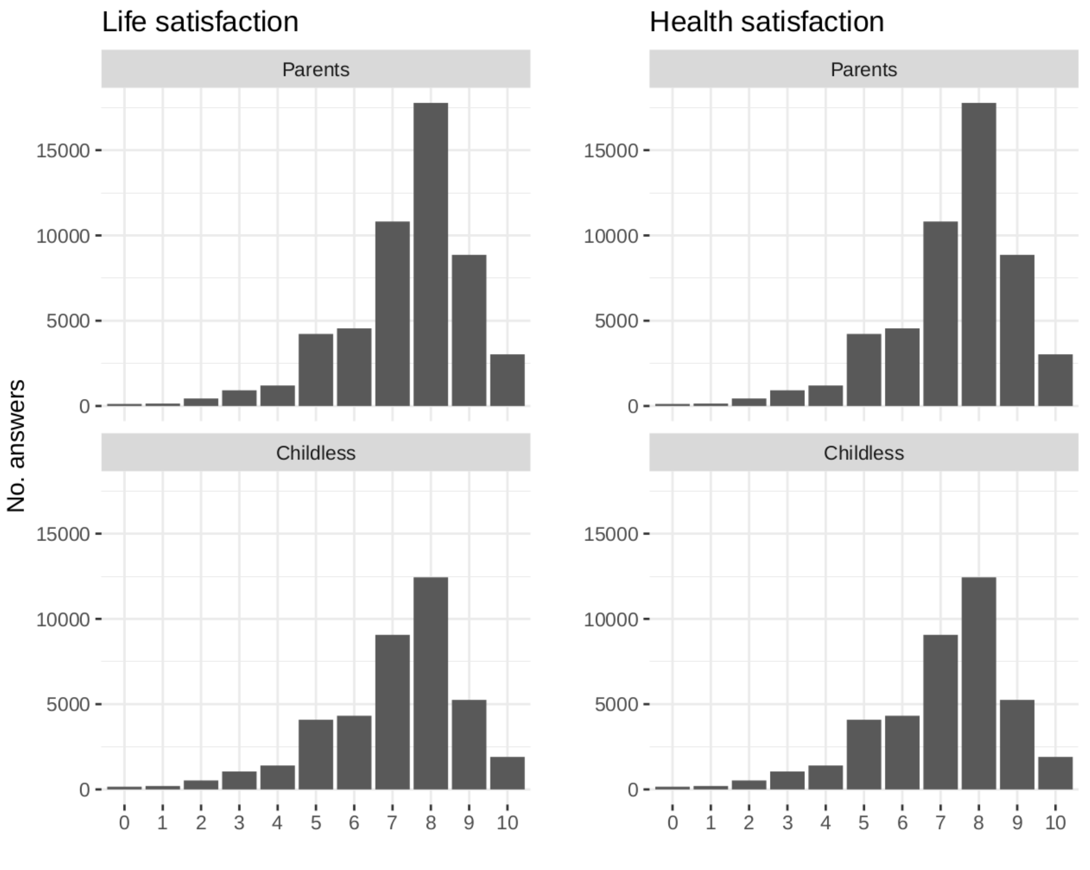
Table A.8: LEZ effect on health outcomes

	LS	Doctor visits	Hypertension	Cancer
ATT	−0.132	−1.411	-0.046^{+}	0.006
	(0.102)	(0.960)	(0.024)	(0.015)
N.Obs	7540	7540	7540	7540
N.Individuals	2121	2120	2121	2121
N.Groups	4	4	4	4
N.Periods	5	5	5	5

Notes: Callaway and Sant'Anna difference-in-differences (CS-DD) estimates of the impact of LEZs on life satisfaction and objective health outcomes of individuals living inside the LEZs. The control sample is restricted to individuals living in cities with CAAP but without LEZ. Standard errors clustered at the household level. Significance levels denoted by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$

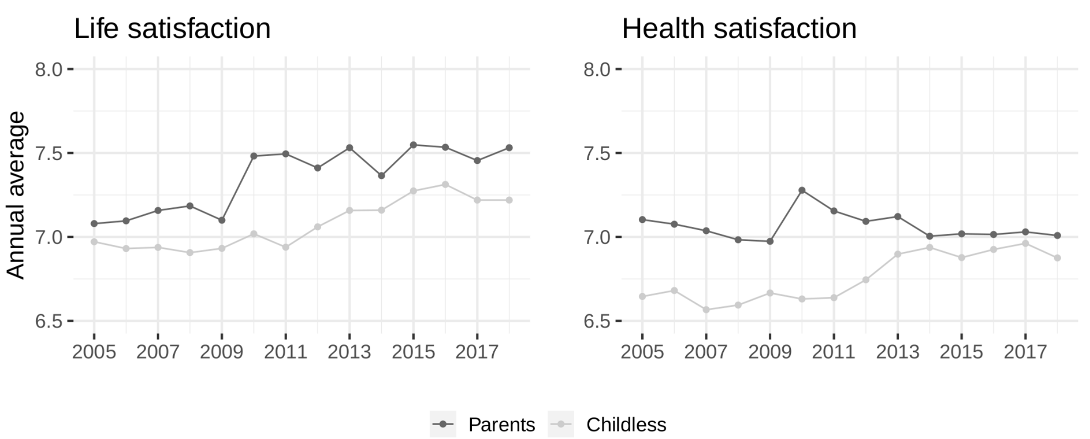
Appendix B to accompany Chapter 3

Figure B.1: Life and health satisfaction of SOEP individuals, by child status



Notes: The figure depicts the number of responses of SOEP parents and childless individuals per category of life and health satisfaction, respectively, for the period 2005-2018.
Source: SOEP, version 35.

Figure B.2: Life and health satisfaction of SOEP individuals over time, by child status



Notes: The figure depicts annual average values of life and health satisfaction of SOEP parents and childless individuals for the period 2005-2018.
Source: SOEP, version 35.

Table B.1: Short-term effect of ozone on health satisfaction, full sample

	Dependent Variable: Health satisfaction					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Ozone	0.0000	0.0001	0.0001	0.0001	-0.0003	-0.0002
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Income		0.0006^{+}	0.0006^{+}	0.0006^{+}	0.0006^{+}	0.0006^{+}
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Is married		-0.0693	-0.0685	-0.0687	-0.0686	-0.0685
		(0.0541)	(0.0541)	(0.0541)	(0.0541)	(0.0541)
Is employed		-0.0143	-0.0119	-0.0119	-0.0105	-0.0109
		(0.0250)	(0.0251)	(0.0251)	(0.0251)	(0.0251)
Fixed-effects						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
Day-of-the-week	No	No	No	Yes	Yes	Yes
Control variables						
Age bins	No	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	Linear	Non-linear
Fit statistics						
Individuals	16,423	16,423	16,423	16,423	16,423	16,423
Observations	86,101	86,101	86,101	86,101	86,101	86,101
Adjusted R^2	0.57661	0.57699	0.57703	0.57703	0.57705	0.57702

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of health satisfaction on average ozone exposure during the week prior to the SOEP interview. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. Column (2) adds the sociodemographic covariates income, employment status, marital status, and categorical five-year age bins; (3) adds fixed effects for the month of the interview; (4) adds day-of-the-week fixed effects; (5) adds linear weather controls (sunshine duration, temperature, precipitation); (6) controls for non-linear weather impacts through indicator variables for weather quintiles. Robust standard errors clustered at the household level in parentheses.

Table B.2: Effect of ozone on life and health satisfaction, full sample, multi-pollutant model

Dependent Variable:	Life satisfaction			Health satisfaction		
Ozone average:	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
Ozone	-0.0009	-0.0014	-0.0021	-0.0005	-0.0013	-0.0001
	(0.0006)	(0.0009)	(0.0013)	(0.0007)	(0.0010)	(0.0015)
Income	0.0009*	0.0009*	0.0009*	0.0006+	0.0006+	0.0007+
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Is married	0.2552***	0.2552***	0.2544***	-0.0649	-0.0653	-0.0661
	(0.0583)	(0.0581)	(0.0581)	(0.0554)	(0.0554)	(0.0554)
Is employed	0.0505*	0.0502*	0.0524*	-0.0138	-0.0123	-0.0119
	(0.0221)	(0.0221)	(0.0220)	(0.0259)	(0.0259)	(0.0259)
Coarse particulate matter	-0.0008	-0.0015	0.0011	-0.0007	-0.0010	-0.0031
	(0.0007)	(0.0012)	(0.0019)	(0.0009)	(0.0014)	(0.0022)
Nitrogen dioxide	0.0010	0.0013	0.0003	-0.0005	0.0004	-0.0006
	(0.0010)	(0.0014)	(0.0017)	(0.0011)	(0.0016)	(0.0019)
Fixed-effects						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes
Control variables						
Age bins	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Non-linear	Non-linear	Non-linear	Non-linear	Non-linear	Non-linear
Fit statistics						
Individuals	15,868	15,868	15,877	15,868	15,868	15,877
Observations	81,839	81,921	82,067	81,839	81,921	82,067
Adjusted R^2	0.53878	0.53887	0.53917	0.57644	0.57644	0.57668

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure for the full sample based on a multi-pollutant specification. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, indicator variables for weather quintiles (sunshine duration, temperature, precipitation), and rolling averages of coarse particulate matter and nitrogen dioxide. Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

Table B.3: Effect of ozone on life and health satisfaction, by child status, multi-pollutant model

Dependent Variables:	Life satisfaction		Health satisfaction	
Ozone average	Parents	Childless	Parents	Childless
Weekly	-0.0014+	-0.0003	0.0009	-0.0021*
	(0.0008)	(0.0009)	(0.0009)	(0.0010)
Monthly	-0.0026*	0.0005	-0.0010	-0.0008
	(0.0011)	(0.0014)	(0.0014)	(0.0015)
Quarterly	-0.0038*	0.0006	-0.0004	0.0007
	(0.0018)	(0.0020)	(0.0021)	(0.0023)
Individuals	9,277	6,591	9,277	6,591
Observations	45,682	36,157	45,682	36,157

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure among parents and non-parents based on a multi-pollutant specification. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, indicator variables for weather quintiles (sunshine duration, temperature, precipitation), and rolling averages of coarse particulate matter and nitrogen dioxide. Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

Table B.4: Effect of ozone on life and health satisfaction of parents, by child health, multi-pollutant model

Dependent Variables:	*Life satisfaction*		*Health satisfaction*	
Ozone average	Respiratory	Healthy	Respiratory	Healthy
Weekly	-0.0034*	-0.0010	0.0025	0.0013
	(0.0016)	(0.0012)	(0.0020)	(0.0016)
Monthly	-0.0066**	-0.0005	-0.0040	-0.0009
	(0.0022)	(0.0018)	(0.0028)	(0.0022)
Quarterly	-0.0105**	-0.0016	-0.0059	0.0012
	(0.0034)	(0.0029)	(0.0045)	(0.0034)
Individuals	1,429	3,354	1,429	3,354
Observations	9,441	17,307	9,441	17,307

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure among parents with at least one child with doctor-diagnosed respiratory disease and parents with healthy children based on a multi-pollutant specification. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, indicator variables for weather quintiles (sunshine duration, temperature, precipitation), and rolling averages of coarse particulate matter and nitrogen dioxide. Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

Table B.5: Descriptives on sample of parents, by child health

	Respiratory		*Healthy*	
	Mean	SD	Mean	SD
SOEP variables				
Life satisfaction	7.53	1.55	7.58	1.59
Health satisfaction	7.03	2.04	7.32	1.99
Age	40.55	6.70	39.64	7.22
Income	51.12	32.40	43.87	25.45
Is employed	0.81	0.39	0.75	0.43
Is married	0.81	0.39	0.81	0.39
Number kids	2.27	1.05	2.12	0.99
Pollution				
Ozone (O_3)	53.55	17.11	52.54	17.13
Nitrogen dioxide (NO_2)	29.04	14.13	29.43	14.13
Coarse particulate matter (PM_{10})	21.36	9.43	21.22	9.56
Weather				
Temperature	10.12	6.74	10.27	6.56
Precipitation	1.90	1.19	1.94	1.22
Sunshine	5.32	2.22	5.32	2.22
Individuals	1,477		3,488	
Observations	9,896		18,212	

Notes: The table lists descriptives on socio-demographic variables and pollution exposure of SOEP parents with at least one child with doctor-diagnosed respiratory disease and parents with healthy children, averaged over the period 2005-2018. Employment (marriage) is a binary variables indicating if the person is employed (married) in each year or not. Income is monthly net household income measured in thousand Euro. All pollutants are measured in $\mu g/m^3$.
Source: SOEP, version 35, and German Environmental Agency.

Table B.6: Effect of ozone on health satisfaction of parents, by income group and by child health

	Low income		*High income*	
Ozone average	Respiratory	Healthy	Respiratory	Healthy
Weekly	0.0017	0.0008	0.0023	-0.0005
	(0.0034)	(0.0023)	(0.0026)	(0.0020)
Monthly	-0.0015	-0.0007	-0.0056	-0.0017
	(0.0046)	(0.0033)	(0.0039)	(0.0030)
Quarterly	0.0011	0.0010	-0.0098	-0.0038
	(0.0076)	(0.0052)	(0.0059)	(0.0046)
Individuals	962	2,544	1,035	2,003
Observations	4,233	9,768	5,632	8,417

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of health satisfaction on ozone exposure among above-median and below-median earning parents with sick vs. healthy children. The income subsamples are split into parents with at least one child with doctor-diagnosed respiratory disease and parents of healthy children. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

Table B.7: Probit estimations of effect of ozone on life and health satisfaction of childless people

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ozone average	*Dependent variable: Life satisfaction*								
Weekly	0.0006	0.0020	-0.0005	-0.0013	-0.0024	-0.0019	-0.0014	-0.0002	0.0019
	(0.0113)	(0.0060)	(0.0037)	(0.0024)	(0.0019)	(0.0016)	(0.0013)	(0.0012)	(0.0016)
Monthly	-0.0104	0.0017	-0.0019	0.0027	-0.0019	-0.0012	0.0005	-0.0022	0.0031
	(0.0150)	(0.0089)	(0.0054)	(0.0038)	(0.0030)	(0.0024)	(0.0021)	(0.0019)	(0.0024)
Quarterly	-0.0102	0.0032	-0.0051	-0.0012	-0.0045	-0.0024	-0.0000	-0.0039	0.0065·
	(0.0193)	(0.0118)	(0.0083)	(0.0060)	(0.0046)	(0.0036)	(0.0031)	(0.0028)	(0.0037)
Individuals	94	217	471	921	1,406	2,288	2,909	3,526	2,401
Observations	685	1,572	3,419	6,786	10,099	16,037	20,203	23,453	15,267
	Dependent variable: Health satisfaction								
Weekly	-0.0088·	-0.0085**	-0.0026	-0.0014	-0.0009	-0.0015	-0.0026*	-0.0012	-0.0004
	(0.0047)	(0.0033)	(0.0024)	(0.0017)	(0.0015)	(0.0013)	(0.0013)	(0.0013)	(0.0015)
Monthly	-0.0031	-0.0078	-0.0038	-0.0024	-0.0023	-0.0022	-0.0017	0.0005	0.0025
	(0.0079)	(0.0054)	(0.0037)	(0.0028)	(0.0025)	(0.0021)	(0.0020)	(0.0020)	(0.0023)
Quarterly	-0.0004	-0.0172*	-0.0008	0.0002	0.0009	-0.0003	0.0011	0.0019	0.0026
	(0.0122)	(0.0084)	(0.0059)	(0.0042)	(0.0037)	(0.0032)	(0.0030)	(0.0030)	(0.0035)
Individuals	259	475	881	1,435	1,974	2,577	2,922	3,282	2,600
Observations	1,896	3,492	6,801	10,879	14,960	19,057	21,125	21,924	15,766

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Fixed-effects probit regressions of life satisfaction and health satisfaction on ozone exposure of childless people. All regressions control for individual fixed effects, year fixed effects, month fixed effects and day-of-the-week fixed effects, sociodemographic covariates income, employment status, marital status, and categorical five-year age bins, and indicator variables for weather quintiles (sunshine duration, temperature, precipitation). Estimations are performed using three different temporal aggregations of pollution exposure: weekly, monthly, and quarterly. Each columm relates to a specific cut-off point between 1 and 9 used to transform the original 11-point scale into a happiness status of 0 or 1. The estimated specifications and cut-off points $c_j \in j = (1, ..., 9)$ are related as follows: $[(1) = c_1, ..., (9) = c_9]$. Robust standard errors clustered at the household level in parentheses.

Appendix C to accompany Chapter 4

Table C.1: Gas (Trillion cf), condensate (Million bbl), oil (Million bbl) production and number of wells per year in PA

	Unconventional wells				Conventional wells			
Year	Gas	Cond.	Oil	Count	Gas	Cond.	Oil	Count
2000	0.00	0.00	0.00	0	0.14	0.00	1.38	39,733
2001	0.00	0.00	0.00	0	0.15	0.00	1.47	44,361
2002	0.00	0.00	0.00	0	0.15	0.00	1.64	42,305
2003	0.00	0.00	0.00	0	0.16	0.00	1.95	45,492
2004	0.00	0.00	0.00	5	0.16	0.00	1.88	45,313
2005	0.00	0.00	0.00	11	0.18	0.00	1.94	51,915
2006	0.00	0.00	0.00	26	0.20	0.00	2.07	52,374
2007	0.00	0.00	0.03	89	0.17	0.00	1.47	41,432
2008	0.01	0.00	0.09	212	0.21	0.00	2.39	63,304
2009	0.08	0.00	0.30	520	0.20	0.00	1.91	56,314
2010	0.37	0.38	0.30	1,255	0.20	0.01	2.49	70,823
2011	1.06	0.68	0.39	2,288	0.25	0.02	2.33	71,842
2012	2.04	1.79	0.06	3,628	0.22	0.16	2.30	73,612
2013	3.10	2.96	0.21	4,973	0.21	0.13	2.01	73,115
2014	4.07	3.98	0.38	6,111	0.19	0.26	2.22	78,314
2015	4.60	5.25	0.04	7,077	0.17	0.17	1.63	77,176
2016	5.10	4.71	0.03	7,705	0.12	0.13	1.36	73,857
2017	5.36	5.28	0.01	8,403	0.11	0.05	1.13	71,789

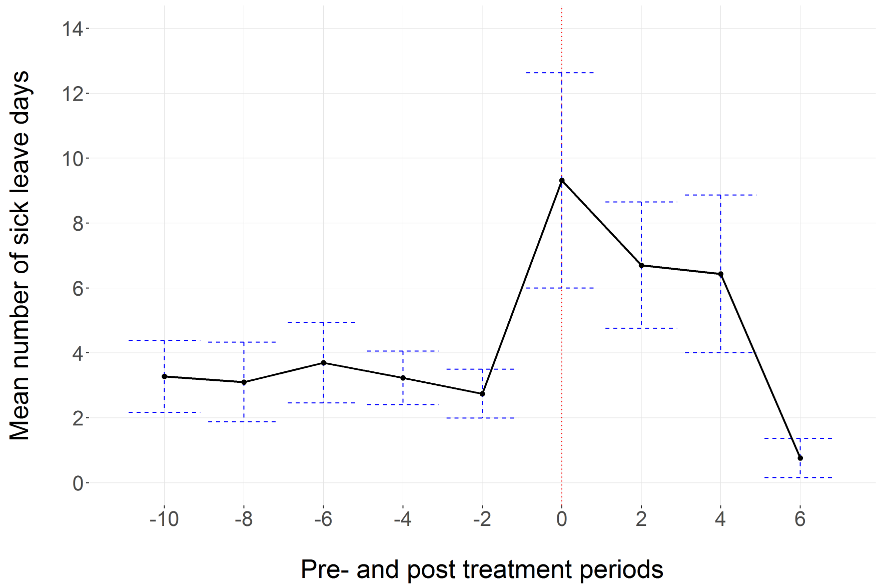
Source: PA DEP Oil and Gas Production Reports, `https://www.paoilandgasreporting.state.pa.us`, accessed on November 21st 2018, own tabulations.

Table C.2: Descriptive statistics on census block area [km^2] in PA

	Min	Q1	Q5	Q25	Med	Mean	Q75	Q95	Q99	Max	Var
Area [km2]	0.0000	0.0004	0.0016	0.0069	0.0190	0.2858	0.0994	1.4294	4.2890	83.4048	1.3640
Share of land	0.0009	98.1641	100.0000	100.0000	100.0000	99.7179	100.0000	100.0000	100.0000	100.0000	20.9801
Share of water	0.0000	0.0000	0.0000	0.0000	0.0000	0.2821	0.0000	0.0000	1.8359	99.9991	20.9801

Source: Cartographic boundary shapefiles from US Census Bureau, own calculations.

Figure C.1: Number of sick leave days in treatment group for centered pre- and post-treatment periods (2000-2014)



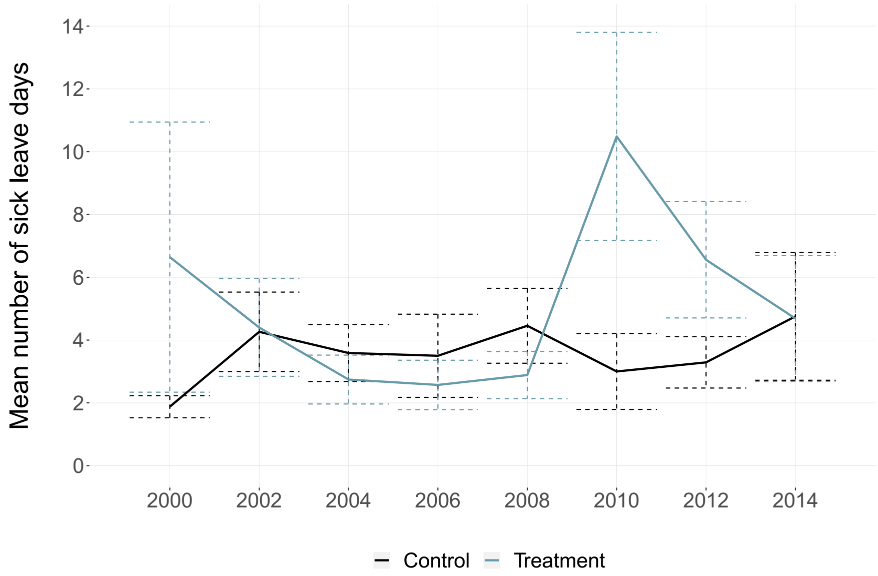
Note: The time periods have been centered such that zero indicates the period in which an individual is treated. Positive values of the centered period indicate observations from post-treatment years; negative values indicate observations from pre-treatment years. Table C.3 lists the underlying descriptive statistics.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table C.3: Descriptive statistics on number of sick leave days in treatment group for centered pre- and post-treatment periods

Centered period	N	Mean	Std. Dev.	Std. Err.
-12	x	x	x	x
-10	18	3.28	4.70	1.11
-8	34	3.10	7.15	1.23
-6	35	3.70	7.33	1.24
-4	35	3.23	4.88	0.83
-2	35	2.74	4.45	0.75
0	35	9.31	19.62	3.32
2	32	6.70	11.02	1.95
4	30	6.43	13.31	2.43
6	17	0.76	2.49	0.60
8	x	x	x	x
Sum	280			

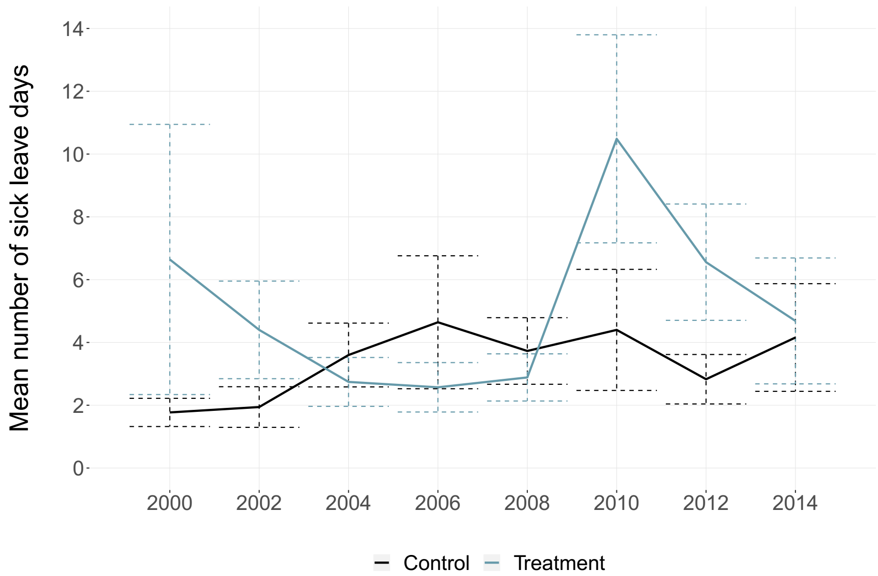
Note: The time periods have been centered such that zero indicates the period in which an individual is treated. Positive values of the centered period indicate observations from post-treatment years; negative values indicate observations from pre-treatment years. Note that x stands for cells with 10 or less observations that must not be reported.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Figure C.2: Time trend in treatment and unmatched control group



Note: This figure depicts the average number of sick leave days per year in treatment ($N_1 = 35$) and unmatched control group ($N_0 = 57$). The error bars depict standard errors for each group and year.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Figure C.3: Time trend in treatment and matched control group (PS matching on average values from 2000 to 2004)



Note: This figure depicts the average number of sick leave days per year in treatment ($N_1 = 35$) and matched control ($N_0 = 35$) group. The control group is based on PS matching on pre-treatment average values from 2000 to 2004. The error bars depict standard errors for each group and year.
Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table C.4: Descriptives on number of sick leave days per sample and year

	Median	Mean	Variance	Std. Dev.	Sum	N
Full sample						
2000	0	3.6902	251.7958	15.8681	339.5	92
2002	0	4.3152	87.7677	9.3684	397	92
2004	0	3.2663	36.953	6.0789	300.5	92
2006	0	3.1467	69.8491	8.3576	289.5	92
2008	0	3.8587	57.9414	7.6119	355	92
2010	0	5.8478	208.1085	14.426	538	92
2012	0	4.5326	70.8176	8.4153	417	92
2014	0	4.7283	197.6616	14.0592	435	92
Treatment group						
2000	0	6.6429	647.8466	25.4528	232.5	35
2002	1	4.4	84.5853	9.197	154	35
2004	0	2.7429	21.1966	4.604	96	35
2006	0	2.5714	21.6639	4.6544	90	35
2008	0	2.8857	19.7513	4.4442	101	35
2010	3	10.4857	384.2571	19.6025	367	35
2012	0	6.5571	120.0702	10.9577	229.5	35
2014	0	4.6857	140.7071	11.862	164	35
Unmatched control group						
2000	0	1.8772	7.0382	2.653	107	57
2002	0	4.2632	91.2599	9.553	243	57
2004	0	3.5877	46.9029	6.8486	204.5	57
2006	0	3.5	100.0179	10.0009	199.5	57
2008	1	4.4561	81.2079	9.0115	254	57
2010	0	3	83.1786	9.1202	171	57
2012	0	3.2895	38.0442	6.168	187.5	57
2014	0	4.7544	235.7689	15.3548	271	57
Matched control group (PS matching on 2000 values)						
2000	0	2.0571	8.3496	2.8896	72	35
2002	0	2.7143	20.3866	4.5151	95	35
2004	0	4.4429	63.4231	7.9639	155.5	35
2006	0	4.7286	156.7256	12.519	165.5	35
2008	0	2.6286	13.6521	3.6949	92	35
2010	0	1.8286	7.9109	2.8126	64	35
2012	0	2.8571	21.7731	4.6662	100	35
2014	0	6.8286	373.9256	19.3372	239	35
Matched control group (PS matching on 2000-2004 average values)						
2000	0	1.7714	7.0639	2.6578	62	35
2002	0	1.9429	14.6437	3.8267	68	35
2004	0	3.6	36.1294	6.0108	126	35
2006	0	4.6429	156.9349	12.5274	162.5	35
2008	1	3.7286	39.3433	6.2724	130.5	35
2010	0	4.4	130.1294	11.4074	154	35
2012	0	2.8286	21.7345	4.662	99	35
2014	0	4.1571	102.8349	10.1408	145.5	35

Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table C.5: Descriptives on unmatched sample

	Control		Treated		
Variable	Mean	Nobs	Mean	Nobs	Mean difference
Individual-level variables					
Number of sick leave days	3.5910	456	5.1214	280	1.5304*
Age in years	45.9408	456	44.2464	280	-1.6944**
Education in years	13.9123	456	13.4929	280	-0.4194*
Is male	0.4737	456	0.4857	280	0.0120
Is self-employed	0.1820	456	0.0964	280	-0.0856***
Is government employee	0.2721	408	0.1818	264	-0.0902***
Labor income[a]	56.4604	456	48.0010	280	-8.4594***
Health status	2.0066	456	2.4107	280	0.4041***
Number of nights in hospital	0.1447	456	0.1250	280	-0.0197
Ever had heart attack	0.0241	456	0.0179	280	-0.0063
Ever had heart disease	0.0373	456	0.0393	280	0.0020
Ever had hypertension	0.2895	456	0.3071	280	0.0177
Ever had asthma	0.1491	456	0.1000	280	-0.0491**
Ever had lung disease	0.0066	456	0.0000	280	-0.0066*
Ever had diabetes	0.0548	456	0.1179	280	0.0630***
Ever had cancer	0.0439	456	0.0321	280	-0.0117
Ever had psychological problems	0.0504	456	0.0643	280	0.0138
Household-level variables					
Number of children	0.8925	456	0.9500	280	0.0575
Age of youngest child	4.1140	456	3.4893	280	-0.6247
Number of births per year	0.0285	456	0.0286	280	0.0001
Household member older than 60	0.1053	456	0.0964	280	-0.0088
Is home owner	0.8311	456	0.8357	280	0.0046
House value[a]	187.2365	455	130.0429	280	-57.1936***
Health care expenditure[a]	3.6836	456	2.3995	280	-1.2840***
Expenditure for doctors visits etc.[a]	0.7339	456	0.3886	280	-0.3453***
Expenditure for prescriptions etc.[a]	0.3863	456	0.3180	280	-0.0682

[a] In thousand dollars.

Note: The last column reports the mean differences between treatment and control group, including significance levels of t-tests on mean equality: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table C.6: Descriptives on matched sample (PS matching on average values from 2000 to 2004)

Variable	Mean: Control	Mean: Treated	Mean difference	Normalized difference
Individual-level variables				
Number of sick leave days	3.3839	5.1214	1.7375*	0.1110
Age in years	44.4821	44.2464	-0.2357	-0.0167
Education in years	13.8964	13.4929	-0.4036*	-0.1370
Is male	0.4571	0.4857	0.0286	0.0404
Is self-employed	0.0786	0.0964	0.0179	0.0446
Is government employee[b]	0.2684	0.1818	-0.0866*	-0.1471
Labor income[ac]	60.2347	48.0010	-12.2337*	-0.2155
Health status	2.0000	2.4107	0.4107*	0.3423
Number of nights in hospital	0.1214	0.1250	0.0036	0.0032
Ever had stroke	0.0000	0.0000	0.0000	−−
Ever had heart attack	0.0357	0.0179	-0.0179	-0.0782
Ever had heart disease	0.0357	0.0393	0.0036	0.0133
Ever had hypertension	0.2536	0.3071	0.0536	0.0843
Ever had asthma	0.1571	0.1000	-0.0571*	-0.1209
Ever had lung disease	0.0071	0.0000	-0.0071	-0.0847
Ever had diabetes	0.0214	0.1179	0.0964*	0.2723
Ever had cancer	0.0286	0.0321	0.0036	0.0147
Ever had psychological problems	0.0321	0.0643	0.0321*	0.1062
Household-level variables				
Number of children	1.0071	0.9500	-0.0571	-0.0344
Age of youngest child	4.2107	3.4893	-0.7214	-0.0961
Number of births[c]	0.0357	0.0286	-0.0071	-0.0286
Household member plus 60	0.0929	0.0964	0.0036	0.0086
Is home owner	0.9143	0.8357	-0.0786*	-0.1689
House value[ac]	181.5914	130.0429	-51.5486*	-0.3124
Health care expenditure[ac]	2.8396	2.3995	-0.4400	-0.0969
Expenditure for doctors visits etc.[a]	0.6351	0.3886	-0.2466*	-0.1862
Expenditure for prescriptions etc.[a]	0.4008	0.3180	-0.0827	-0.0863
Number of observations	280	280		
Number of individuals	35	35		

[a] In thousand dollars.

[b] This covariate exhibits missings: it is based on 272 observations in the control and 264 observations in the treatment group.

[c] These are the covariates used for PS matching.

Note: The fourth column reports the mean differences between treatment and control group, including significance levels of t-tests on mean equality: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The last column lists the normalized mean difference, calculated as $(\bar{x}_1 - \bar{x}_0)/\sqrt{\sigma_1^2 + \sigma_0^2}$, where $\bar{x}_1$ and $\bar{x}_0$ are the means in treatment and control group, respectively, and σ_1^2 and σ_0^2 are the respective variances .

Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Table C.7: Descriptives on categorical variables per sample

Variable	Levels	N_0	N_1	N	χ^2-statistic
Full sample					
Rural or urban[a]	Metro	442	225	667	54.1468***
Rural or urban[a]	Nonmetro	14	55	69	
	Sum	456	280	736	
Type of housing[a]	One-family house	395	252	647	24.2888***
Type of housing[a]	Two-family house	15	0	15	
Type of housing[a]	Apartment	30	12	42	
Type of housing[a]	Mobile home	x	x	24	
Type of housing[a]	Row or town house	x	x	x	
Type of housing[a]	Other	x	x	x	
	Sum	456	280	736	
Industry	Agriculture, Forestry, Fishing, Mining	x	x	x	50.3116***
Industry	Construction	18	27	45	
Industry	Finance, Insurance and Real Estate	x	x	49	
Industry	Manufacturing	70	42	112	
Industry	Public Administration and Active Duty Military	51	11	62	
Industry	Services industries	156	118	274	
Industry	Transportation, Communication and Other Public Utilities	54	31	85	
Industry	Wholesale and Retail Trade	53	46	99	
	Sum	456	280	736	
PS matching on 2000 values					
Rural or urban[a]	Metro	266	225	491	26.4471***
Rural or urban[a]	Nonmetro	14	55	69	
	Sum	280	280	560	
Type of housing[a]	One-family house	249	252	501	8.2653**
Type of housing[a]	Two-family house	x	0	x	
Type of housing[a]	Apartment	19	12	31	
Type of housing[a]	Mobile home	x	x	24	
Type of housing[a]	Row or town house	x	0	x	
Type of housing[a]	Other	0	0	0	
	Sum	280	280	560	
Industry	Agriculture, Forestry, Fisheries, Mining	x	x	x	30.3691***
Industry	Construction	16	27	43	
Industry	Finance, Insurance and Real Estate	x	x	18	
Industry	Manufacturing	53	42	95	
Industry	Public Administration and Active Duty Military	29	11	40	
Industry	Services industries	96	118	214	
Industry	Transportation, Communication and Other Public Utilities	33	31	64	
Industry	Wholesale and Retail Trade	30	46	76	
	Sum	280	280	560	
PS matching on 2000-2004 average values					
Rural or urban[a]	Metro	266	225	491	26.4471***
Rural or urban[a]	Nonmetro	14	55	69	
	Sum	280	280	560	
Type of housing[a]	One-family house	259	252	511	8.5626*
Type of housing[a]	Two-family house	x	x	x	
Type of housing[a]	Apartment	x	x	20	
Type of housing[a]	Mobile home	x	x	24	
Type of housing[a]	Row or town house	x	0	x	
Type of housing[a]	Other	0	0	0	
	Sum	280	280	560	
Industry	Agriculture, Forestry, Fisheries, Mining	x	x	x	26.0460***
Industry	Construction	18	27	45	
Industry	Finance, Insurance and Real Estate	x	x	18	
Industry	Manufacturing	46	42	88	
Industry	Public Administration and Active Duty Military	29	11	40	
Industry	Services industries	101	118	219	
Industry	Transportation, Communication and Other Public Utilities	30	31	61	
Industry	Wholesale and Retail Trade	33	46	79	
	Sum	280	280	560	

[a] These are the covariates used for PS matching.

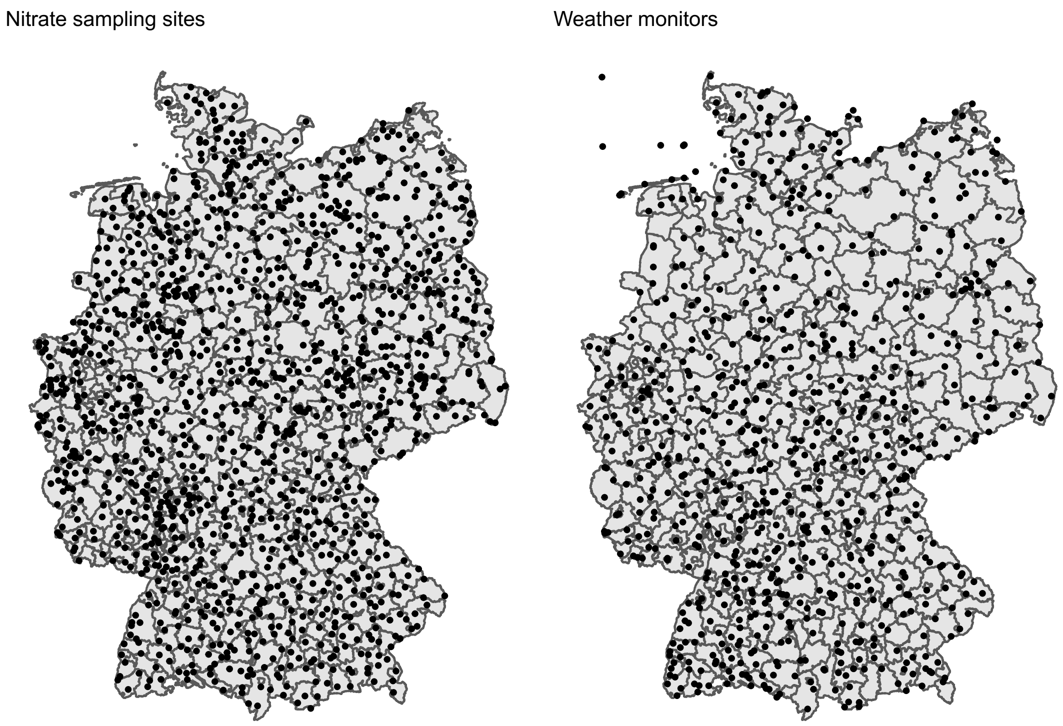
Note: This table displays the number of observations per category of the rural-urban-dummy, the type-of-housing variable and the industries of employees: N_0 is the number of observations from the control group; N_1 is the number of observations from the treatment group; N is the total number of observations. Note that x stands for cells with 10 or less observations that must not be reported. The last column reports results of Pearson's χ^2 tests on equal distributions in treatment and control groups; significance levels are denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: Panel Study of Income Dynamics, 2001-2015, restricted use data, own tabulations. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI.

Appendix D to accompany Chapter 5

D.1 Additional descriptives

Figure D.1: Locations of nitrate sampling sites and weather monitors in Germany



Notes: This figure depicts the locations of nitrate sampling sites and weather monitors in Germany. Each dot represents a sampling site or weather monitor, respectively, that was active between 2008 and 2016.

Table D.1: Organic farming and groundwater nitrate: variables, descriptions, and data sources

Variable	Definition	Unit	Data Source
Nitrate	Yearly average nitrate concentration	mg/l	Umweltbundesamt
Mineral fertilizer dummy	Mineral fertilizer supply of more than 100 kg/ha in the sampling station's district	kg n/ha	Häußermann et al. (2019)
Share organic	Share of organic farmland relative to UAA of the sampling station's district	ha	Regional Statistics
Share farmland	Share of arable land (CLC211) within a 500 meter radius around the sampling station	%	CORINE Land Cover
Share wine	Share of wine growing (CLC221) within a 500 meter radius around the sampling station	%	CORINE Land Cover
Share fruit	Share of fruit cultivation (CLC222) within a 500 meter radius around the sampling station	%	CORINE Land Cover
Share greenland	Share of greenland (CLC231) within a 500 meter radius around the sampling station	%	CORINE Land Cover
Share forest	Share of forest (CLC311+312+313) within a 500 meter radius around the sampling station	%	CORINE Land Cover
Mean precipitation	Average daily precipitation rate at site	mm/year	German Weather Service
Sum precipitation	Yearly sum of precipitation at site	mm/year	German Weather Service
Mean temperature	Average daily temperature at site	C°	German Weather Service

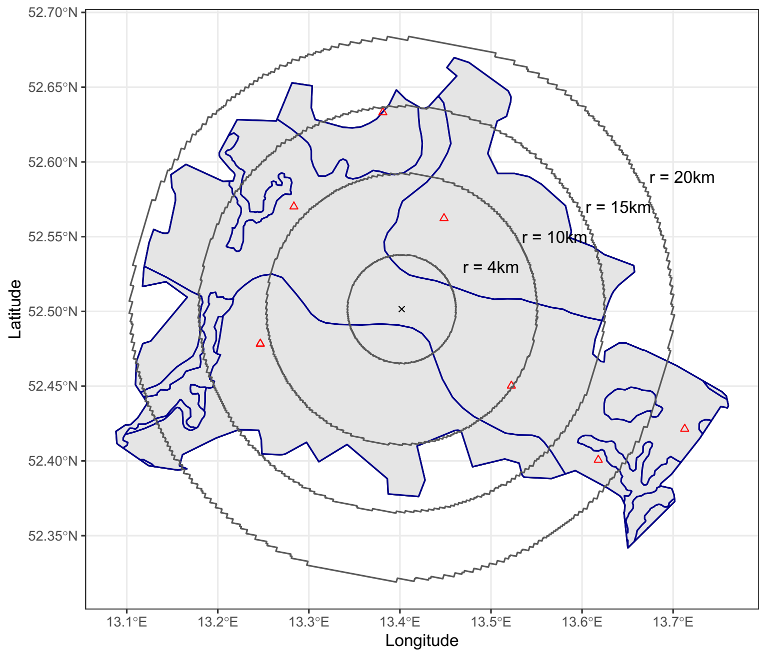
Notes: This table describes all variables and data sources used to analyze the link between nitrate pollution and organic farming.

Table D.2: Water quality and firm's treatment cost: variables, descriptions, and data sources

Variable	Definition	Unit	Data Source
Nitrate	Weighted average groundwater nitrate content, based on a 4km radius surrounding the water abstraction plant	mg/l	UBA
Total cost	Total expenditures	1000 €	RDC (2017)
Treatment cost	Expenditures for raw materials and supplies	1000 €	RDC (2017)
Total water abstraction	Total volume of abstracted raw water	1000 m^3	RDC (2016)
Total water abstraction	Total volume of ground and surface water abstracted	1000 m^3	RDC (2016)
Groundwater abstraction	Total volume of groundwater abstracted	1000 m^3	RDC (2016)
Water purchase	Total volume of external water purchases	1000 m^3	RDC (2016)
Total water delivered	Total volume of water delivered to endusers and other water supply firms	1000 m^3	RDC (2016)
Water delivered to endusers	Water delivered to endusers (households and industry)	1000 m^3	RDC (2016)
Residential water delivered	Water delivered to residential customers (households)	1000 m^3	RDC (2016)
Bulk water delivered	Water delivered to other water suppliers	1000 m^3	RDC (2016)
Employees	Total number of employees		RDC (2017)
Abstraction plants	Total number of water abstraction plants of the water supplier		RDC (2016)
Labor price	Labor costs divided by hours worked	€	RDC (2017)
Capital price	Capital costs (sum of depreciation and interest payments) divided by capital stock	€	RDC (2017)
Capital stock	Industry capital stock estimated according to (Wagner, 2010)	1000^2 €	
Population served	Total number of citizens supplied with water		RDC (2016)
Population density	Number of citizens per km^2	[0,1]	Regional Statistics
Mean precipitation	Average daily precipitation rate (municipality-level)	mm/year	German Weather Service
Sum precipitation	Yearly sum of precipitation rate (municipality-level)	mm/year	German Weather Service
Mean temperature	Average daily temperature (municipality-level)	C°	German Weather Service

Notes: This table describes all variables and data sources used to analyze the link between nitrate pollution and water supply costs.

Figure D.2: Visualization of approach to approximate nitrate concentrations at water abstraction plants



Notes: This figure depicts the approach to impute nitrate concentrations at the plant location, using Berlin as an example. The abstraction plant is denoted by x and assumed to be located in the municipality's center. Groundwater sampling sites are displayed by red triangles, and the underlying groundwater bodies are plotted by blue lines. Depending on the chosen radius more or less monitoring stations are taken into account in the inverse-distance weighted average. E.g., imposing a 10km radius yields two groundwater monitors to calculate the weighted average of nitrate concentrations. Additionally imposing the hydrogeological restriction leaves only one monitor to approximate nitrate in the concerning groundwater water.

Table D.3: Mean equivalence tests for companies with limit exceeding nitrate levels vs. without limit exceedances

Variable	Mean $NO_3 < 50$ mg/l	Mean $NO_3 \geq 50$ mg/l	Difference in Means	
Total cost [1000 €]	13056.57	19880.82	-6824.25	***
Treatment cost [1000 €]	1801.81	2891.91	-1090.09	*
Treatment cost per abstracted unit [€per m^3]	0.65	0.78	-0.14	*
Treatment cost per supplied unit [€per m^3]	0.38	0.54	-0.16	***
Share treatment cost [%]	13.01	15.03	-2.03	***
Total water abstraction [1000 m^3]	2632.31	4291.44	-1659.13	***
Groundwater abstraction [1000 m^3]	1919.06	3867.41	-1948.35	***
Water purchase [1000 m^3]	581.32	755.59	-174.28	
Total water delivered [1000 m^3]	3213.62	5047.03	-1833.41	***
Water delivered to endusers [1000 m^3]	2114.19	3521.34	-1407.15	***
Residential water delivered [1000 m^3]	1611.71	2712.51	-1100.81	***
Bulk water delivered [1000 m^3]	789.70	1052.39	-262.68	
Population served [number]	37246.54	64584.68	-27338.13	***
Employees [number]	56.86	100.25	-43.39	***
Abstraction plants [number]	9.68	11.07	-1.39	*
Nitrate [mg/l]	14.77	72.71	-57.95	***
Mean precipitation [mm/day]	2.04	1.88	0.16	***
Sum precipitation [mm/year]	665.05	623.89	41.16	***
Mean temperature [° C]	9.49	9.82	-0.33	***

Notes: This table list mean values and differences in means across two groups: Water supply firms with average nitrate content below the legal limit value of 50 mg/l (nobs = 2090), and firms with limit exceeding nitrate levels in at least one year (nobs = 664). Significance levels of t-tests on mean equivalence are denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

Table D.4: Descriptives on subsample of companies for total cost analysis

Variable	Mean	Median	SD
Cost and input prices			
Total cost [1000 €]	16794.28	4752.57	53096.52
Labor price [€]	34.87	34.11	8.45
Capital price [€]	0.18	0.06	2.97
Input quantities			
Capital stock [1000^2 €]	63490.06	26537.64	128963.30
Labor hours [1000 h]	114.65	36.00	328.87
Total water abstraction [1000 m^3]	3052.09	1288.50	8617.35
Water purchase [1000 m^3]	567.16	20.00	1772.10
Output quantities			
Total water delivered [1000 m^3]	3619.25	1557.00	9026.48
Population served [number]	53415.56	24250.33	118626.48
Environmental variables			
Share groundwater abstraction [%]	73.25	89.06	31.60
Share residential water [%]	66.85	68.39	15.13
Population density [inh/km^2]	352.16	214.82	403.61
Nitrate [mg/l]	29.48	17.00	36.59
$30 <$ Nitrate < 50 [%]	18.31	0.00	38.69
Nitrate ≥ 50 [%]	18.04	0.00	38.46

Notes: This table lists descriptive statistics on the panel of drinking water supply companies that abstract groundwater resources within a four km radius of a nitrate groundwater sampling site. The panel consists of 342 companies companies with 1,846 company-year observations between 2008 and 2016.
Source: RDC (2016) and RDC (2017), own calculations.

D.2 Robustness

Table D.5: GMM regression results with different instrument specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged nitrate	0.553***	0.550***	0.551***	0.553***	0.551***	0.550***
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Share organic	−0.297***	−0.298***	−0.298***	−0.296***	−0.297***	−0.298***
	(0.097)	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)
Mineral fertilizer dummy	1.589**	1.598*	1.594*	1.587*	1.593*	1.597*
	(0.808)	(0.820)	(0.818)	(0.814)	(0.818)	(0.819)
Mean temperature	1.079*	1.086*	1.083*	1.077*	1.082*	1.085*
	(0.609)	(0.609)	(0.608)	(0.606)	(0.607)	(0.608)
Sum precipitation	0.001	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean precipitation	0.564	0.563	0.563	0.564	0.563	0.563
	(1.114)	(1.121)	(1.118)	(1.113)	(1.118)	(1.120)
Share farmland	0.134***	0.134***	0.134***	0.133***	0.134***	0.134***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Share wine	0.409**	0.411**	0.410**	0.408**	0.410**	0.411**
	(0.179)	(0.180)	(0.180)	(0.179)	(0.180)	(0.180)
Share fruit	0.049	0.049	0.049	0.049	0.049	0.049
	(0.110)	(0.111)	(0.111)	(0.110)	(0.110)	(0.111)
Share greenland	−0.040*	−0.041*	−0.040*	−0.040*	−0.040*	−0.041*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Share forest	−0.058***	−0.058***	−0.058***	−0.058***	−0.058***	−0.058***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Station FEs	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	7311	7311	7311	7311	7311	7311
N [stations]	1323	1323	1323	1323	1323	1323
% explained	0.858	0.857	0.857	0.858	0.857	0.857
sarganp	0.655	0.789	0.142	0.188	0.067	0.083
hansenp	0.918	0.975	0.875	0.912	0.816	0.889
No. instruments	20	21	22	23	24	25

Notes: Similar to Table 5.5, this table shows BB system-GMM regression results for the effect of the share of organically farmed land on groundwater nitrate concentrations with a varying number of instruments. Control variables include lagged nitrate levels, a dummy for mineral fertlizer use $\geq$ 100kg/ha, shares of land use within 500m radius around nitrate monitor locations (farmland, wine growing, fruit cultivation, greenland and forest), and inverse-distance weighted weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). We also include year and station fixed effects. We treat lagged nitrate levels as endogenous and instrument it with two lags in the levels- and first-differenced equations using collapsed instruments. All other controls are treated as exogenous. Reported model statistics are the p-value of the Hansen test of overidentifying restrictions (hansenp), the p-value of the Sargan test of overidentifying restrictions (sarganp), and % is the percent of variation in the dependent variable explained by factors other than time dummies, measured as one minus the mean squared error of the respective regression divided by the mean squared error of a regression on the time dummies alone. Standard errors are clustered at the level of nitrate sampling sites. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D.6: GMM regression results for water quality at the district level

	(1)	(2)	(3)
Lagged nitrate	0.586^{***}	0.591^{***}	0.593^{***}
	(0.139)	(0.131)	(0.130)
Share organic	-0.562^{***}	-0.242^{**}	-0.220^{**}
	(0.174)	(0.105)	(0.105)
Mineral fertilizer dummy		0.651	1.011
		(0.892)	(0.876)
Share farmland		0.137^{***}	0.155^{***}
		(0.048)	(0.053)
Share wine		0.749^{*}	0.696
		(0.451)	(0.443)
Share fruit		−0.066	−0.080
		(0.150)	(0.152)
Share greenland		−0.070	−0.023
		(0.057)	(0.055)
Share forest		−0.063	−0.015
		(0.062)	(0.054)
Mean temperature			1.797^{*}
			(0.923)
Sum precipitation			−0.004
			(0.004)
Mean precipitation			0.571
			(1.433)
Year FEs	Yes	Yes	Yes
Station FEs	Yes	Yes	Yes
Nobs	2448	2448	2448
N [districts]	335	335	335
% explained	0.855	0.866	0.868
sarganp	0.000	0.000	0.000
hansenp	0.090	0.087	0.080
No. instruments	12	18	21

Notes: Similar to Table 5.5, this table shows BB system-GMM regression results for the effect of the share of organically farmed land on groundwater nitrate concentrations for the aggregated district level. Control variables include lagged nitrate levels, a dummy for mineral fertlizer use $\geq$ 100kg/ha, shares of land use within 500m radius around nitrate monitor locations (farmland, wine growing, fruit cultivation, greenland and forest), and inverse-distance weighted weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). We also include year and station fixed effects. We treat lagged nitrate levels as endogenous and instrument it with two lags in the levels- and first-differenced equations using collapsed instruments. All other controls are treated as exogenous. Reported model statistics are the p-value of the Hansen test of overidentifying restrictions (hansenp), the p-value of the Sargan test of overidentifying restrictions (sarganp), and % is the percent of variation in the dependent variable explained by factors other than time dummies, measured as one minus the mean squared error of the respective regression divided by the mean squared error of a regression on the time dummies alone. Standard errors are clustered at the level of nitrate sampling sites. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D.7: GMM regression results with different instrument specifications at the district level

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged nitrate	0.530***	0.593***	0.599***	0.555***	0.554***	0.537***
	(0.152)	(0.130)	(0.123)	(0.129)	(0.128)	(0.129)
Share organic	−0.251**	−0.220**	−0.218**	−0.239**	−0.240**	−0.248**
	(0.122)	(0.105)	(0.104)	(0.111)	(0.110)	(0.114)
Mineral fertilizer dummy	1.155	1.011	0.999	1.099	1.101	1.139
	(0.966)	(0.876)	(0.861)	(0.932)	(0.934)	(0.965)
Mean temperature	2.087**	1.797*	1.772*	1.974**	1.978**	2.056**
	(1.052)	(0.923)	(0.910)	(0.951)	(0.947)	(0.973)
Sum precipitation	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mean precipitation	0.676	0.571	0.562	0.635	0.637	0.664
	(1.610)	(1.433)	(1.420)	(1.534)	(1.536)	(1.581)
Share farmland	0.177***	0.155***	0.153***	0.168***	0.169***	0.174***
	(0.064)	(0.053)	(0.052)	(0.057)	(0.057)	(0.058)
Share wine	0.827	0.696	0.685*	0.776	0.778	0.812
	(0.527)	(0.443)	(0.415)	(0.503)	(0.502)	(0.523)
Share fruit	−0.085	−0.080	−0.079	−0.083	−0.083	−0.085
	(0.171)	(0.152)	(0.150)	(0.163)	(0.164)	(0.169)
Share greenland	−0.028	−0.023	−0.023	−0.026	−0.026	−0.028
	(0.062)	(0.055)	(0.054)	(0.059)	(0.059)	(0.061)
Share forest	−0.019	−0.015	−0.014	−0.017	−0.017	−0.018
	(0.061)	(0.054)	(0.053)	(0.058)	(0.058)	(0.060)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Station FEs	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	2448	2448	2448	2448	2448	2448
N [districts]	335	335	335	335	335	335
% explained	0.852	0.868	0.869	0.859	0.859	0.854
sarganp	0.015	0.000	0.001	0.000	0.000	0.000
hansenp	0.623	0.080	0.170	0.027	0.052	0.008
No. instruments	20	21	22	23	24	25

Notes: Similar to Table 5.5, this table shows BB system-GMM regression results for the effect of the share of organically farmed land on groundwater nitrate concentrations with varying instruments at the district-level. Control variables include lagged nitrate levels, a dummy for mineral fertlizer use $\geq$ 100kg/ha, shares of land use within 500m radius around nitrate monitor locations (farmland, wine growing, fruit cultivation, greenland and forest), and inverse-distance weighted weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). We also include year and station fixed effects. We treat lagged nitrate levels as endogenous and instrument it with two lags in the levels- and first-differenced equations using collapsed instruments. All other controls are treated as exogenous. Reported model statistics are the p-value of the Hansen test of overidentifying restrictions (hansenp), the p-value of the Sargan test of overidentifying restrictions (sarganp), and % is the percent of variation in the dependent variable explained by factors other than time dummies, measured as one minus the mean squared error of the respective regression divided by the mean squared error of a regression on the time dummies alone. Standard errors are clustered at the level of nitrate sampling sites. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table D.8: Regressions results for treatment cost across different samples

DV: ln(Treatment cost)	(1)	(2)	(3)
ln(Nitrate)	0.044**	0.045**	0.030
	(0.020)	(0.021)	(0.020)
ln(Water abstracted)	0.716	1.128*	1.171**
	(0.483)	(0.669)	(0.591)
ln(Share groundwater)	0.154	0.125	0.065
	(0.095)	(0.395)	(0.100)
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Weather controls	Quadratic	Quadratic	Quadratic
Nobs	2726	2124	2030
N	484	397	387
Adj.R2	0.891	0.886	0.871

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on treatment costs of water suppliers for three different samples: The first column is based on water suppliers that are observed for at least two years in the panel. The second column is based on water suppliers with at least 50 percent of raw water abstracted from groundwater resources. The third column is based on water suppliers that are "pure water utilities" that do not operate in any other economic sector, e.g., sewage. Nitrate is measured as a volume-weighted average of nitrate measurements within a four kilometer radius around the plant location. Control variables include the volume of water abstracted, the share of abstracted groundwater relative to total abstraction, and quadratic weather controls (annual average of daily temperature and precipitation, sum of annual precipitation). All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.

Table D.9: Regression results for total costs with alternative capital price definition

DV: ln(Total cost)	(1)	(2)
ln(Nitrate)	0.020*	0.020*
	(0.011)	(0.011)
ln(Labor price)	0.790***	0.789***
	(0.109)	(0.109)
ln(Water delivered)	0.861***	0.794***
	(0.169)	(0.171)
ln(Population served)	0.214	0.296*
	(0.156)	(0.162)
ln(Share groundwater)		0.032
		(0.066)
ln(Share households)		−0.048
		(0.098)
ln(Population density)		−0.070
		(0.088)
Nobs	1846	1846
N	342	342
Adj.R2	0.984	0.984

Notes: This table depicts OLS estimates on the impact of groundwater nitrate on toal costs of water suppliers. Nitrate is measured as a volume-weighted average of nitrate measurements within a four kilometer radius around the plant location. We include the labor price, and delivered water volumes and population served as outputs. Total cost and labor price are standardized by capital price. The capital price is defined as residual between total cost and labor cost divided by the capital stock. Control variables are share of groundwater abstraction, share of residential water deliveries, and population density of the area served by the water company. All models include firm and year fixed effects. Standard errors are clustered at the firm level. Significance levels denoted by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Source: RDC (2016) and RDC (2017), own calculations.