Low Depression Zones? The Effect of Driving Restrictions on Air Pollution and Mental Health*

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Abstract

Does exposure to air pollution impact mental health? This paper uses administrative health insurance data to estimate the medium-term cumulative effects of air pollution exposure on mental health outcomes. For identification, we exploit the staggered introduction of Low Emission Zones (LEZs) across German cities, which restrict access for emission-intensive vehicles. We find that LEZs reduce various air pollutants and improve the population's mental health measured by depression and anxiety diagnoses, prescriptions, and specialist visits. The health benefits emerge gradually, with younger individuals benefiting the most. Our findings suggest substantial mental health co-benefits and avoided health costs from improved air quality.

Keywords: mental health, air pollution, low emission zones
JEL Codes: I18, Q53, Q58

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1 Introduction

According to the World Health Organization (WHO), nearly one billion people worldwide, including 14% of adolescents, suffered from mental health disorders in 2019. Suicide alone accounted for more than 1 in 100 deaths globally (WHO, 2022). Mental health, much like physical health, is crucial to economic productivity. Depression and anxiety, two of the most common conditions, cost the global economy an estimated US$1 trillion annually (WHO, 2022). The rising demand for mental health services further strains healthcare systems across the world, underscoring the need to understand the root causes of mental health conditions in order to develop effective policies and interventions.

While the relationship between the biophysical environment and mental health remains underexplored (Kühn & Gallinat, 2024), recent advances in medical research have increasingly pointed to a link between air pollution exposure and mental health outcomes (see, e.g., Braithwaite et al., 2019, Zundel et al., 2022). Numerous studies have shown that air pollution contributes to cardiovascular and respiratory diseases, partly due to inflammation and oxidative stress (e.g., Kelly & Fussell, 2015, Rückerl et al., 2011). These biological processes are also implicated in psychiatric conditions (Coccaro et al., 2014, Miller & Raison, 2016, Najjar et al., 2013, Salim, 2014), suggesting that air pollution may have broader mental health impacts. However, given the complexity of mental health disorders and potential confounding factors, rigorous causal inference models are needed to clarify the link between air pollution and mental health.

An emerging body of economic research has begun to establish the causal impact of air pollution on neurocognitive disorders such as dementia (Bishop et al., 2023), severe mental health outcomes like suicide (Persico & Marcotte, 2022), and overall well-being or self-reported mental health measures (Beshir & Fichera, 2022, S. Chen et al., 2024, Zheng et al., 2019a). However, no study has yet estimated the causal effects of air pollution on more common mental health conditions such as depression and anxiety using administrative data. When analyzing sensitive outcomes like mental health, administrative data offers significant advantages over self-reported survey data, minimizing biases related to social desirability and recall (see, e.g., Braun et al., 2001, Paulhus, 1984).

This paper conducts the first large-scale study of air pollution and broader mental health relying on administrative data. This data is provided by a large German public health insurance fund covering more than ten percent of the German population (around 9 million individuals). Using depression and anxiety diagnoses as well as antidepressant prescriptions and specialist visits it offers detailed insights into the impact of air pollution on mental health outcomes at the extensive and intensive margin. Our identification strategy rests on the staggered implementation of low-emission zones (LEZs) in German cities after 2008, which by limiting vehicle access to designated areas, has led to significant reductions in coarse particulate matter (PM_{10}), nitrogen dioxide (NO_2), and carbon monoxide (CO) (see e.g., Sarmiento et al., 2023, Wolff, 2014). The regional and spatial variation caused by the introduction of LEZs in Germany offers a favorable setting for identifying the causal effects of air pollution on socio-economic outcomes, as shown by Klauber et al. (2024), Pestel and Wozny (2021), and Sarmiento et al. (2023). To account for the staggered implementation of LEZs, we rely on an estimator proposed by Sun and Abraham (2021) in addition to the standard two-way fixed effects (TWFE) estimation (see e.g., Goodman-Bacon, 2021, for a discussion on potential biases in TWFE estimation).

Our findings indicate that the introduction of LEZs reduced PM_{10} levels by 10.4 percent and NO_2 levels by 15.3 percent in the covered areas. While the measured reduction in $PM_{2.5}$ is smaller, at 3.1 percent, we interpret this as a lower bound due to the limitations of satellite-based measurements, which may not capture traffic-related pollution as accurately as ground-based stations near major roads. These reductions in air pollution translate into significant and robust improvements in mental health outcomes. Specifically, LEZs are associated with a 4% decrease in the likelihood of receiving antidepressant prescriptions, a 5.7% decrease in specialist visits (psychotherapist or psychiatrist), a 3.5% reduction in the likelihood of a depression diagnosis, and a 4.2% reduction in the likelihood of an anxiety diagnosis. Moreover, we find similarly strong effects on the intensive margin: LEZs reduce the number of antidepressant prescriptions by 5.7% and specialist visits by 7.4%. Our analysis of potential mechanisms suggests that the improvements in mental health are primarily driven by the direct effects of reduced air pollution, rather than indirect factors such as improved physical health, noise reduction, or changes in traffic volume or economic activity. Further heterogeneity analyses reveals that the effects are strongest for the youngest group, aged 15 to 29. This may be due to the heightened sensitivity of adolescents to inflammatory stimuli during ongoing brain development (Danese & Baldwin, 2017, Roberts et al., 2019), as well as lifestyle factors that result in greater exposure to traffic pollution among younger individuals. Overall, our findings suggest significant causal effects of traffic-related air pollution on mental health, comparable in magnitude to its effects on cardiovascular health (Margaryan, 2021, Pestel & Wozny, 2021). In addition to identifying a critical avenue for preventing mental health disorders, we estimate substantial fiscal benefits from driving restriction policies. Our cost-benefit analysis indicates that LEZs in Germany prevent approximately 23,000 depression diagnoses annually, yielding public health expenditure savings of €150 to 200 million per year.

We contribute to several strands of the medical and economic literature. First, we add to the understanding of the role of air pollution in the development of mental illnesses. Experimental research on animals (e.g., Levesque et al., 2011) and post-mortem observations in humans (e.g., Calderón-Garcidueñas et al., 2008) have shown that fine and ultrafine particles, such as PM_{10}, $PM_{2.5}$, and NO_x, can penetrate the brain, influencing vasoregulatory pathways and triggering neuroinflammation (Block & Calderón-Garcidueñas, 2009). When air pollutants enter the body, they activate an immune response, leading to elevated cytokine levels in blood and cerebrospinal fluid, which promote inflammation and neuroinflammatory signaling. This process can damage neural tissue in areas such as the prefrontal cortex and olfactory bulb, regions critical for emotional regulation (Brockmeyer & d'Angiulli, 2016). As air pollutants trigger neuroinflammation and oxidative stress, they disrupt neurotransmitter systems like serotonin and dopamine, which are key to mood regulation and linked to depressive symptoms and suicide risk (Ganança et al., 2016, Janelidze et al., 2011). Oxidative stress further leads to neuronal damage in brain regions such as the hippocampus, affecting cognitive functioning and emotional regulation (Salim, 2014). This growing body of evidence suggests a direct link between air pollution and psychopathology, with numerous meta-studies reporting associations between pollution exposure and adverse mental health outcomes such as depression (Borroni et al., 2022, Braithwaite et al., 2019, Zeng et al., 2019, Zundel et al., 2022), anxiety (Zundel et al., 2022), psychological stress (Trushna et al., 2021), and suicide rates (Davoudi et al., 2021, Heo et al., 2021). However, Trushna et al. (2021) and other studies have emphasized substantial between-study (e.g., Fan et al., 2020) and between-sample (e.g., Zijlema et al., 2016) heterogeneity. Consequently, Braithwaite et al. (2019) advocates for further high-quality investigations to explore potential causal associations, calling for continued efforts to enhance our understanding of the complex relationship between air pollution and mental health. Our study provides causal evidence for the effect of air pollution on psychopathology in the general population of a large industrialized country.

Second, our study adds to the economic literature on the effects of air pollution on mental health and well-being. Several studies, predominantly conducted in China using the China Family Panel Study (S. Chen et al., 2024, Ju et al., 2022, Ju et al., 2023, M. Li et al., 2021, Ren et al., 2023, Xue et al., 2019, X. Zhang et al., 2017), have explored the effects of air pollution on various subjective well-being outcomes. A first strand uses linear regression models, thereby relying on the assumption that air pollution exposures are quasi-random after accounting for individual-level factors and that all potential omitted confounders are time-invariant.[1] Other authors employ contemporaneous variations in air pollution, such as thermal inversions (e.g., Balakrishnan & Tsaneva, 2023, S. Chen et al., 2024), or cross-boundary air pollution flows (e.g., Zheng et al., 2019b), as instrumental variables to establish causality.[2] While these studies provide vital insights into the causal effects of self-reported mental health in China and India, it remains unclear whether these findings hold external validity for Western countries due to differences in traffic and healthcare infrastructure, culture, and pollution levels. Evidence from Western countries on the causal effects of air pollution on mental health is extremely scarce. Beshir and Fichera (2022) investigate the effects of London's ultra-low emission zone (ULEZ) on mental health, concluding that the ULEZ improved feelings of happiness, worthiness and satisfaction. However, the study suffers from the limitation that inner-city London, where

[1] For instance, X. Zhang et al. (2017) maintains that hazardous air pollution correlates with heightened hedonic unhappiness, depressive symptoms, and decreased mental well-being. Additionally, M. Li et al. (2021) find that a 15-point increase in mean Air Pollution Index (API) correlates with a 5.5 percent increase in psychological distress among Chinese adolescents, along with a 0.9 percent decrease in self-esteem.

[2] Zheng et al. (2019b), using a happiness index derived from 210 million geo-tagged tweets on the Chinese micro-blog platform *Sina Weibo* (equivalent to Twitter), demonstrate that $PM_{2.5}$ air pollution significantly reduces expressed happiness. Similarly, S. Chen et al. (2024) and Balakrishnan and Tsaneva (2023) find that higher pollution levels in China and India respectively had significant negative impacts on self-reported measures of well-being and mental health.

the ULEZ is located, is arguably different from other cities in the UK in many respects. In contrast, LEZs in Germany were introduced in many different cities, creating more favorable conditions for estimating difference-in-difference models. In addition, similar to the studies from China and India, Beshir and Fichera (2022) measure effects on self-reported mental health. Especially when measuring sensitive outcomes like mental health, survey data may encompass social desirability response bias leading to inaccurate self-reporting (see e.g., Paulhus, 1984, on the concept of social desirability bias). Administrative data can provide a more comprehensive and objective view of healthcare utilization, while also ensuring a larger, more representative sample. Persico and Marcotte (2022) is the only study using administrative cause of death data from all death certificates in the U.S. between 2003 and 2010. They provide compelling evidence for the causal relationship between air pollution and suicide rates. However, suicide is only one extreme outcome of psychopathology. We aim to offer a broader perspective on the causal effect of air pollution on mental health.

In addition, we contribute to the existing knowledge on the effectiveness of the German LEZs as an example of driving restriction policies that could be implemented in other countries as well. Here, our contribution is twofold: First, we expand the evidence on the effect of the policy on pollution levels, by exploiting monthly global satellite-based fine particulate matter concentrations ($PM_{2.5}$) compiled by (Van Donkelaar et al., 2021). Previous papers (e.g., Gehrsitz, 2017, Pestel & Wozny, 2021, Sarmiento et al., 2023, Wolff, 2014) have focused on the policies' effect on coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2), as well as carbon monoxide (CO) and ground-level ozone (O_3) in the case of Sarmiento et al. (2023).[3] While all air pollutants have adverse effects on health, recent estimates by the European Environment Agency (EEA) show that with approximately 238,000 premature deaths attributable to fine particulate matter ($PM_{2.5}$) in the 27 EU Member States in 2020, $PM_{2.5}$ is associated with the most substantial health impacts (European Environment Agency, 2024). Therefore, more knowledge on which policies effectively reduce $PM_{2.5}$ is urgently needed. Second, we add to our understanding of German LEZs on socio-economic and health outcomes through their effect on air pollution. Pestel and Wozny (2021) and Margaryan (2021) demonstrate that the implementation of LEZs in Germany led to a reduction in hospitalizations related to circulatory and respiratory conditions. In terms of economic benefits, Wolff (2014) provide evidence that the policy's health benefits translate into lower health expenditures. Moreover, Klauber et al. (2024) find that newborns exposed to cleaner air required less medication for respiratory diseases. Gehrsitz (2017) finds only minor effects on the number of stillbirths and no impact on infant health. Brehm et al. (2022) use the exogenous variation induced by the introduction of LEZs to study human capital effects of pollution, finding that LEZs increased the share of elementary school children transitioning to the highest secondary school track increases by 0.9-1.6 percentage points. In terms of self-rated life satisfaction, however, Sarmiento et al. (2023) show that LEZs temporarily had adverse effects on the well-being of residents. Given the strong link of mental health with both physical health and well-being and the

[3] See Pestel and Wozny (2021) for an overview on how these different pollutants pose risks to human health.

opposing effects found in the literature, it is not clear in which ways LEZs affect mental health.

The remainder of the paper is structured as follows. Section 2 provides insights into the institutional setting. Section 3 describes the data sources used and Section 4 the empirical strategy. Section 5 presents the result, including heterogeneity and robustness analyses as well as a discussion of the mechanisms at play. Section 6 presents a cost-benefit analysis while Section 7 concludes.

2 Institutional Setting

2.1 Low Emission Zones

In response to increasing evidence on the health risks of air pollution in the early 2000s, the EU has issued a series of Clean Air Directives, targeting fine particles, coarse particles (PM_{10}), nitrogen dioxide (NO_2), and other ambient pollutants, defining specific numerical limits on their ambient levels.[4] Directive 1999/30/EC divided the PM_{10} limits into two phases, with the first phase spanning from 2005 to 2009 and the second phase starting in 2010 and continuing thereafter. In the first phase, PM_{10} regulations stipulated that, at a city's highest-polluting station, the daily average must not exceed 50 $\mu g/m^3$ for more than 35 days per year, and the yearly average must not exceed 40 $\mu g/m^3$. Cities failing to meet EU air quality standards were required to develop "Clean Air Plans" laying out policies and measures to comply with the targets. Between 2005 and 2007, 79 German large cities violated the 35-day limit (Wolff & Perry, 2010).[5]

Among various measures, the most popular was the introduction of Low Emission Zones (LEZs), which restricted the access of high-emitting vehicles, such as older diesel cars, from entering certain areas, mainly in the city centers. Starting in 2008, vehicles must display a colored windscreen sticker based on EU-wide tailpipe emissions categories in order to enter the designated areas. Initially, vehicles without stickers were banned, followed by those with red or yellow stickers. Over time, only cars with green stickers are permitted in these zones.[6] Enforcement is carried out by the police and public order office, with violations resulting in fines of €100.[7]

LEZ implementation is decided at the regional level, involving city administrations, councils, and local stakeholders, although state governments can overrule local authorities.

[4] The 1999 Directive required basic $PM_{2.5}$ monitoring, while only the 2008 directive established specific thresholds for $PM_{2.5}$.

[5] These legally binding standards have been in effect since 2005. Directive 2008/50/EC (EU, 2008) defines the current lawfully binding limits and detailed measurement procedures for all criteria pollutants (NO_2, SO_2, PM_{10}, CO, and O_3). It is a revised version of Directives 1999/30/EC (EU, 1999), 2000/69/EC (EU, 2000), and Directive 2002/3/EC (EU, 2002).

[6] Stickers are assigned based on the tax class and EURO standard recorded in the car registration book and regulated by the labeling regulation in the 35th Ordinance for the Implementation of the Federal Immission Control Act (35. BImSchV). Neu-Ulm is an exception, where yellow stickers are still allowed.

[7] See Wolff and Perry (2010) for more details on the implementation of LEZs in Germany.

The need for a Clean Air Plan and LEZ varies based on prior pollution levels and regional decision-making processes, which are influenced by various interests. Stakeholders can both support and oppose LEZs, with legal actions taken on both sides. Due to frequent conflicts of interest between state and local policymakers, the decision-making process for introducing LEZs can vary significantly in duration. Further, NGOs and private citizens often resort to legal action to support or oppose air quality regulations, leading to further plausibly exogenous variation in the timing of LEZ implementation (see Klauber et al., 2024, for a detailed discussion).

By 2022, the number of LEZs had increased to 56 (Table A.1). Despite the evident success of the LEZs in curbing pollution and improving public health, a first wave of LEZs in five cities in the federal state of Baden-Wuerttemberg was abolished in 2023[8], followed by a second wave in June 2024, operating under the assumption that pollution levels would not significantly rise and that European Union air quality standards could still be met without the imposition of LEZs. Currently, there are 38 active LEZs in Germany.

2.2 Mental Health in the German Healthcare System

Germany provides universal access to high-quality healthcare, ensuring that its population receives necessary medical services. Public health insurance is mandatory for employees earning below a certain income threshold (currently around €69,300 annually) and for various other groups such as students, pensioners, and the unemployed. Those above this income threshold, as well as self-employed individuals and civil servants, can opt for private health insurance. Approximately 90 percent of the German population is covered by public health insurance. Coverage includes prescribed drugs and therapies, including psychotherapy, ensuring that patients have access to necessary medications and treatments without significant out-of-pocket expenses. Germany's healthcare system is characterized by a robust infrastructure. In 2017, there were approximately 8.0 hospital beds per 1,000 inhabitants compared to 2.9 hospital beds in the United States. In addition, there were 4.5 doctors per 1,000 inhabitants in 2020 compared to 3.6 doctors in the US. The density of psychotherapists in Germany is 13.2 (2015) per 100,000 inhabitants compared to 10.5 (2016) in the US (WHO, 2024b).

Mental health care is predominantly provided through a collaborative approach involving psychiatrists, psychologists, psychotherapists, and general practitioners. Patients typically access mental health care by first consulting a general practitioner who can refer them to specialized services as needed. However, there are notable issues regarding the availability of psychotherapists, especially for outpatient care, often leading to excess demand. An analysis by the Federal Chamber of Psychotherapists in 2019 found that, on

[8]One LEZ in Erfurt had been abolished earlier in 2021.

average, people had to wait nearly five months to start therapy after a need for treatment was identified (Bundespsychotherapeutenkammer, 2021).[9]

2.3 Mechanisms linking LEZs to Mental Health

Medical research suggests that reductions in air pollution can have direct effects on the brain (see Section 1), making this the primary mechanism through which LEZs may influence mental health outcomes. However, other pathways could also play a role:

Indirect Effects Through Improved Physical Health. Improved air quality through LEZs may benefit mental health indirectly by enhancing physical health, particularly cardiovascular health. Reduced cardiovascular risk lowers stress and depressive symptoms, as cardiovascular diseases are often linked to psychological distress (Goldfarb et al., 2022, Rafiei et al., 2023). Improved physical health also promotes physical activity, which provides mental health benefits.

Noise and Traffic Volume Reduction. LEZs may also help reduce noise pollution by limiting heavy-duty vehicle traffic and modernizing the vehicle fleet with newer models that typically feature improved noise control technologies. Chronic exposure to noise has been linked to mental health conditions such as depression, anxiety, behavioral problems, and sleep disorders (Hahad et al., 2024, Hegewald et al., 2020). The impact on sleep disorders could be particularly relevant in our context, as heavy-duty vehicles, which are restricted by LEZs, typically deliver goods to large cities during off-peak hours, such as during the night or early morning. This activity can significantly disrupt the sleep of residents living along major roads. Sleep deprivation can, in turn, exacerbate symptoms of depression and anxiety (Guarnieri & Balmes, 2014). In addition, traffic volume itself can act as a direct source of stress, with heavy, congested traffic creating a hectic environment, increasing the risk of accidents, and contributing to feelings of stress and anxiety.

Economic Activity. Lastly, LEZs can influence economic activity in the affected areas, both through direct productivity gains and improved health outcomes. Numerous studies have highlighted the detrimental effects of air pollution on productivity in both low-skilled (T. Chang et al., 2016, T. Y. Chang et al., 2019) and high-skilled (Archsmith et al., 2018, Künn et al., 2023) occupations. Cleaner air can also lead to a decrease in work absenteeism and long-term disabilities through its impact on better health, which can enhance overall economic performance. However, LEZs may also have short-term negative economic impacts, particularly by imposing costs on businesses and individuals who rely on older, high-emission vehicles through the need to upgrade, replace, or retrofit these vehicles.

LEZs can further affect the socio-economic composition of neighborhoods by attracting individuals who place higher value on improved air quality and quality of life, potentially

[9] Since April 1, 2017, the reformed psychotherapy directive has been in effect. Psychotherapists are now required to offer initial consultations and can provide acute treatment for patients in acute mental crises (Bundespsychotherapeutenkammer, 2018)

leading to changes in the local population. Even though our analysis excludes individuals who move during the observation period, the mental health of remaining residents may still be affected by changes in their neighborhood's socio-economic makeup. Shifts in local business dynamics and employment opportunities driven by changes in the population composition could indirectly affect residents' mental health outcomes.

3 Data

3.1 Administrative Health Insurance Data

Our primary data source is administrative health records for nine million individuals (over ten percent of the German population) insured with one of Germany's largest public health insurers (Grobe & Szecsenyi, 2023). Figure A.1 displays the geographical distribution of insured individuals across Germany. In addition to all inpatient and outpatient health records, diagnoses, prescriptions, and medical billings, it includes detailed individual-level characteristics such as age, sex, education and the most recent residence on zip code level.[10] We consider working age individuals (15-65 years old) who were insured without interruptions between 2005 and 2019.[11] We further exclude individuals who move their residency (county level) during the sample period to address potential selection biases related to changes in residence within LEZs during the study period.[12]

Following Pestel and Wozny (2021) and Ahammer et al. (2023), we use the ICD-10-GM for diagnoses[13] and the Anatomical Therapeutic Chemical (ATC) Classification System for prescriptions[14] to analyze health outcomes. We also include specialist visits[15] and specific outpatient billings[16] to identify therapy sessions. Our outcomes for diagnoses, prescriptions, and specialist visits are averaged at the zip code level, thus defining an average risk. In addition, we analyze the average number of defined daily dosages (DDD)[17] of prescriptions and specialists billings as a measure of the intensive margin. See Table 1

[10] Education information is derived from the *Tätigkeitsschlüssel* (occupation key), a numeric code used to classify the professional activities of employees for social security reporting purposes. Employers use it to report to social security authorities, providing detailed information about the types of jobs their employees perform. Due to the conversion of a 5-digit code to a 9-digit code in 2010, which significantly altered schooling information, we use the largest common denominator across time. We define a binary education variable, where one indicates the insured individual has earned the *Abitur* (university entrance qualifying exam) and zero otherwise.

[11] See Figure A.2 for detailed information on age distribution.

[12] In Section 5.4 we show that our results are robust to including individuals that change their residence.

[13] We consider relevant ICD codes for depression (F32 and F33) and anxiety (F40-F48), arm injuries (S52) as well as cardiovascular diseases (I). See Table A.3 for more details.

[14] In Germany, strong medications such as antidepressants require a prescription. We consider relevant prescriptions with drugs categorized as antidepressants (N06A and N06CA) and cardiac medications (C). See Table A.4 for more details.

[15] Specialist groups are identified by the eighth and ninth digits of the lifetime physician number. Psychiatrists and psychotherapists are coded as "58", "60", "61", "68" and "69."

[16] Outpatient billing data from health insurance companies consist of codes from the standardized evaluation scale (EBM). We select relevant codes (21220, 21221, 22211, 22212, 22222, 22230, 23211, 23212, 23214, 23220, 23210) identifying therapy sessions, see Table A.2 for more details.

[17] The assumed average maintenance dose per day for a drug used for its main indication in adults (WHO, 2024a).

for a descriptive summary of our outcome variables.

Table 1: Descriptive statistics: Outcomes

	Outside LEZs				Inside LEZs			
Mental health outcomes	mean	sd	min	max	mean	sd	min	max
Extensive Margin								
Depression probability	0.07	0.03	0	0.2	0.07	0.03	0	0.19
Anxiety probability	0.06	0.02	0	0.18	0.06	0.02	0	0.14
Antidepressant probability	0.07	0.02	0	0.18	0.07	0.02	0	0.15
Specialist visit probability	0.06	0.03	0	0.23	0.06	0.03	0	0.18
Intensive margin								
Antidepressant prescriptions	0.25	0.1	0	0.67	0.27	0.09	0	0.63
Antidepressant DDD	17.78	8.31	0	64.38	18.91	7.44	0	49.03
Specialist visits	0.18	0.08	0	0.62	0.19	0.09	0	0.54
Specialist billings	1.75	0.89	0.03	9.32	1.71	0.85	0	6.34
Confirmatory and Placebo Outcomes								
Cardiovascular disease probability	0.32	0.08	0	0.63	0.3	0.07	0.03	0.56
Cardiovascular prescription probability	0.21	0.07	0	0.42	0.19	0.06	0	0.45
Cardiovascular prescriptions DDD	128.06	48.74	0	342.95	113.52	45.36	0	346.63
Injury probability	0.11	0.03	0	0.21	0.1	0.03	0	0.21
Observations	10,738				9,332			

Note: This table displays different health outcomes for zip codes inside and outside of LEZs for 2005 to 2019. Mean and standard deviation are weighted by the number of insured individuals in our sample.

3.2 Low Emission Zone and Air Pollution Data

The German Environmental Agency (UBA) provides data on the history of implementation, stringency (such as the ban of Euro 1-3 vehicles), and geographic coverage of LEZs.[18] To enhance the spatial accuracy of our analysis, we use *OpenStreetMap* to incorporate the exact boundaries of each LEZ. In our analysis, the main treatment variable is a binary indicator for whether an individual is located within a zip code that is at least partly covered by an active LEZ.

Air pollution level data is provided by the air pollution monitoring system of the German Federal Environment Agency. We use data from all stations measuring nitrogen dioxide (NO_2) and particulate matter (PM_{10}) concentrations between 2005 and 2018. We aggregate the station data to the zip code-year level by assigning each zip code the closest station with non-missing pollution readings for that year. We ensure that stations within LEZs are not assigned to zip codes outside of LEZs, and conversely, stations outside LEZs are not assigned to zip codes within LEZs. Table 2 provides an overview of air pollution levels for zip codes inside and outside LEZs, based on more than 128 stations within LEZs. As Table 2 highlights, pollution levels are significantly higher within LEZs compared to outside LEZs.

[18] Table A.1 lists the name, state, stringency, adoption and abolish dates as well as covered area and circumference of all LEZs in Germany.

Additionally, we use monthly global satellite-based data on fine particulate matter concentrations ($PM_{2.5}$) compiled by Van Donkelaar et al. (2021). Although $PM_{2.5}$ has been linked to severe health threats (see e.g., Feng et al., 2016), the effectiveness of LEZs to lower $PM_{2.5}$ in Germany has not been thoroughly studied due to data limitations. Since the station-based data from the German Environmental Agency is available only from 2008 onwards and has significant data gaps in the initial years, previous studies on the effectiveness of LEZs on $PM_{2.5}$ (Klauber et al., 2024) are likely underpowered.

3.3 Socioeconomic and Weather Data

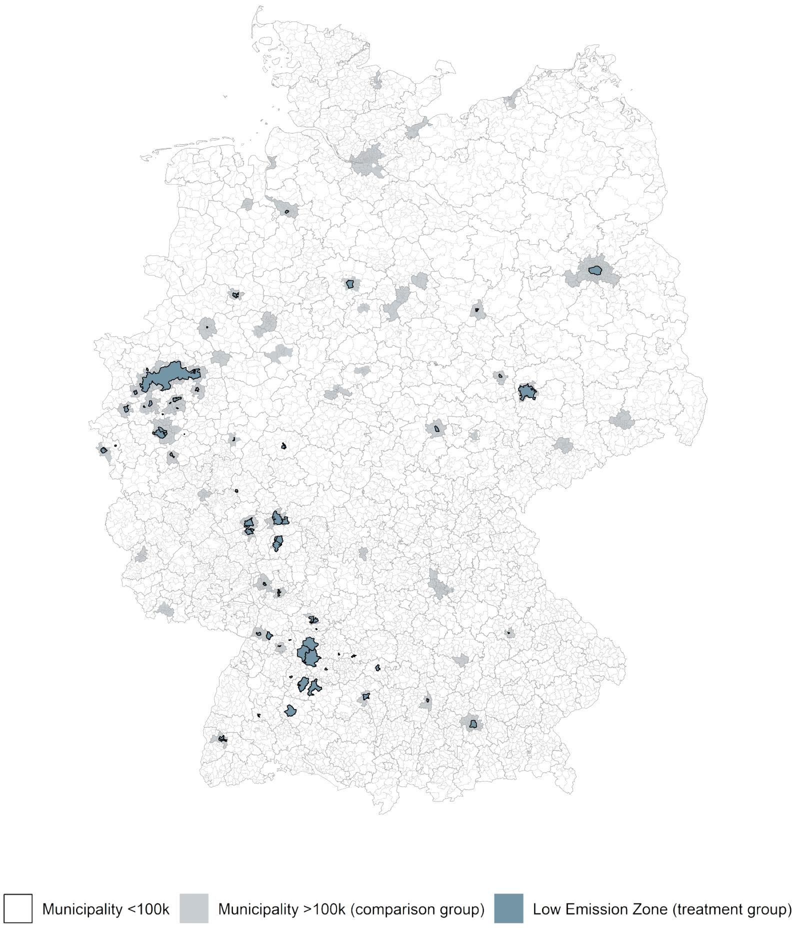
We use the RWI-GEO-GRID data (Breidenbach & Eilers, 2018) to incorporate socioeconomic characteristics at the $1 \times 1 km^2$ level. We aggregate the information from the grid to the zip code level to match the level of the outcomes. We control for various socioeconomic factors, including the yearly average number of inhabitants, purchasing power per capita, and the number of vehicles per household. The RWI-GEO-GRID data spans from 2005 to 2021, with a three-year gap between 2006 and 2008, which we interpolate linearly to ensure a balanced dataset.

In addition to socioeconomic factors, we consider several quarterly weather conditions, as they correlate with both pollution and mental health outcomes. Extensive literature documents the association between mental health and weather conditions such as heat (Hansen et al., 2008, Thompson et al., 2018), precipitation, and other factors. Sunlight, in particular, has been observed to accelerate recovery from severe depression in hospitals (Beauchemin & Hays, 1996), while decreased sunlight exposure is linked to the onset of seasonal affective disorder (Menculini et al., 2018, Rosenthal et al., 1984). Weather metrics such as precipitation, temperature, and wind speed also influence air pollution (Makar et al., 2015, H. Zhang et al., 2017). We obtain monthly weather data from the German Weather Service (DWD) for each German weather station. To capture weather at the zip code level, we select the geographically closest active weather station to each zip code's centroid. Our regression model controls for sunshine duration, wind speed, vapor pressure, humidity, and precipitation and mean, minimum, and maximum temperatures.

3.4 Treatment and Control Group

Our treatment group comprises zip codes partially covered by a LEZ. Our control group consists of zip codes outside of LEZs that lie within large cities (over 100,000 inhabitants), i.e., densely populated areas. This restriction ensures similarity with our treatment group in terms of socioeconomic and demographic characteristics, as LEZs are predominantly established in large cities and city centers (Pestel & Wozny, 2021). The zip codes treated by a LEZ and control zip codes in large cities are displayed in Figure 1. We aggregate individual-level outcomes on the zip code year level for data protection reasons and on computational grounds. This yields a sample size of 20,070 zip code by year observations, inhabited by more than 2 million insured individuals.[19]

Figure 1: Empirical Setup: LEZs and Large Cities



Note: This Figure displays our treatment and control group on county level. The treatment group is shown at its widest expansion in 2018.

Table 2 displays descriptive statistics for our time-varying zip code characteristics. There are only small socio-economic differences between treatment and control group. Within LEZs, there is a slightly larger share of individuals with a university entrance-qualifying exam (*Abitur*), albeit also a slightly higher share of individuals without schooling information. Treated zip codes also exhibit a slightly higher unemployment rate and lower purchasing power compared to the control group. Demographically, areas covered by LEZs have a higher proportion of individuals in their prime age (20-45 years old), whereas the share of older individuals is higher outside of LEZs. Further, baseline pollution levels are slightly higher within LEZs than in the control areas.

[19] We do not observe all individuals over the entire observation period. For example, the sample may include persons who were born in 2003 and appear in 2018 at the age of 15. We exclude individuals that move to a different country within the observation period.

Table 2: Descriptive statistics treatment and control group

	Outside LEZs					Inside LEZs				
Controls	mean	sd	min	max	n	mean	sd	min	max	n
Socioeconomic										
Less than Abitur	0.38	0.11	0.05	0.59	10,738	0.34	0.1	0.07	0.62	9,332
Abitur	0.28	0.09	0.04	0.53	10,738	0.3	0.09	0.05	0.56	9,332
No info on school	0.34	0.09	0.12	0.88	10,738	0.36	0.09	0.11	0.88	9,332
Purchasing power per capita	22,485	4,526	11,934	42,257	10,738	22,946	4,757	12,362	41,332	9,332
Cars per household	0.74	0.23	0.18	1.47	10,738	0.66	0.26	0.25	1.53	9,332
Number of inhabitants	15,135	7,193	610	38,587	10,738	15,946	6,824	1,028	61,667	9,332
Number of insured individuals	968	537	21	7103	10,738	823	443	21	6388	9,332
Weather										
Humidity	77.34	3.14	66.97	88.11	10,738	75.47	3.33	66.02	86.14	9,332
Precipitation	1.95	0.44	0.73	4.18	10,738	1.99	0.44	0.73	4.18	9,332
Temperature	10.24	0.97	4.17	17.32	10,738	10.74	1.01	4.14	17.8	9,332
Maximal temperature	14.5	1.23	7.77	23.05	10,738	15.16	1.14	7.75	23.54	9,332
Minimal temperature	5.95	0.97	0.19	12.28	10,738	6.41	1.15	-0.34	12.69	9,332
Vapor pressure	10.1	0.55	6.78	15.5	10,738	10.16	0.55	6.92	16.29	9,332
Wind speed	3.53	0.65	1.77	8.77	10,738	3.25	0.65	1.02	8.77	9,332
Sunny hours	4.74	0.53	2.58	7.68	10,738	4.9	0.54	2.39	7.54	9,332
Air Pollution										
PM_{10}	23.1	5.1	7.03	64.89	10,136	22.95	5.97	7.03	44.76	8,834
$PM_{2.5}$	13.6	2.1	8.9	20.71	6,516	13.89	2.11	9.18	20.77	5,679
NO_2	31.56	14.38	1.85	98.71	10,136	33.23	17.14	1.85	98.71	8,834

Note: This table displays control-variables for zip-codes inside and outside of LEZs for 2005 to 2019. Mean and standard deviation are weighted by the number of insured individuals in our sample except for the number of insured individuals itself.

4 Empirical Strategy

For identification, we exploit the staggered introduction of LEZs in Germany as exogenous variation. We first establish a Two-Way Fixed Effects (TWFE) model represented by the following regression equation:

$$Y_{it} = \beta^{TWFE} LEZ_{it} + \gamma X_{it} + \lambda_i + \phi_t + t \times \theta_c + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the average health outcome for individuals in zip code i in year t. LEZ_{it} is the treatment variable, indicating whether zip code i is within an LEZ in year t. We include zip code (λ_i) and year fixed effects (ϕ_t) and a county-specific time trend ($t \times \theta_c$) to ensure parallel trends between the treatment and control groups. Moreover, we include a set of time-varying socio-economic characteristics on zip code level X_{it}, in particular the education level as well as the purchasing power per capita. Furthermore, to ensure consistency with the estimation of LEZs on pollution, we include weather conditions as they can directly influence both mental health outcomes and pollution levels. We cluster standard errors at the county level ε_{it} since the decision where LEZs are implemented are taken by local authorities (see Section 2.1 for details). Lastly, we use the number of insured individuals per zip code in our sample as weights.

To estimate dynamic treatment effects, we establish the following event study model:

$$Y_{it} = \sum_{k=-5}^{-2} \beta_k \, \mathrm{EventTime}_{it}^{k} + \sum_{k=0}^{7} \beta_k \, \mathrm{EventTime}_{it}^{k} + \gamma \, X_{it} + \lambda_i + \phi_t + t \times \theta_c + \varepsilon_{it}, \qquad (2)$$

where $\mathrm{EventTime}_{it}^{k}$ is an indicator variable that equals 1 if zip code i is k periods away from the treatment event in period t. The coefficients β_k capture the causal impact of the LEZ introduction at different event times k relative to the reference period $k = -1$. The treatment window includes five years before and seven years after the treatment.

However, recent contributions have cast doubt on the conventional interpretation of the difference-in-differences coefficient (β^{TWFE}) in settings with numerous periods and staggered treatment implementation (see e.g., Callaway & Sant'Anna, 2021, de Chaisemartin & D'Haultfœuille, 2020a, Goodman-Bacon, 2021, Wooldridge, 2021). In these scenarios, β^{TWFE} may not accurately represent the true underlying Average Treatment Effect on the Treated (ATT). This is because it estimates a weighted average of all 2×2 comparisons of "switchers" and "non-switchers," which can introduce bias when treatment effects vary over time or between groups. These comparisons include potentially problematic scenarios, such as comparing later treated units to earlier treated ones (Goodman-Bacon, 2021). Consequently, these comparisons in the weighted average can induce a downward bias or even yield a negative coefficient, irrespective of all underlying ATTs being positive (de Chaisemartin & D'Haultfœuille, 2020b). Such issues are more pronounced when treatment outcomes differ across treatment groups or over time. In our study, the staggered implementation of LEZs may have led to time-varying treatment effects, particularly as the vehicle fleet composition changed between the initial and subsequent LEZ adoptions.

To address the concern at hand, we employ the staggered Difference-in-Differences (DiD) design proposed by Sun and Abraham (2021). This method estimates dynamic treatment effects while correcting for the biases associated with TWFE models in the presence of staggered treatment adoption. Sun and Abraham (2021) construct interaction weights that account for the timing of treatment adoption. These weights are derived from an auxiliary regression where the dependent variable is the event time indicator, and the independent variables include interactions between cohort and time indicators. This step ensures that the weights reflect the distribution of treatment timing across cohorts. The event study regression is then re-estimated using the interaction weights that adjust for the heterogeneity in treatment timing.

5 Results

5.1 LEZ Effects on Air Pollution

Table 3 displays the effect of LEZ adoption on yearly traffic-related pollutants, specifically coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2) from pollution monitors

(Columns 1-2), and fine particular matter ($PM_{2.5}$) derived from cross-validated satellite images (Column 3). All outcomes are aggregated at the zip code and year level and are log-transformed, allowing for the coefficients to be interpreted as percentage changes. The regressions follow Sun and Abraham (2021), and include time-varying socio-economic and weather controls, year and zip code fixed effects, and a county-year trend (see Section 4).

Table 3: LEZ on Air Pollution

Data source:	Pollution monitors		Cross-validated satellite estimates
Dependent variables:	$\log(PM_{10})$ (1)	$\log(NO_2)$ (2)	$\log(PM_{2.5})$ (3)
All Zip Codes			
ATT	-0.1036***	-0.1532**	-0.0309***
	(0.0314)	(0.0590)	(0.0092)
N	17,304	17,304	10,935
Zip Codes with Large Streets (≥ 3 lanes)			
ATT	-0.1227***	-0.1884***	-0.0290***
	(0.0313)	(0.0606)	(0.0077)
N	11,819	11,819	7,493
Socio-economic controls	✓	✓	✓
Weather controls	✓	✓	✓
Year fixed effects	✓	✓	✓
Zip code fixed effects	✓	✓	✓

Note: This table displays the average treatment effect on the treated of Low Emission Zones on the concentrations of different air pollutants. The dependent variables in Column (1) and (2) are measurements from air pollution monitors and in Column (3) the dependent variable are cross-validated satellite estimates from 2010 to 2018 based on Van Donkelaar et al. (2021). Socio-economic controls include information on the number of cars per household, purchasing power per capita, and the number of inhabitants. Weather controls include information on humidity, vapor pressure, precipitation, and wind speed as well as mean, minimum, and maximum temperature. The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

We find that the introduction of LEZs reduced yearly coarse particulate matter concentrations in zip codes covered by a LEZ by on average 10.4 percent. This ATT is statistically significant at the one percent level. The effect size is consistent with previous studies on the effectiveness of LEZs in reducing coarse particulate matter (Sarmiento et al., 2023, Wolff, 2014) and translates into a reduction of 2.5 $\mu g/m^3$. Regarding nitrogen dioxide (Column 2), we find that the introduction of LEZs decreased yearly pollution levels by an average of 15.3 percent, which is statistically significant at the five percent level. It translates into a reduction of 4.8 $\mu g/m^3$. This effect aligns with recent findings by Sarmiento et al. (2023).

In Column (3), we use cross-validated satellite images to measure fine particulate matter levels aggregated to the zip code level, extending beyond pollution monitor data (Van Donkelaar et al., 2021). We find that the introduction of LEZs reduced yearly $PM_{2.5}$ levels by on average 3.1 percent, a statistically significant effect at the one percent level. This translates into a reduction of 0.4 μg/m^3. However, this reduction is notably smaller than the reduction observed for coarse particulate matter (PM_{10}). Two factors could explain the differences in the measured impacts of LEZs on PM_{10} and $PM_{2.5}$. First, the distinct sources and behaviors of these pollutants are highlighted. Coarse particulate matter (PM_{10}), primarily emitted from vehicular activities such as diesel engine exhaust, is more strongly impacted by driving restriction policies. In contrast, $PM_{2.5}$ includes finer particles that, while also resulting directly from vehicle exhausts, often form through regional atmospheric chemical reactions involving sulfate and nitrate particles (Pope & Dockery, 2006). The satellite-based $PM_{2.5}$ data reflect these broader regional influences, which can dilute the local effects of LEZs.[20] Second, satellite measurements may not fully capture ground-level reductions in pollution, potentially underestimating the policy's impact with respect to $PM_{2.5}$ (Holloway et al., 2021).[21,22]

In the lower part of Table 3 we focus on zip codes with large streets ($\geq$ 3 lanes) as we expect larger effect sizes in areas with higher traffic volume.[23] As expected, estimates based on monitor data (Columns 1-2) become larger in magnitude and the statistical significance tends to increase. The exception is fine particulate matter ($PM_{2.5}$) where the coefficient becomes marginally smaller. The underlying reason may again be connected to satellites not being able to precisely capture ground-level reductions. In Figure B.2, we perform the same analysis on air pollution levels instead of logs, and similar picture emerges.

Figure 2 displays dynamic treatment effects for all pollutants corresponding to the estimations presented in Table 3. In line with evidence from the existing literature, the dynamic results suggest that LEZs have become more effective over time in reducing pollutants (e.g., Margaryan, 2021, Sarmiento et al., 2023). One reason for this finding may be changes in the vehicle fleet composition, as vehicles not allowed to enter LEZs are substituted with cleaner ones over time (Margaryan, 2021, Wolff, 2014). In the Appendix, in Figure B.1 we analyze whether LEZ introduction also affects other pollutants recorded by the pollution monitors (SO_2 and O_3) and find statistically significant reductions for SO_2.

5.2 LEZ Effects on Mental Health Outcomes

Table 4 presents the average treatment effects on the treated for our primary mental health indicators. These indicators are defined as average probabilities at the year-zip code level,

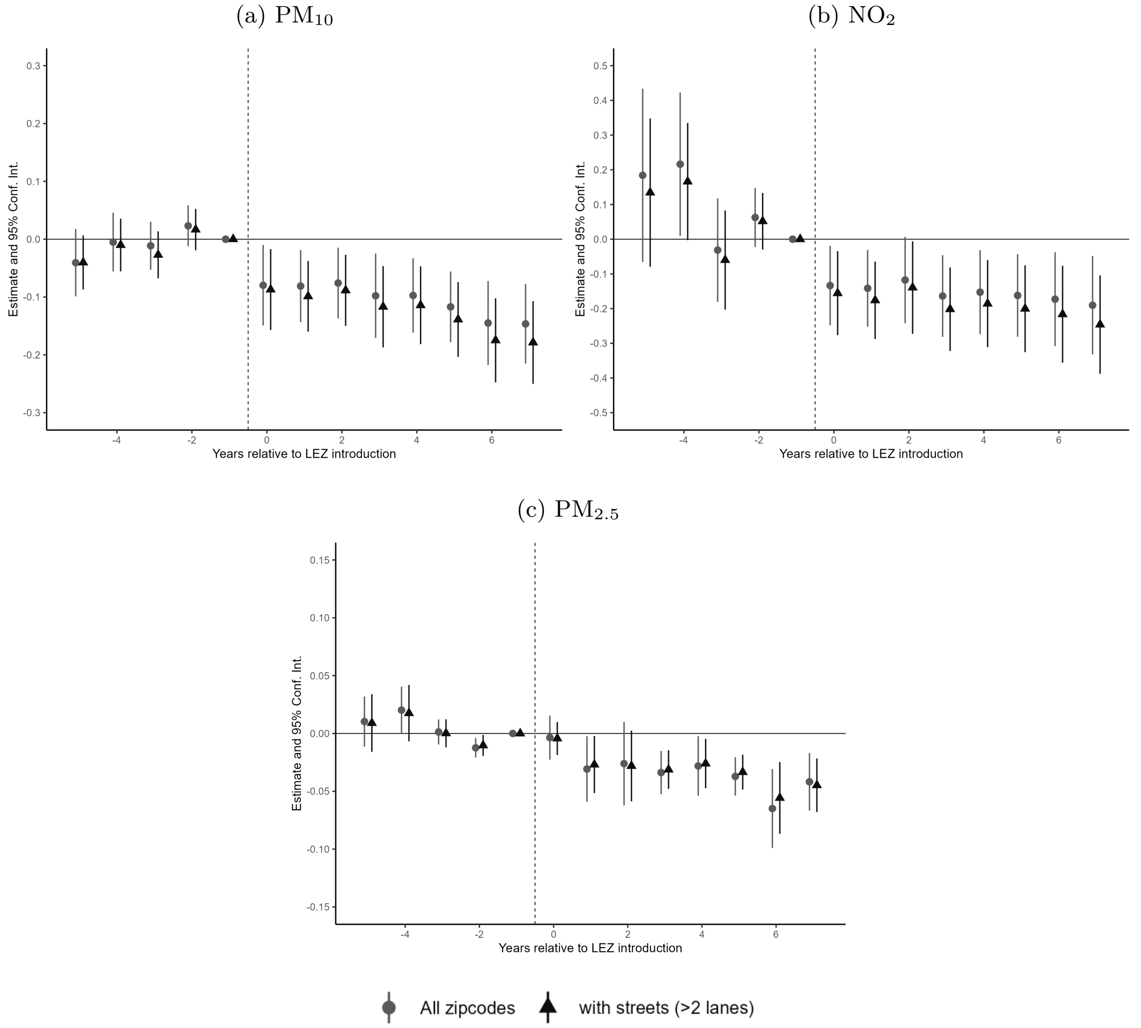
[20] Indeed, Van Donkelaar et al. (2021) make the following disclaimer: "Note that these estimates are primarily intended to aid in large-scale studies. Gridded datasets are provided to allow users to agglomerate data as best meets their particular needs. Datasets are gridded at the finest resolution of the information sources that were incorporated ($0.01° \times 0.01°$), but do not fully resolve $PM_{2.5}$ gradients at the gridded resolution due to influence by information sources at coarser resolution."

[21] The limited "vertical sensitivity", i.e., the (in)ability of satellite instruments to detect and accurately measure concentrations of pollutants at different altitudes within the atmosphere, is due to factors such as surface reflectivity, cloud cover, viewing geometry, and decreased instrument sensitivity near the ground caused by atmospheric scattering and reduced thermal contrast (see e.g., Martin, 2008).

[22] Using a subset of pollution monitor data due to data constraints, Klauber et al. (2024) find no effect of LEZ introduction on $PM_{2.5}$.

[23] We use a publicly available landscape model that contains every main road within Germany (Bundesamt für Kartographie und Geodäsie, 2021).

Figure 2: Effect of LEZ Introduction on Air Pollutants



Note: This figure displays dynamic effects of Low Emission Zones on yearly particulate matter (PM_{10}) and nitrogen dioxide (NO_2) from pollution monitors (a and b) and fine particular matter ($PM_{2.5}$) derived from cross-validated satellite images (c) in logs. Specifications correspond to Table 3. The effects are estimated using estimators proposed by Sun and Abraham (2021). Estimates are shown including 95% confidence intervals.

interpreted as an extensive margin. We begin by examining the impact of air quality improvements following the introduction of LEZs on the average probability of being prescribed antidepressants (Column 1) and on visiting a specialist, such as a psychotherapist or psychiatrist (Column 2). We find a statistically significant 4 percent reduction in the probability of being prescribed antidepressants. This translates into a reduction of the zip code incidence from 7.3 to 7 percent. For the probability of visiting a specialist, our estimated effect is a 5.7 percent reduction, which corresponds to a decrease in the zip-code level incidence from 6.2 to 5.9 percent. Moreover, we report the effects of LEZs on mental health diagnoses such as depression (Column 3, Table 4) and anxiety disorder diagnoses (Column 4). Our findings indicate that individuals residing in zip codes with LEZs have a 3.5 percent lower probability of being diagnosed with depression, a statistically significant result at the five percent level. That is, the incidence decreases from 6.7 to 6.5 percent at the zip-code level. Similarly, the introduction of LEZs results in a statistically significant 4.2 percent reduction in the probability of being diagnosed with an anxiety disorder, which in turn translates into an incidence reduction from 6.2 to 6 percent. These effect sizes are meaningful and the relative magnitude lies between the effects of LEZs on hospitalizations related to cardiovascular diseases reported by Margaryan (2021) and Pestel and Wozny (2021).

Table 4: Effect of LEZ Introduction on Extensive Margin Mental Health Outcomes

Dependent variables in log:	Antidepressant probability	Specialist visit probability	Depression probability	Anxiety probability
Model:	(1)	(2)	(3)	(4)
ATT	-0.0403***	-0.0573**	-0.0350**	-0.0416***
	(0.0102)	(0.0218)	(0.0140)	(0.0146)
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓
Mean of dependent variable	0.0734	0.0618	0.0669	0.0624
R^2	0.90	0.88	0.91	0.88
N	17,896	17,886	17,894	17,893

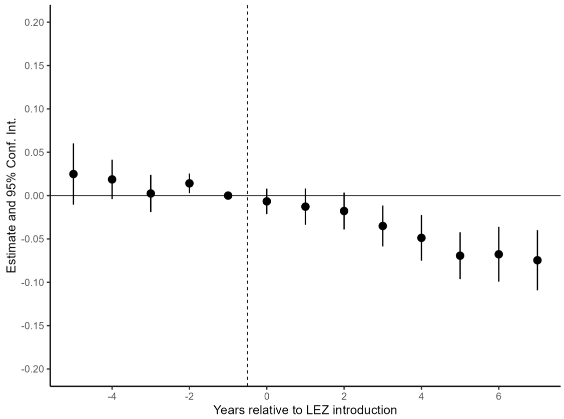
Note: This table displays the average treatment effect on the treated of Low Emission Zones on different average probabilities in logs. All variables are on zipcode-year level. Column (1) shows the estimated effects on the probability to be described antidepressants. Column (2) shows the estimated effects on the probability of a specialist visit (for detailed information on how a specialist visit is defined see section 3). Columns (3) and (4) show estimated effects on the probability of depression and anxiety diagnoses. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

Figure 3 illustrates the dynamic treatment effects for our mental health outcomes at the extensive margin, corresponding to Columns 1-4 in Table 4. The event studies confirm the absence of statistically significant pre-treatment trends, which supports our identifying assumption of parallel trends. A general pattern emerges: all outcomes begin to decline after the introduction of LEZs, but the improvement in mental health materializes only gradually. The dynamic treatment effect tends to peak five to six years after LEZ adoption, suggesting that the cumulative improvement in air quality over time leads to meaningful reductions in mental health issues within the population. The findings align with recent evidence on the health effects of LEZs (Klauber et al., 2024, Pestel & Wozny, 2021), where the authors find that effects become larger over time. This likely occurs because it takes time for longer-term exposure to air pollution to manifest in health outcomes (see e.g., Health Effects Institute, 2022, for a systematic review of the health effects of long-term exposure to air pollution).

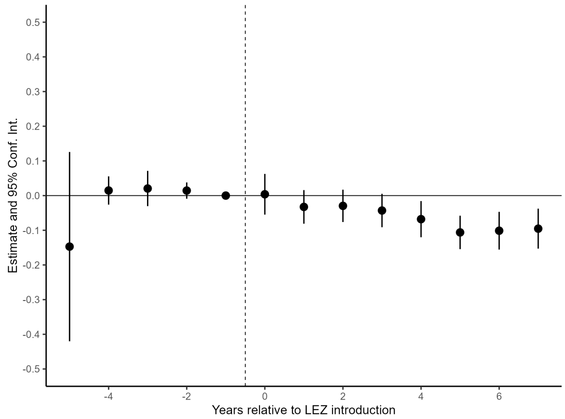
Turning to intensive margin, Table 5 displays our estimated effects of LEZs in terms of intensity of the treatment effect. We present the intensive margin by including the average

Figure 3: Event Studies of LEZ Introduction on Extensive Margin Mental Health Outcomes

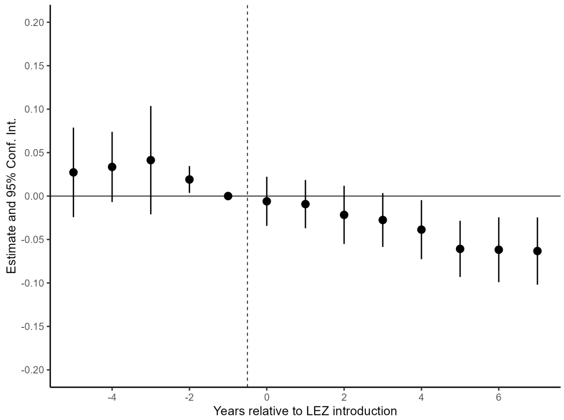
(a) Antidepressant probability



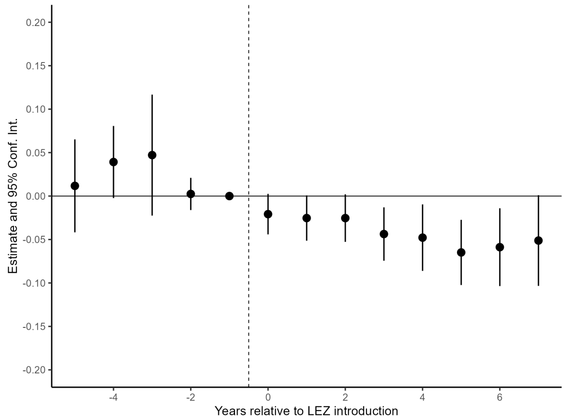
(b) Specialist visit probability



(c) Depression probability



(d) Anxiety probability



Note: This figure displays the dynamic effects of Low Emission Zones on different average probabilities in logs. The effects are estimated using estimators proposed by Sun and Abraham (2021). Panel (a) shows the estimated effects on the probability to be described antidepressants (for detailed information on ATCs see Appendix A.4). Panel (b) shows the estimated effects on the probability of a specialist visit (for detailed information on how a specialist visit is defined see section 3). Panel (c) and (d) show estimated effects on Depression and Anxiety diagnosis (for detailed information on ICDs see Appendix A.3). Specifications correspond to Table 4. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

number of antidepressant prescriptions. To improve interpretability, we also include the average defined daily doses (DDD) per individual. This approach accounts for the intensity of each prescription, by weighting individuals according their clinical need. We find that LEZs reduce the number of prescriptions by approximately 5.7 percent and DDDs by about 5.2 percent. In other words, the average number of yearly prescriptions per individual is reduced from 0.26 to 0.24. Similar to Column (2) in Table 4, we also include an intensive measure for specialist visits (Column 3)[24]. In Column (4), we include the number of specialist billings as an outcome, covering all available psychotherapy billings[25]. The estimated effect of LEZs on specialist visits is a reduction of 7.4 percent, while the effect on specialist billings is a reduction of about 5 percent. Those effects translate into

[24]Counting specialist visits in Germany is challenging because actual visits are not directly observable; researchers only observe quarterly cases.

[25]Billings include different quantities of therapy sessions.

Table 5: Effect of LEZ Introduction on Intensive Margin Mental Health Outcomes

Dependent variables in log:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
Model:	(1)	(2)	(3)	(4)
ATT	-0.0574***	-0.0513***	-0.0739***	-0.0495***
	(0.0113)	(0.0138)	(0.0218)	(0.0172)
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓
Mean of dependent variable	0.26	18.53	0.18	1.67
R^2	0.89	0.91	0.88	0.92
N	17,896	17,896	17,886	17,910

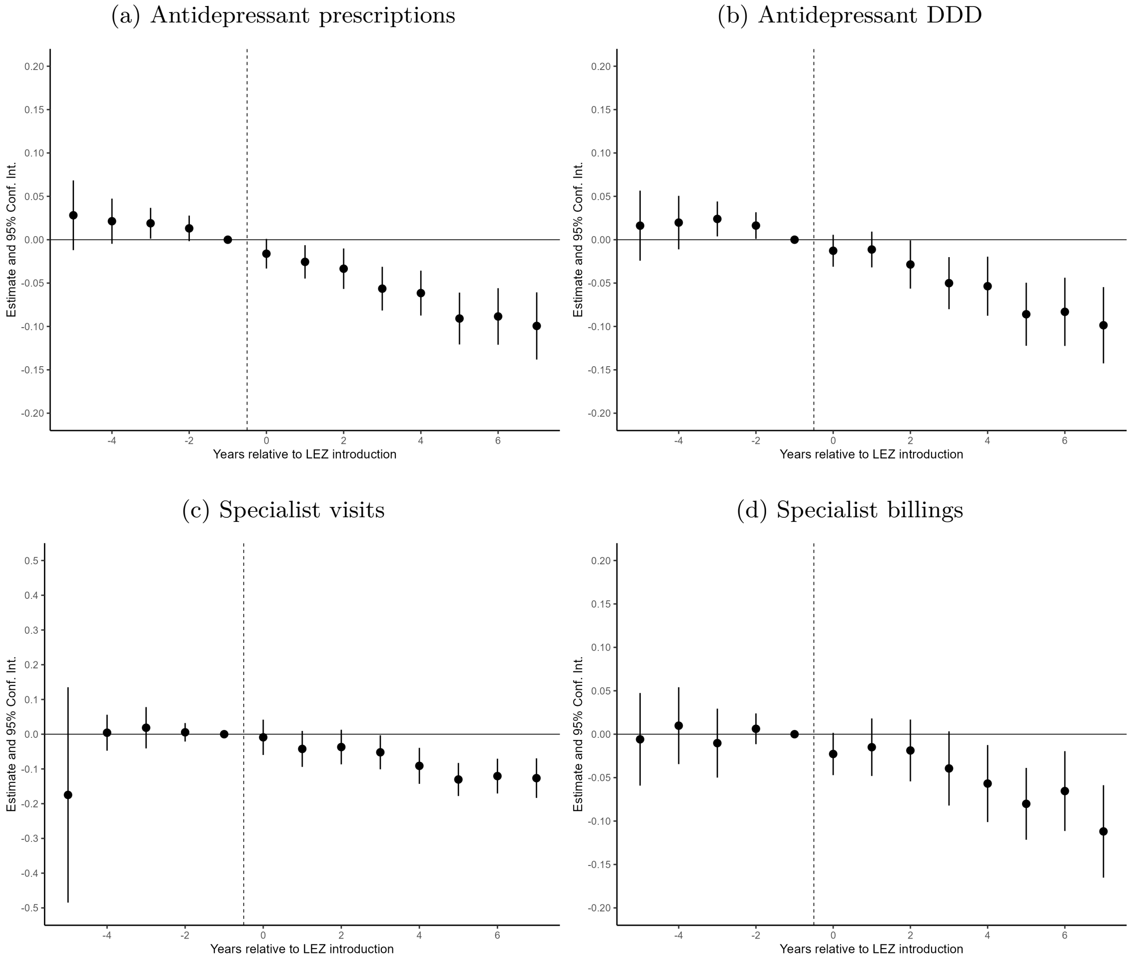
Note: This table displays the average treatment effect on the treated of Low Emission Zones on different intensive measures in logs. All variables are on the zipcode-year level. Columns (1) and (2) show estimated effects on Antidepressants. Column (1) describes the effect on the average number of prescriptions, Column (2) the effect on the average number of defined daily dosages (DDD). Column (3) shows the estimated effects on the average number of specialist visits. A visit is defined on the quarterly level resulting in a maximum of 4 visits per doctor (for detailed information on specialists see section 3). Column (4) shows the estimated effects on the average number of specialist billings in terms of psychotherapy. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

an average reduction of the number of yearly specialist visits per individual from 0.18 to 0.17 and a reduction of the average number of specialist billings from 1.67 to 1.59. Both estimates are significant at the one percent level. All estimates at the intensive margin are larger than the corresponding estimates at the extensive margin. This suggests that air quality improvements reduce the probability of getting a new diagnosis but may also alleviate the mental health suffering of those already diagnosed with a mental health issue.

Figure 4 displays the dynamic treatment effects for the intensive margin of our mental health outcomes. We estimate the largest effects in all outcomes around 5 to 6 years after LEZs were adopted effect. Similar to the results displayed in Figure 3, the cumulative effects of cleaner air on the mental health outcomes take time to materialize.

We do not observe large discrepancies in the timing of the effect across outcomes in Figures 3 and 4. Antidepressant Prescriptions (Figure 4, Panel a) decrease slightly sooner than depression and anxiety diagnoses (Figure 3, Panel c and d), which become statistically significant two and three years after treatment. Specialist visits tend to take the longest to decrease (Figure 3, Panel b, and Figure 4, Panels c and d). This chronology makes sense because antidepressant prescriptions can be prescribed by general practitioners and psychiatrists. Patients experiencing acute symptoms (like feeling down or having trouble sleeping) might receive medication relatively quickly as an initial treatment. Psychotherapy visits may involve longer delays due to patient behavior (delaying seeking specialist

Figure 4: Event Studies LEZ Introduction on Mental Health Outcomes at the Intensive Margin



Note: This figure displays dynamic effects of Low Emission Zones on different intensive measures in logs. The effects are estimated using estimators proposed by Sun and Abraham (2021). All variables are on zipcode-year level. Panel (a) and (b) show estimated effects on antidepressants. Panel (a) describes the effect on the average number of prescriptions, Panel (b) the effect on the average number of defined daily dosages (DDD). For detailed information on ATCs see Table A.4. For information on DDD see section 3. Panel (c) shows the estimated effects on the average number of specialist cases. A case is defined on quarterly level resulting in a maximum of 4 visits per doctor (for detailed information on specialists see section 3). Panel (d) shows the estimated effects on the average number of specialists billings in terms of psychotherapy (for detailed information on specialist billings see Appendix A.2). Specifications correspond to Table 5. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

help) and systemic factors (waiting periods for therapy appointments, see Section 2.2).

Overall, a consistent picture emerges from our analyses of mental health outcomes. First, the introduction of LEZs results in significant reductions in the probability of mental health issues within treated zip codes. These effects are statistically significant and economically meaningful. Second, the effects of air quality improvements on mental health outcomes are cumulative and take time to materialize. Last, we observe consistent effects at both the extensive and intensive margins, indicating that LEZs and the resulting air quality improvements reduce the intensity of mental health issues.

5.3 Confirmatory and Placebo Exercises

Next, we assess whether our method effectively replicates established findings from the literature and identifies effects in a placebo exercise. Several papers have demonstrated the effectiveness of LEZs in reducing diagnoses and prescriptions for cardiovascular diseases (Margaryan, 2021, Pestel & Wozny, 2021). In Table 6 we display the effect of the introduction of LEZs on the probability of a diagnosis related to cardiovascular diseases (Column 1), respective prescriptions (Column 2), and their DDDs (Column 3). We find that LEZs reduce the probability of a diagnosis by 2.1 percent, prescriptions by 2.8 percent and their DDDs by 3.1 percent. The estimates are statistically significant at conventional significance levels. Moreover, the effect sizes fall between those reported by Margaryan (2021) and Pestel and Wozny (2021). Figure 5 displays the dynamic treatment effects for those outcomes in an event study approach with the estimations corresponding to Table 6. Again, we find no evidence of statistically significant pre-trends but clear evidence of statistically significant dynamic effects, which increase in size over time.

Table 6: Effect of LEZ Introduction on Cardiovascular Diseases and Injuries

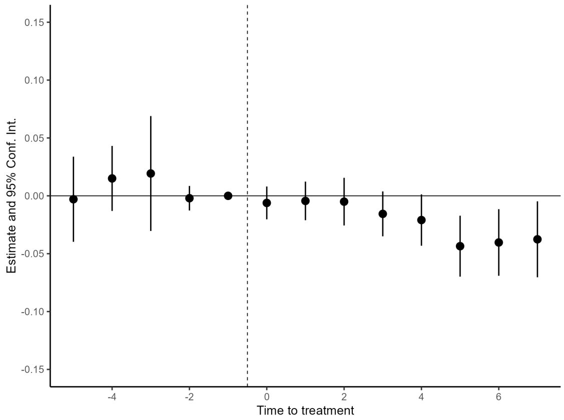
Dependent variables in log:	Cardiovascular disease probability	Cardiovascular prescriptions probability	Cardiovascular prescriptions DDD	Injury probability
Model:	(1)	(2)	(3)	(4)
ATT	-0.0209**	-0.0275***	-0.0310***	-0.0061
	(0.0093)	(0.0098)	(0.0115)	(0.0136)
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓
Mean of dependent variable	0.33	0.21	128.3	0.1
R^2	0.90	0.92	0.92	0.85
N	17,910	17,903	17,903	17,904

Note: This table displays the average treatment effect on the treated of Low Emission Zones on different average probabilities in logs. All variables are on zipcode-year level. Column (1) and (2) show estimated effects on outcomes related to Cardiovascular diseases. Column (1) in terms of diagnosis and Column (2) in terms of prescriptions. Column (3) shows the estimated effects on the probability of a diagnosis related to an injury. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

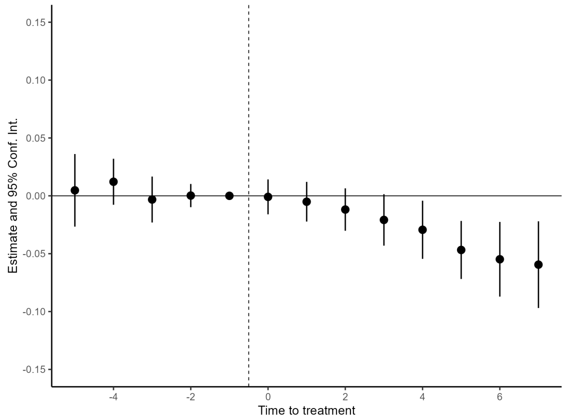
To investigate whether our empirical strategy identifies effects where we would not theoretically expect any, we perform a placebo exercise. For this purpose, we identify ICD codes related to injuries[26] and estimate the effect of LEZ introduction on their probability. We find that the introduction of LEZs did not affect the probability of injuries (Table 6, Column 4 and Figure 5, Panel d).

Figure 5: Event Studies Confirmatory and Placebo Excercise

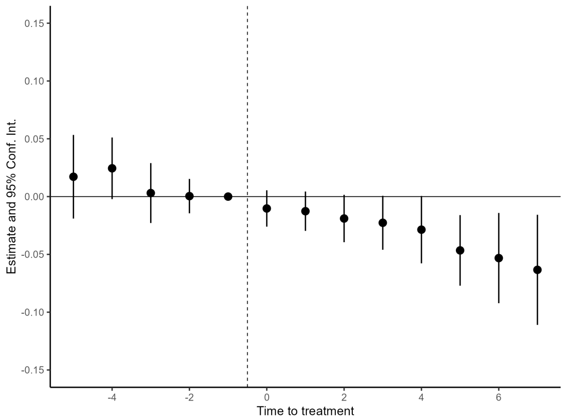
(a) Probability of cardiovascular diseases



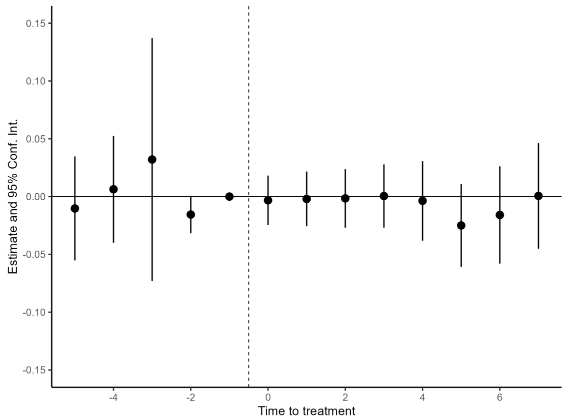
(b) Probability of cardiovascular prescription



(c) Prescriptions cardiovascular DDD



(d) Injury probability



Note: This figure displays dynamic effects of Low Emission Zones on different average probabilities in logs. All variables are on zipcode-year level. Panels (a) and (b) show estimated effects on outcomes related to cardiovascular diseases. Panel (a) in terms of diagnosis (for detailed information on ICDs see Appendix A.3), Panel (b) of prescriptions, and Panel (c) of the defined daily dosage (DDD) of prescriptions. For detailed information on ICDs and ATCs see Appendix A.3 and A.4. For information on DDD, see section 3. Panel (d) shows the estimated effects on the probability of a diagnosis related to an injury. Specifications correspond to Table 6. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals. *p<0.1; **p<0.05; ***p<0.01

5.4 Robustness Checks

In this section, we investigate the robustness of our estimations regarding spatial spillovers, alternative sample construction and estimators. First, LEZs could affect the health of those living in zip located just outside their borders. Theoretically, these areas could either benefit from improved air quality or be disadvantaged by increases in pollution as drivers circumvent the LEZ with emission-intensive cars. The latter scenario is particularly concerning as it could lead to overestimation of the treatment effects as pollution levels increase in parts of the control group. To address these concerns, we adopt the approach of Klauber et al. (2024) and include a treatment indicator for zip codes within a 10-kilometer radius of LEZs, set to one if the neighboring LEZ is active and zero otherwise. We generally observe negative coefficients for neighboring zip codes that are not statistically significant, while our main treatment effects remain consistent (Rows 2 and 4

[26] ICD-Chapter S: This chapter specifically covers injuries to specific body parts.

Table 7: Accounting for Spillovers

	Extensive margin			
Dependent variables in log:	Antidepressant prescription probability	Specialist visit probability	Depression probability	Anxiety probability
Spillover: neighbouring zip codes				
ATT on LEZ-zip codes	-0.0413**	-0.0597**	-0.0297	-0.0419*
	(0.0178)	(0.0300)	(0.0253)	(0.0232)
ATT on neighbouring zip codes (10 km)	-0.0037	-0.0085	0.0186	-0.0012
	(0.0446)	(0.0500)	(0.0560)	(0.0607)
N	17,896	17,886	17,894	17,893

	Intensive margin			
Dependent variables in log:	Antidepressant prescriptions	Antidepressant prescriptions DDD	Specialist visits	Specialist billings
Spillover: neighbouring zip codes				
ATT on LEZ-zip codes	-0.0587***	-0.0507**	-0.0755**	-0.0560**
	(0.0188)	(0.0220)	(0.0303)	(0.0263)
ATT on neighbouring zip codes (10 km)	-0.0046	0.0023	-0.0055	-0.0228
	(0.0431)	(0.0457)	(0.0524)	(0.0570)
N	17,896	17,896	17,886	17,910
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓

Note: This table displays the average treatment effect on the treated of Low Emission Zones on different average probabilities in logs. Row 1 and 2 report outcomes at the extensive margin while Row 3 and 4 report outcomes measured at the intensive margin. All variables are on zipcode-year level. Row 1 and Row 3 display the coefficients of a standard TWFE estimation. Row 2 and 4 add an additional binary variable for zip codes neighbouring an active LEZ. Column (1) shows the estimated effects on the probability to be described antidepressants. Column (2) shows the estimated effects on the probability of a specialist visit (for detailed information on how a specialist visit is defined see Section 3). Column (3) and (4) show estimated effects on Depression and Anxiety diagnosis. Columns (5) and (6) show estimated effects on Antidepressants. Column (5) describes the effect on the average number of prescriptions, (6) the effect on the average number of defined daily dosages (DDD). Column (7) shows the estimated effects on the average number of specialist visits. A visit is defined on the quarterly level resulting in a maximum of 4 visits per doctor (for detailed information on specialists see Section 3). Column (8) shows the estimated effects on the average number of specialist billings in terms of psychotherapy. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021) unless othewise specified. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

of Table 7). These findings are in line with Klauber et al. (2024) who report that German LEZs had no negative spillovers but rather positive effects on air quality and vehicle fleet composition in neighboring counties. Overall, these findings suggest that our treatment effects are not overestimated due to negative spillovers of polluting traffic into the control group.

Second, we examine the robustness of our results to altering the sample construction. In our main sample, we exclude individuals who change their county of residence during the sample period to address potential selection biases related to relocations within LEZs during the study. Table B.3 displays the estimation without excluding any individual that moves their residence during the sample period. The coefficients remain qualitatively similar, but the statistical significance of the estimates increases due to the larger sample size. We interpret these findings as further evidence that compositional changes are not driving the results.

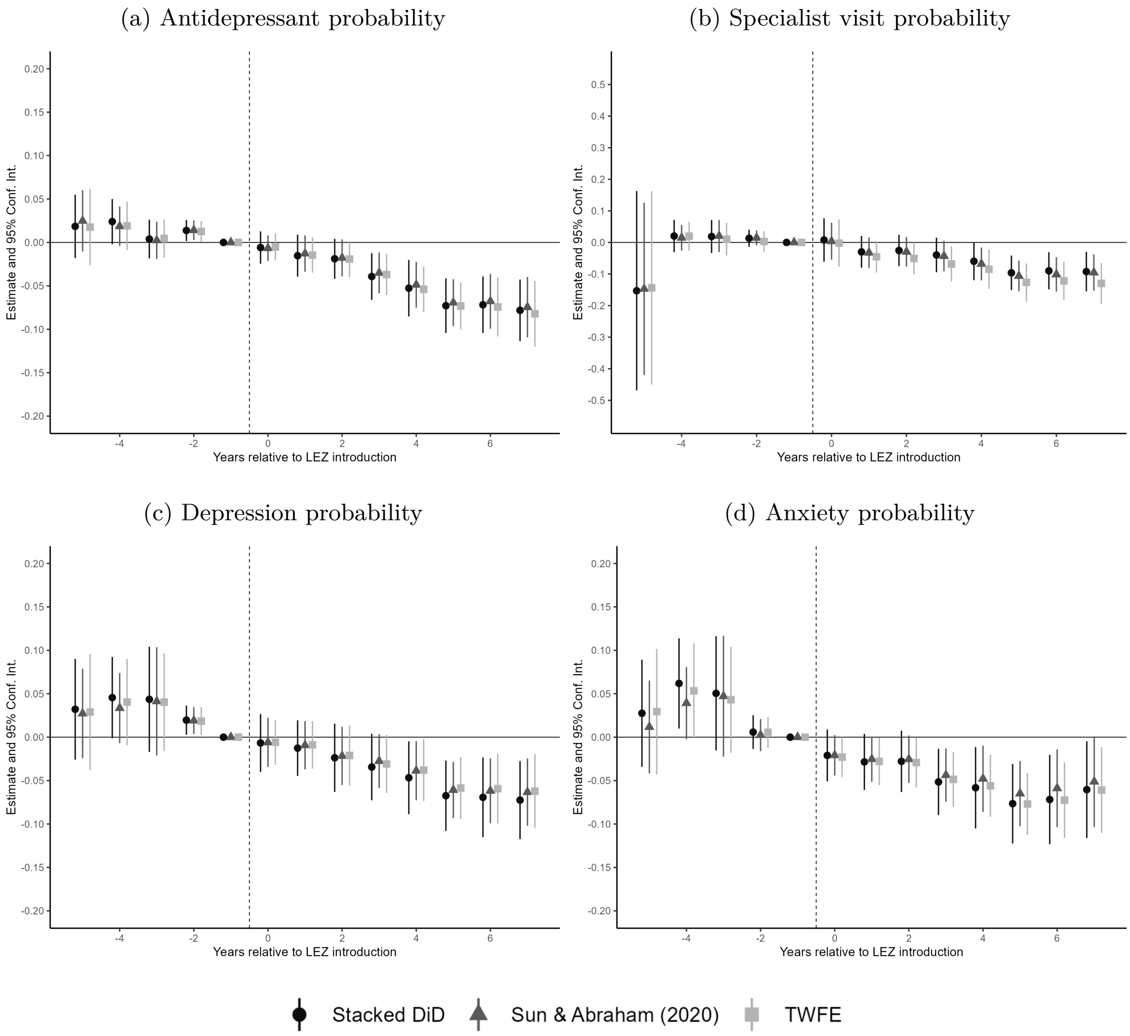
Finally, several estimators have been proposed to address concerns regarding biases arising from the combination of potentially heterogeneous treatment effects and negative weighting in staggered treatment settings. In our main analysis, we employ the estimator proposed by Sun and Abraham (2021). To test whether our results are robust to an alternative estimator choice, we use the canonical and stacked DID estimator. This estimator is a flexible and intuitive approach which has been applied in various contexts (see e.g. Baker et al. 2022, Cengiz et al. 2019, Deshpande and Li 2019, Klauber et al. 2024). Essentially, we select a control group of never-treated and not-yet-treated observations for each year in which an LEZ was introduced to ensure a clean comparison group. These event-specific datasets are then stacked and aligned based on treatment timing and not calender time which addresses the negative weight issue. Table B.4 displays the results using the TWFE as well as the stacked DID approach. The results stay qualitatively the same. Figure 6 displays the dynamic treatment effects for those estimators, in addition to the estimator proposed by Sun and Abraham (2021). The eventstudies display a similar pattern, independent of the estimation method used.

5.5 Heterogeneities

In this section, we examine whether our findings vary across age groups, building on findings from the previous literature (e.g., Bishop et al., 2023, Currie & Neidell, 2005, Ju et al., 2023) indicating that different age groups exhibit varying levels of vulnerability to air pollution. In Figure 7 we show results for three age groups: 15 to 29, 30 to 49, and 50 to 65 year olds. Overall, the effect appears to be more pronounced for the youngest age group of 15 to 29 years, which is also the group with the highest depression rates (see e.g., Hapke et al., 2019). While the observed effects are only statistically different from one another for the antidepressant prescription probability (Figure 7, Panel c), it is striking that the same pattern emerges for all outcomes.

One possible explanation for this is that exposure to inflammatory stimuli may exert a more pronounced effect during adolescence due to ongoing brain development (Danese & Baldwin, 2017, Roberts et al., 2019). For example, children exposed to high levels of air pollution in Mexico City exhibited significant differences in white matter volumes and associated cognitive impairments compared to those in less polluted areas (Calderón-Garcidueñas et al., 2015). In addition, due to their higher breathing rate to body size ratio, and less developed natural barriers in the lungs warding against inhaled particles, children and adolescents are more susceptible to airborne pollutants in their environment (Brockmeyer & d'Angiulli, 2016). Another factor may relate to differences in lifestyle, as younger people tend to spend more time engaging in outdoor activities (Brasche & Bischof, 2005), thereby increasing their exposure to air pollution. The stronger effects for young people are also consistent with the economic literature on the long-term health

Figure 6: Eventstudies of Alternative Estimators

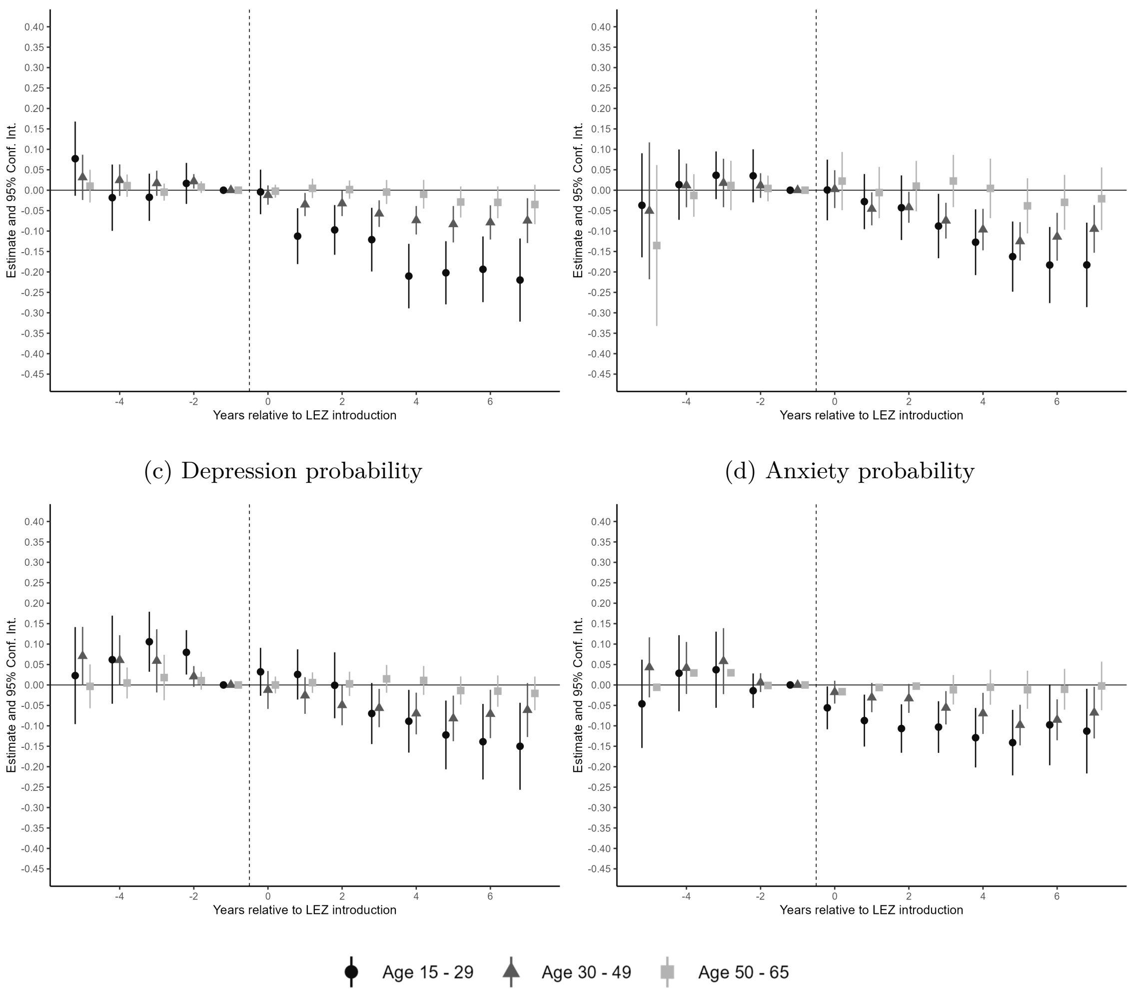


Note: This figure displays the dynamic effects of Low Emission Zones on different average probabilities in logs, see Table 4 for a description of the outcomes. The figure displays the estimates using the estimator proposed by Sun and Abraham (2021), the stacked difference-in-differences approach (Cengiz et al., 2019, Klauber et al., 2024) as well as the canonical TWFE. Specifications correspond to Table 4 and Table B.4. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

effects of early exposure to air pollution (e.g., Chay & Greenstone, 2003, Currie & Neidell, 2005, Luechinger, 2014), as well as the short- and medium-term effects of air pollution on schooling outcomes (e.g., Brehm et al., 2022, Persico & Marcotte, 2022).

Interestingly, we consistently observe no effects on the oldest age group (aged 50 to 65). Recent research has documented a positive relationship between long-term cumulative exposure to fine-particulate air pollution later in life and neurodegenerative diseases like dementia (Bishop et al., 2023, Peters et al., 2019), which are also associated with neuroinflammation due to $PM_{2.5}$ accumulation in brain tissue (Kang et al., 2021, Maher et al., 2016). Thus, exposure to air pollution and the resulting inflammatory processes may have age-specific implications for brain-related outcomes: younger individuals may face an increased risk of depression and anxiety, while older individuals may face a higher risk of neurodegenerative diseases.

Figure 7: Event Studies Age Heterogeneity



(a) Antidepressant prescription probability

(b) Specialist visit probability

(c) Depression probability

(d) Anxiety probability

Note: This figure displays dynamic effects of Low Emission Zones on different average probabilities in logs for sub samples in terms of age. The effects are estimated using estimators proposed by Sun and Abraham (2021). All variables are on zipcode-year level. Panel (a) shows the estimated effects on the probability to be described antidepressants (for detailed information on ATCs see Appendix A.4). Panel (b) shows the estimated effects on the probability of a specialist visit (for detailed information on how a specialist visit is defined see Section 3). Panels (c) and (d) show estimated effects on Depression and Anxiety diagnosis (for detailed information on ICDs see Appendix A.3). Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. Estimators are shown including 95% confidence intervals.

5.6 Mechanisms

In this section, we conduct a series of complementary analyses to evaluate the potential mechanisms through which LEZs may impact mental health, as discussed in Section 2.3. Although our data does not allow for a direct examination of biological pathways, such as the effects of reduced air pollution on brain function via inflammation and oxidative stress, we test three alternative channels.

Indirect Effects Through Improved Physical Health. Improved air quality through LEZs may affect mental health indirectly by enhancing physical health. Particularly cardiovascular diseases, which are known to be affected by air pollution (see e.g. Margaryan (2021), Pestel and Wozny (2021) and Figure 5, Panel (a) and (b)), are often linked to psychological distress (Goldfarb et al., 2022, Rafiei et al., 2023). To test whether this indirect channel drives our results, we estimate the effect of LEZ introduction on our main outcomes for two sub-samples: individuals diagnosed with cardiovascular disease during the study period and those without any cardiovascular issues. Figure B.5 displays the dynamic effects of LEZs on our main outcomes for the two sub-samples. We find that the effects are more pronounced in the sub-sample without cardiovascular-related diagnoses, suggesting that the indirect channel through cardiovascular health is unlikely to explain our main results.

Noise and Traffic Volume Reduction. While we cannot directly control for traffic noise[27], we address this potential confounder by conducting a robustness check with a sample limited to zip codes with lower traffic volumes, excluding those with major roads. Since air pollution spreads farther than noise (Khan et al., 2018), any remaining air quality improvements should persist, while noise reductions would be minimized. Contrary to expectations, we find slightly larger point estimates, as shown in Table B.1, indicating that noise does not substantially affect our results.[28]

Additionally, given that sleep disorders can be linked to both air pollution (Cao et al., 2021, Liu et al., 2020) and chronic noise exposure (Hahad et al., 2024, Hegewald et al., 2020), we test whether LEZs resulted in a spatially explicit lower probability of diagnosed sleep disorders. We find sizable and statistically significant effects, which, however, do not seem to depend on the presence of large streets (Table B.2). As with our main analyses, it is not possible to fully disentangle the effects of air pollution reduction from those of noise reduction on the outcome. However, since noise would likely have a more direct impact on sleep next to main roads, we interpret this result as evidence that noise reduction is not the primary mechanism driving our main findings.[29]

Furthermore, we investigate the impact of LEZs on traffic volume using vehicle count data from German traffic monitors provided by the Federal Highway Research Agency (BASt). Our findings show no significant changes in traffic volume (Table B.3), which aligns with existing research suggesting that the impact of German LEZs on air pollution is primarily driven by changes in the vehicle fleet composition rather than traffic volume reductions.[30]

[27] Although there are three waves of noise maps for Germany (2007, 2012, and 2017) that span our observation period, inconsistencies in the data generation methodology across these waves prevent the construction of a reliable panel.

[28] One possible reason for the slight increase in estimates could be that by excluding major roads, we also exclude highways such as the Federal Highway 100 (*Bundesautobahn 100*) in Berlin, which are geographically within LEZs but exempt from LEZ regulations.

[29] Nonetheless, we cannot entirely rule out the possibility that changes in noise levels contribute to the observed effects. Even if noise plays a role in the impact on mental health, it is likely that this factor would also affect other traffic-related policies aimed at reducing air pollution, such as license plate restrictions, scrapping schemes, and bans on older vehicles.

[30] Specifically, Pestel and Wozny (2021) and Klauber et al. (2024) also find no significant effects of LEZs on traffic volumes, while Wolff (2014) and Klauber et al. (2024) document effects on the composition of the vehicle fleet.

Economic Activity. Lastly, we examine whether LEZs influenced local economic activity, either through productivity gains or changes in the socio-economic composition of the population. Although our analysis excludes individuals who move during the observation period, their mental health could still be affected by shifts in neighborhood economic conditions. However, Figure B.4 shows no significant impact of LEZs on local unemployment rates or purchasing power. This lack of substantial changes in key economic indicators suggests that economic activity is unlikely to be a primary mechanism driving the observed mental health improvements.

Overall, while we cannot fully discard additional channels, our analyses provide evidence that the direct biological effects of reduced air pollution on the are the primary driver of the observed improvements in mental health outcomes, rather than indirect pathways through improved physical health, noise reduction, or economic activity.

5.7 Retrospective Design Analysis

We conduct a retrospective design analysis to assess the plausibility of our effect sizes, recognizing that the interpretation of statistically significant results depends on the plausible size of the underlying effect. We follow Gelman and Carlin (2014), calculating the probability of an estimate being in the wrong direction (Type S error) and the factor by which the magnitude of our effects might be overestimated (Type M error, magnitude error or exaggeration ratio). The first step involves positing true effect sizes based on the literature. However, as mentioned earlier, very few causal studies exist on the link between air pollution and mental health. Beshir and Fichera (2022) find that the introduction of ULEZ reduced anxiety by 6.5 percent based on self-reported survey data. Pestel and Wozny (2021) is most comparable in terms of our sample and set-up and provides evidence for reductions in circulatory and respiratory diseases ranging from 8 to 16 percent. The issue is further complicated as effect estimates from the literature may themselves be overestimated due to power issues. Consequently, we posit a wide range of plausible effects (one to eight percent) and examine how our power, type S error, and type M error rates change accordingly. Given the various outcomes, we focus on depression diagnosis probability and the number of antidepressant prescriptions as they are the most conservative estimates with the highest p-value in both extensive and intensive margins.

Table B.5 displays a range of effect sizes as well as their corresponding power and the Type S and Type M errors. Our retrospective design analysis suggests that the probability that our estimates have the wrong sign is essentially zero. Our estimated effect and standard error for the probability of a depression diagnosis, suggest a power of 0.71, with an exaggeration rate of 1.2. This suggests that we may be overestimating the true effect size by a factor of 1.2 on average (Timm, 2024). However, as mentioned, we follow a conservative approach by taking the estimate with the highest p-value as a reference group. If we instead use the estimate and standard error of antidepressant prescriptions (Table B.5) even the overestimation error vanishes. To conclude, while some coefficients may be slightly exaggerated in the most conservative estimation, we conclude that power issues and exaggeration errors do not seem to be a major problem in our analysis.

6 Cost-benefit Analysis

Our analyses demonstrate that policy measures targeting reductions in air pollution have far-reaching effects on human health. Despite the substantial impact of mental health on society and public health expenditures, it has been largely overlooked in discussions about the cost-effectiveness of policies like driving restrictions. This study offers the first estimates based on administrative health insurance data to quantify the mental health related economic benefits of LEZs.

First, we perform a back-of-the-envelope calculation for the benefits of reduced depression diagnoses (excluding costs related to potentially overlapping diagnoses such as anxiety). In our sample (15-65 year old individuals living in large cities), an average of 6.8 percent of the population is diagnosed with depression each year. Since the administrative health insurance data is representative of the German population, we can approximate the number of yearly depression diagnoses in large cities covered by future LEZs by multiplying this rate by the population in these areas that are of the same age. According to the RWI-GEO-GRID data, on average 9,965,120 individuals from our age cohort reside in zip codes with (future) LEZs, resulting in 677,628 depression diagnoses each year. To determine the number of depression diagnoses prevented by implementing LEZs, we start with the average number of depression diagnoses in (future) LEZ areas and multiply it with the average reduction in depression diagnoses found in our study (3.5 percent). This calculation results in 23,717 fewer depression diagnoses annually (677,628 individuals $\times$ 3.5 percent reduction $=$ 23,717 avoided depression diagnoses). To estimate the avoided health costs, we multiply the number of prevented depression cases by the average health costs associated with a diagnosis. According to Eden et al. (2021), the average total costs per depression patient per year in Germany range from €3,000 to €5,000, excluding indirect costs. Using these figures, the prevented depression diagnoses translate into €71.2 million to €118.6 million in avoided annual total health care costs for our age group.

In addition to the health care cost savings, the broader welfare implications include the willingness to pay (WTP) of individuals to avoid depression. According to Eaton and Hunt (2024), the WTP to avoid depression is estimated at 6% of an individual's stated income. With the average net income in Germany in 2023 (Statista, 2024) being €2,426 per month, this equates to an annual WTP of €1,747 per person. For 23,717 cases of depression prevented, this amounts to €41.4 million annually. Furthermore, depression significantly contributes to workplace absenteeism and productivity losses. Krauth et al. (2014) report that the average cost of absenteeism due to depression in Germany was €1,063 per employee per year in 2014. Eßl-Maurer et al. (2022) estimate that sick leave costs for moderate to severe depressive symptoms amounts to €2,194, compared to sick leave costs for those with no to mild symptoms. Using the average of these estimates, preventing 23,717 cases of depression could result in an additional saving of €38.6 million annually in productivity losses. While the loss in tax revenue due to depression-related work stoppages is another important consideration, reliable estimates for Germany are not available.[31] Even without accounting for potential tax revenue losses, the direct and indirect monetary benefits of Low Emission Zones (LEZs) in reducing depression amount to approximately €150 to €200 million.

Finally, we compare the avoided mental health costs to the private and social costs of vehicle replacements required by LEZ introduction. However, coming up with an estimate of the private costs is challenging. Wolff (2014) considers private costs at US$1,650 per car and estimate that LEZs caused upgrading costs of US$1.09 billion. In contrast, Khan et al. (2018) assume the same costs per vehicle but find that the total upgrading costs only amount to US$82.5 million. Those numbers indicate a high uncertainty range of the private costs. However, the cumulative direct and indirect monetary benefits of avoided conservatively estimated depression diagnoses likely outweigh or equalize the private upgrading costs. When factoring in additional health savings, such as reductions in asthma prescriptions and improvements in child health (Klauber et al., 2024), reductions in hospital visits (Pestel & Wozny, 2021), lower ambulatory care claims (Margaryan, 2021), and improved human capital (Brehm et al., 2022), a retrospective cost-benefit analysis is likely to reveal substantial net benefits.

[31] Occupational disability and early retirement are difficult to attribute directly to depressive disorders (Krauth et al., 2014).

7 Conclusion

This paper explores the intersection between two of today's most pressing global challenges: mental health and air pollution. We present the first large-scale causal estimates of traffic-related air pollution and mental health using administrative data from one of Germany's largest public health insurance providers. To identify causal effects, we leverage the staggered introduction of Low Emission Zones (LEZs) across German cities starting in 2008, which restrict access for emission-intensive vehicles. Consistent with previous studies, we find that the adoption of LEZs led to significant improvements in air quality by reducing traffic-related pollutants. Being the first study to estimate the effects of German LEZs on $PM_{2.5}$, we find statistically significant but smaller effects for these satellite-based estimates compared to the station-based data on PM_{10} and NO_2, suggesting that ground-level measurements may better capture the full effects of traffic policies on air pollutants.

We find that these reductions in air pollution led to significant improvements in mental health. Specifically, the introduction of LEZs reduced the likelihood of being prescribed antidepressants, of visiting a mental health specialist (psychotherapist or psychiatrist), and of mental health diagnoses (depression and anxiety) among residents in zip codes covered by an LEZ. These effects are statistically significant and economically meaningful, with effect sizes similar to those found for cardiovascular diseases. We observe consistent effects at both the extensive and intensive margins, indicating that LEZs and the resulting air quality improvements also reduced the intensity of mental health issues. The measured effects of air quality improvements on mental health outcomes are cumulative and emerge only gradually, with most statistically significant effects observed three to four years after LEZ introduction. Our heterogeneity analysis indicates that the youngest age group, 15 to 29-year-olds, experiences the largest mental health benefits from improved air quality. Our findings are robust to alternative estimation strategies and sample definitions, and to accounting for spatial spillovers. Further analyses suggest that air pollution is the primary mechanism affecting mental health, compared to noise reductions and changes in economic activity. Overall, we find that reducing traffic-related air pollution significantly benefits the mental health of the general population.

These findings carry important policy implications. First, they suggest that environmental policies aimed at improving air quality can have far-reaching health benefits, extending beyond respiratory and cardiovascular health to include mental health. Future cost-benefit analyses of LEZs and similar traffic policies should incorporate these broader effects, factoring in the mental health savings highlighted by our estimates. Second, our results emphasize that younger populations benefit the most from reduced traffic pollution in terms of mental health. Policies targeting air pollution can thus play a crucial role in enhancing the mental well-being and productivity of young people, with significant implications for human capital development. This is particularly relevant given the worrying decline in mental health among this age group over the past decade (Blanchflower et al., 2024). Third, the recent abolition of several LEZs in Southern Germany, following the attainment of EU emission targets, may be premature. Germany still exceeds recommended pollutant levels (especially $PM_{2.5}$), according to WHO air quality guidelines (WHO, 2021). The proposed revision of the EU Ambient Air Quality Directive, which seeks to halve the current annual limit for fine particulate matter, may require stricter enforcement of policies like LEZs. As our findings suggest, enhancing policy stringency could yield significant mental health benefits, in addition to respiratory and cardiovascular improvements, and reduce overall health costs. Expanding the scope of LEZs and similar policies could therefore represent a cost-effective strategy to improve public health on multiple fronts, addressing both environmental and health factors to promote overall well-being.

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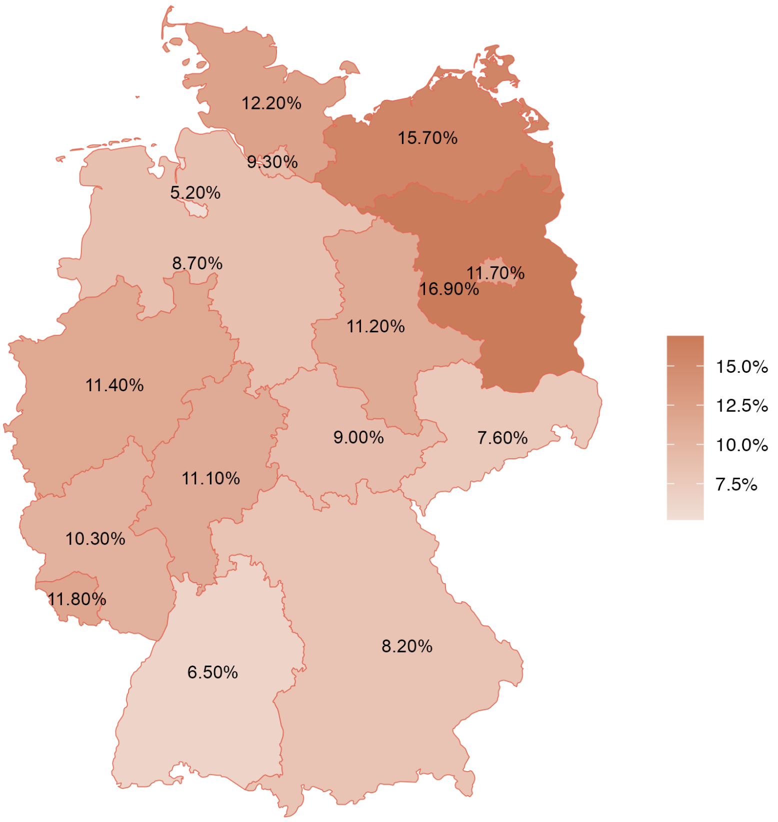
A Descriptives

Table A.1: LEZs in Germany

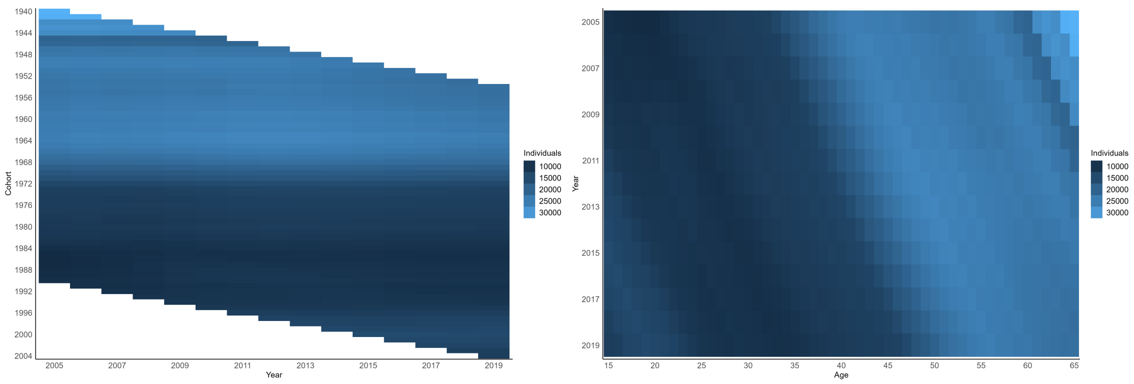
LEZ	Federal State	LEZ type	LEZ type active	Area in km2	Circumference in km
Aachen	NW	Green	01.02.2016	24	28
Augsburg	BY	Green	01.07.2009	6	12
Balingen	BW	Green	01.04.2017 - 01.03.2023	90	50
Berlin	B	Green	01.01.2008	87	37
Bonn	NW	Green	01.01.2010	9	18
Bremen	HB	Green	01.01.2009	7	13
Darmstradt	HE	Green	01.11.2015	106	90
Dinslaken	NW	Green	01.07.2011	4	9
Düsseldorf	NW	Green	15.02.2009	14	16
Erfurt	TH	Green	01.10.2012 - 01.05.2021	16	19
Eschweiler	NW	Green	01.06.2016	2	7
Frankfurta.M.	HE	Green	01.10.2008	98	60
Freiburg	BW	Green	01.01.2010	25	58
Hagen	NW	Green	01.01.2012	9	19
Halle(Saale)	SA	Green	01.09.2011	7	12
Hannover	NI	Green	01.01.2008 - 22.02.2024	43	30
Heidelberg	BW	Green	01.01.2010 - 01.03.2023	10	33
Heidenheim	BW	Green	01.01.2012 - 01.01.2024	17	28
Heilbronn	BW	Green	01.01.2009 - 01.01.2024	38	55
Herrenberg	BW	Green	01.01.2009 - 01.01.2024	4	9
Ilsfeld	BW	Green	01.03.2008 - 01.05.2023	2	5
Köln	NW	Green	01.01.2008	95	88
Karlsruhe	BW	Green	01.01.2009 - 01.03.2023	11	16
Krefeld	NW	Green	01.01.2011	10	16
Langenfeld	NW	Green	01.01.2013	1	6
Leipzig	SN	Green	01.03.2011	182	111
Leonberg/Hemmingen	BW	Green	02.12.2013 - 01.01.2024	131	60
LimburganderLahn	HE	Green	31.01.2018	6	15
Ludwigsburg	BW	Green	01.01.2013	139	58
Mönchengladbach	NW	Green	01.01.2013	21	26
Magdeburg	SA	Green	01.09.2011	7	21
Mainz	RP	Green	01.02.2013	34	35
Mannheim	BW	Green	01.03.2008	7	16
Marburg	HE	Green	01.04.2016	15	34
Müchen	BY	Green	01.10.2008	43	28
Mühlacker	BW	Green	01.01.2009 - 01.08.2024	1	7
Münster	NW	Green	01.01.2010	1	6
Neuss	NW	Green	15.02.2010	2	6
Neu-Ulm	BY	Yellow	01.11.2009 - 04.06.2024	2	21
Offenbach	HE	Green	01.01.2015	39	35
Osnabrück	NI	Green	04.01.2010	17	33
Overath	NW	Green	01.10.2017	0	3
Pfinztal	BW	Green	01.01.2010 - 01.03.2023	31	30
Pforzheim	BW	Green	01.01.2009	2	9
Regensburg	BY	Green	15.01.2018	1	7
Remscheid	NW	Green	01.01.2013	1	6
Reutlingen	BW	Green	01.01.2009 - 04.06.2024	109	91
Ruhrgebiet	NW	Green	01.01.2012	870	276
Schramberg	BW	Green	01.07.2013 - 01.03.2023	4	16
SchwäbischGmünd	BW	Green	01.03.2008 - 01.05.2023	6	17
Siegen	NW	Green	01.01.2015	3	11
Stuttgart	BW	Green	01.03.2008	204	108
Tübingen	BW	Green	01.03.2008 - 04.06.2024	108	73
Ulm	BW	Green	01.01.2009 - 04.06.2024	28	26
Urbach	BW	Green	01.01.2012 - 01.05.2023	2	8
Wendlingen	BW	Green	02.04.2013 - 01.05.2023	4	9
Wiesbaden	HE	Green	01.02.2013	63	77
Wuppertal	NW	Green	15.02.2009	25	48
Mean				49.02	35.53
Median				12.50	21.00
SD				119.63	42.13

Figure A.1: Share of Insured Individuals by Federal State in 2022



Note: This figure displays the share of individuals insured by the health care provider in 2022. *Source*: Grobe and Szecsenyi (2023).

Figure A.2: Age and Cohort Distribution in our Sample



Note: This figure displays age and cohort distribution as well as the underlying number ob observations over time.

Table A.2: GOP - Codes

Code	Description
Psychiatric and psychotherapeutic fee schedule items (psychiatrists)	
21220	Conversation, consultation, discussion, clarification (individual treatment)
21221	Psychiatric treatment (group treatment)
Fee schedule items for psychosomatic medicine and psychotherapy	
22211	Basic flat rate 6th - 59th year of life
22212	Basic flat rate from 60 years of age
22220	Psychotherapeutic consultation (individual treatment)
22221	Psychosomatic medical treatment (individual treatment)
22222	Psychotherapeutic medical treatment (group treatment)
22230	Basic clinical-neurological diagnosis
*Psychotherapeutic fee schedule items**	
23210	Basic flat rate up to 5 years of age
23211	Basic flat rate 6th - 59th year of life
23212	Basic flat rate from 60 years of age
23214	Basic flat rate for child and adolescent psychotherapists
23220	Psychotherapeutic interview (individual treatment)
Services according to the psychotherapy guideline (Services not subject to application)	
35100	Differential diagnostic clarification of psychosomatic disease states
35110	Verbal intervention in psychosomatic disease states
35111	Exercise interventions, individual treatment
35112	Exercise interventions, group treatment
35113	Exercise interventions in children and adolescents, group treatment
35120	Hypnosis
35140	Biographical anamnesis
35141	In-depth exploration
35142	Supplementary survey of neurological and psychiatric findings
35150	Probationary session
35151	Psychotherapeutic consultation
35152	Acute psychotherapeutic treatment
35163 - 35169	Probationary session (group treatment), 3 participants - 9 participants
35173 - 35179	Group psychotherapeutic primary care, 3 participants - 9 participants
Services according to the psychotherapy guideline - Individual therapies	
35401	Depth psychological psychotherapy (short-term therapy 1, individual treatment)
35402	Depth psychological psychotherapy (short-term therapy 2, individual treatment)
35405	Depth psychological psychotherapy (long-term therapy, individual treatment)
35411	Analytical psychotherapy (short-term therapy 1, individual treatment)
35412	Analytical psychotherapy (short-term therapy 2, individual treatment)
35415	Analytical psychotherapy (long-term therapy, individual treatment)
35421	Behavioral therapy (short-term therapy 1, individual treatment)
35422	Behavioral therapy (short-term therapy 2, individual treatment)
35425	Behavioral therapy (long-term therapy, individual treatment)
35431	Systemic therapy (short-term therapy 1, individual treatment)
35432	Systemic therapy (short-term therapy 2, individual treatment)
35435	Systemic therapy (long-term therapy, individual treatment)
Services according to the psychotherapy guideline - Group therapies	
35503 - 35509	Complex for group therapies (depth psychological therapy, short-term therapy)
35513 - 35519	Complex for group therapies (depth psychological therapy, long-term therapy)
35523 - 35529	Complex for group therapies (analytical therapy, short-term therapy)
35533 - 35539	Complex for group therapies (analytical therapy, long-term therapy)
35543 - 35549	Complex for group therapies (behavioral therapy, short-term therapy)
35553 - 35559	Complex for group therapies (behavioral therapy, long-term therapy)
35703 - 35709	Complex for group therapies (systemic therapy, short-term therapy)
35713 - 35719	Complex for group therapies (systemic therapy, long-term therapy)
Psychodiagnostic test procedures	
35600	Test procedures, standardized
35601	Test procedures, psychometric
35601 - 35529	Procedures, projective

Notes: See Kassenärztliche Bundesvereinigung (2024) for the full catalogue. *medical and psychological psychotherapists, child and adolescent psychotherapists.

Table A.3: ICD - Codes

Code	Description
Depression (F32-F33)	
F32	Depressive episode
F33	Recurrent depressive disorder
Anxiety (F40-F41)	
F40	Phobic disorder
F41	Anxiety disorder
Chapter I - Diseases of the circulatory system (I00-I99)	
I00-I09	Acute rheumatic fever
I10-I15	Hypertensive diseases
I20-I25	Ischemic heart diseases
I26-I28	Pulmonary heart disease and diseases of pulmonary circulation
I30-I52	Other forms of heart disease
I60-I69	Cerebrovascular diseases
I70-I79	Diseases of arteries, arterioles, and capillaries
I80-I89	Diseases of veins, lymphatic vessels and lymph nodes, not elsewhere classified
I95-I99	Other and unspecified disorders of the circulatory system
Chapter S - Injuries (S00-S99)	
S00-S09	Injuries to the head
S10-S19	Injuries to the neck
S20-S29	Injuries to the thorax
S30-S39	Injuries to the abdomen, lower back, lumbar spine, pelvis and external genitals
S40-S49	Injuries to the shoulder and upper arm
S50-S59	Injuries to the elbow and forearm
S60-S69	Injuries to the wrist, hand and fingers
S70-S79	Injuries to the hip and thigh
S80-S89	Injuries to the knee and lower leg
S90-S99	Injuries to the ankle and foot

Notes: ICD selection as in C. Chen et al., 2018, Gu et al., 2020, Hwang et al., 2022, Kim et al., 2021, H. Li et al., 2020, Qiu et al., 2019, Wang et al., 2018, Wei et al., 2020, Zhao et al., 2020, Zhou et al., 2021.

Table A.4: ATC Classification and Description

ATC	Description
N06A - Antidepressants	
N06AA	Non-selective monoamine reuptake inhibitors
N06AB	Selective serotonin reuptake inhibitors
N06AF	Monoamine oxidase inhibitors, non-selective
N06AG	Monoamine oxidase A inhibitors
N06AH	Homeopathic and anthroposophic antidepressants
N06AP	Herbal antidepressants
N06AX	Other antidepressants
C - Cardiovascular system	
C01 - Cardiac therapy	
C01A	Cardiac glycosides
C01B	Antiarrhythmics, Class I and III
C01C	Cardiac stimulants excl. cardiac glycosides
C01D	Vasodilators used in cardiac diseases
C01E	Other cardiac preparations
C02 - Antihypertensives	
C02A	Antiadrenergic agents, centrally acting
C02B	Antiadrenergic agents, ganglion blockers
C02C	Antiadrenergic agents, peripherally acting
C02D	Agents acting on arteriolar smooth muscle
C02K	Other antihypertensives
C02L	Antihypertensives and diuretics in combination
C02N	Combinations of antihypertensive agents in ATC group C02
C03 - Diuretics	
C03A	Low-ceiling diuretics, thiazides
C03B	Low-ceiling diuretics, excl. thiazides
C03C	High-ceiling diuretics
C03D	Aldosterone antagonists and other potassium-sparing agents
C03E	Diuretics and potassium-sparing agents in combination
C03X	Other diuretics
C04 - Peripheral vasodilators	
C04A	Peripheral vasodilators
C04B	Combinations of peripheral vasodilators
C05 - Vasoprotectives	
C05A	Agents for treatment of hemorrhoids and anal fissures for topical use
C05B	Anti-varicose agents
C05C	Capillary-stabilizing agents
C05X	Other vasoprotectives
C06 - Other cardiovascular drugs	
C06A	Antihypotensive agents
C07 - Beta-blocking agents	
C07A	Beta-blocking agents
C07B	Beta-blocking agents and thiazides
C07C	Beta-blocking agents and other diuretics
C07D	Beta-blocking agents, thiazides, and other diuretics
C07E	Beta-blocking agents and vasodilators
C07F	Beta-blocking agents, other combinations

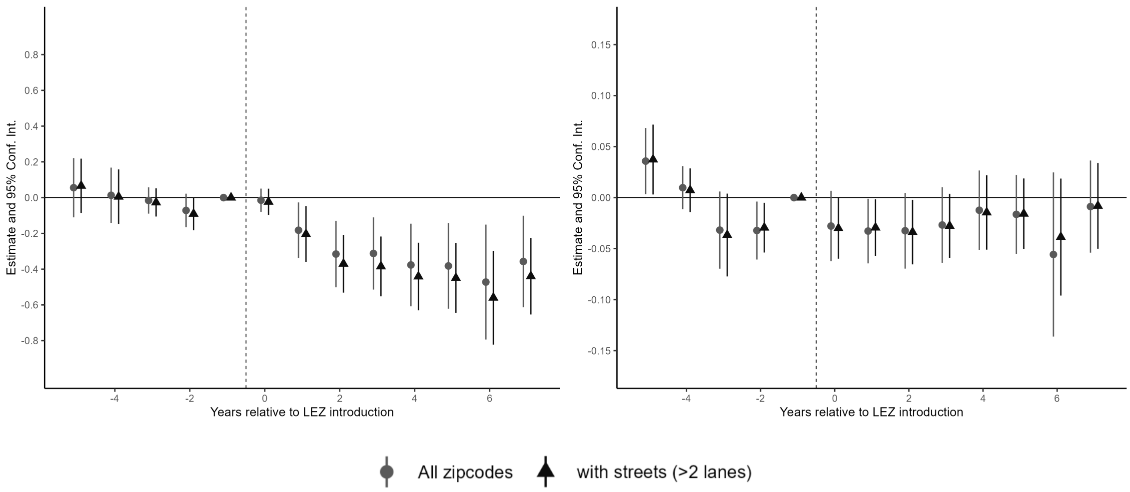
Table A.4 continued from previous page

ATC	Description
C08 - Calcium channel blockers	
C08C	Selective calcium channel blockers with mainly vascular effects
C08D	Selective calcium channel blockers with mainly cardiac effects
C08E	Non-selective calcium channel blockers
C08G	Calcium channel blockers and diuretics
C09 - Agents acting on the renin-angiotensin system	
C09A	ACE inhibitors, plain
C09B	ACE inhibitors, combinations
C09C	Angiotensin II receptor blockers (ARBs), plain
C09D	Angiotensin II receptor blockers (ARBs), combinations
C09X	Other agents acting on the renin-angiotensin system
C10 - Lipid modifying agents	
C10A	Lipid modifying agents, plain
C10B	Lipid modifying agents, combinations

B Additional Analyses

Figure B.1: Effect of LEZ Introduction on Additional Air Pollutants

(a) SO_2 (b) O_3



Note: This figure displays dynamic effects of Low Emission Zones on yearly sulfur dioxide (SO_2) and ozone (O_3) from pollution monitors (a and b) and fine particular matter ($PM_{2.5}$) derived from cross-validated satellite images (b) in logs. Specifications are similar to Table 3. The effects are estimated using estimators proposed by Sun and Abraham (2021). Estimates are shown including 95% confidence intervals.

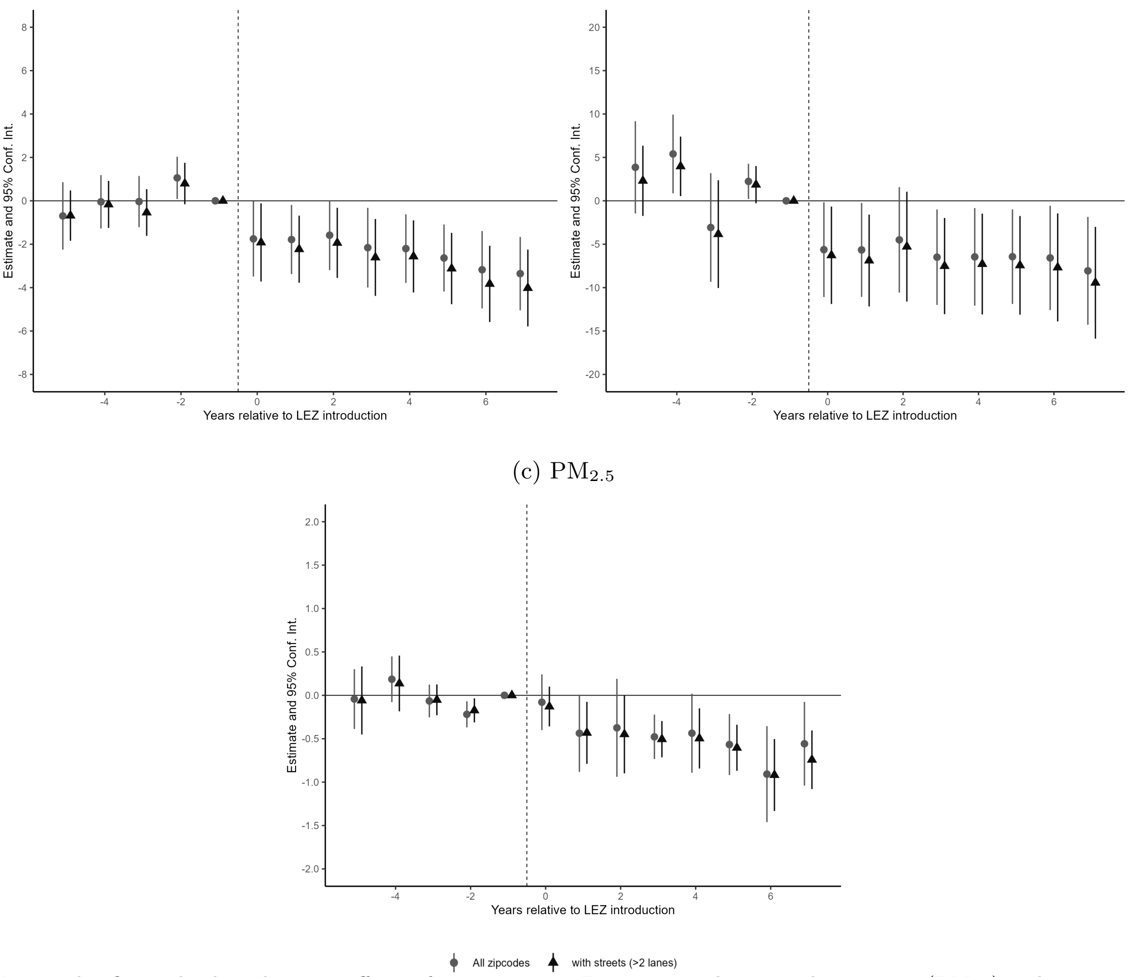
Table B.1: Main Results: Only Zip Codes without Main Streets ($\leq$ 4 lanes)

Dependent variables in log:	Antidepressant probability	Specialist Visit probability	Depression probability	Anxiety probability
ATT	-0.0399***	-0.0753***	-0.0399**	-0.0514***
	(0.0111)	(0.0208)	(0.0154)	(0.0168)
N	13,320	13,309	13,322	13,315
Dependent variables in log:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
ATT	-0.0584***	-0.0488***	-0.0930***	-0.0611***
	(0.0117)	(0.0123)	(0.0209)	(0.0175)
N	13,320	13,320	13,309	13,332
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓

Note: This table displays the average treatment effect on the treated of Low Emission Zones on the concentrations of different air pollutants. The dependent variables in Column (1) and (2) are measurements from air pollution monitors and in Column (3) the dependent variable are cross-validated satellite estimates from 2010 to 2018 based on Van Donkelaar et al. (2021). Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level.*p<0.1; **p<0.05; ***p<0.01.

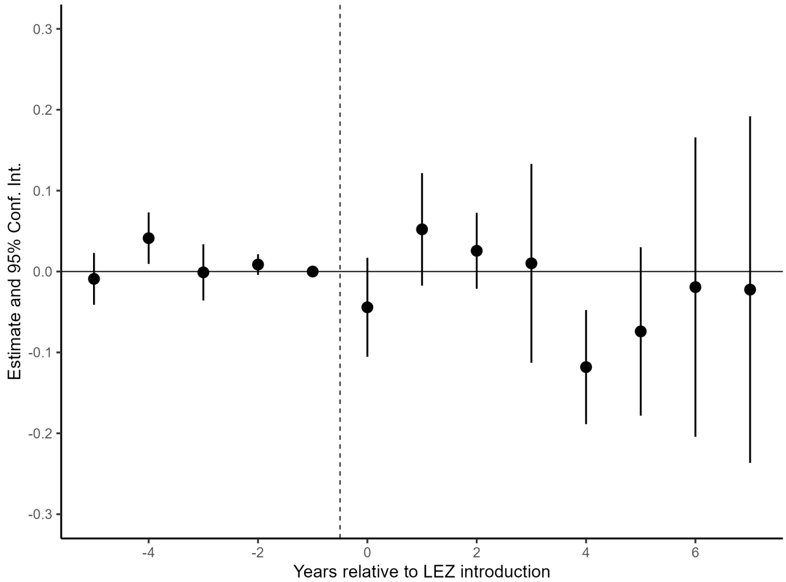
Figure B.2: Effect of LEZ Introduction on Air Pollutant Levels

(a) PM_{10} (b) NO_2 (c) $PM_{2.5}$



Note: This figure displays dynamic effects of Low Emission Zones on yearly particulate matter (PM_{10}) and nitrogen dioxide (NO_2) from pollution monitors (a and b) and fine particular matter ($PM_{2.5}$) derived from cross-validated satellite images (b) in levels. Specifications correspond to Table 3 without logs. The effects are estimated using estimators proposed by Sun and Abraham (2021). Estimates include 95% confidence intervals.

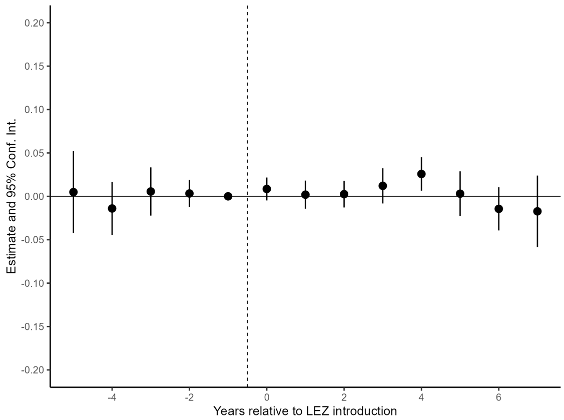
Figure B.3: Effect of LEZ Introduction on Traffic Volume



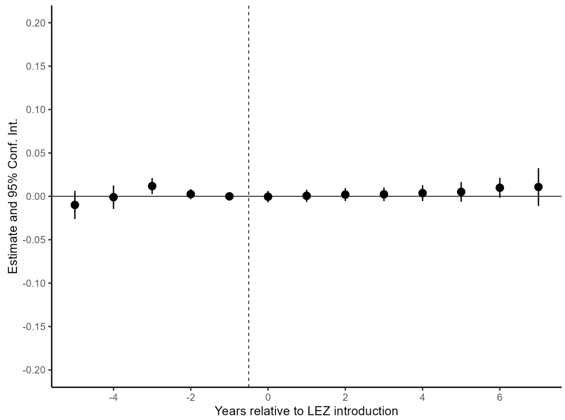
Note: This Figure displays dynamic effects of Low Emission Zones on traffic volume (average number of vehicles per hour between 6 am and 6 pm) in logs. Data is measured at the zip code and year level. Socio-economic controls include information on the number of cars per household, purchasing power per capita, and the number of inhabitants. Weather controls include information on humidity, vapor pressure, precipitation, and wind speed as well as mean, minimum, and maximum temperature. The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

Figure B.4: Effect of LEZ Introduction on Socioeconomic Characteristics

(a) Unemployment rate

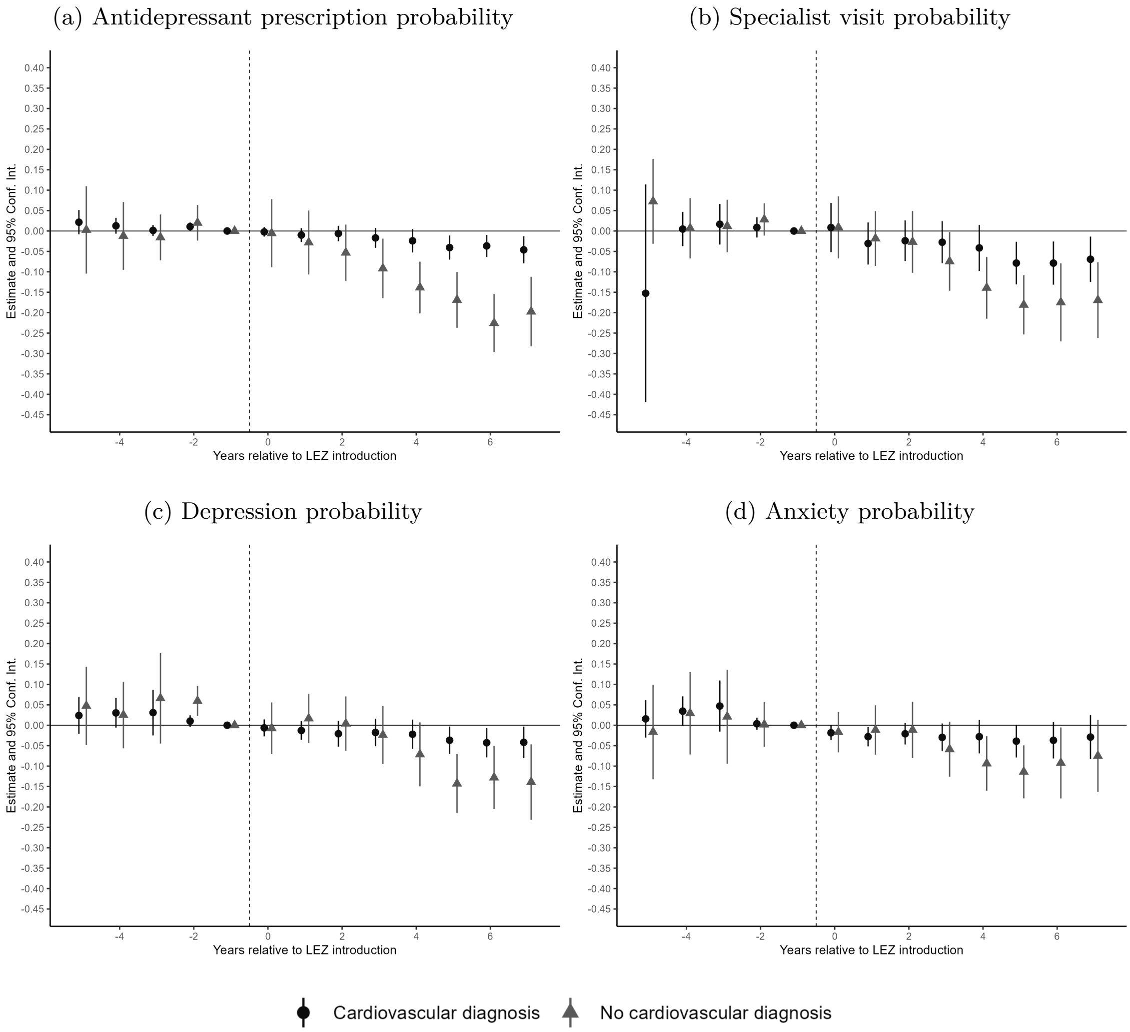


(b) Purchasing power per capita



Note: This Figure displays dynamic effects of Low Emission Zones on the unemployment rate and purchasing power per capita in logs. Data is measured at the zip code and year level and taken from (Breidenbach & Eilers, 2018). Socioeconomic data for the years 2006-2008 is imputed for the main analysis and therefore excluded in this estimation. Socio-economic controls include information on the average education level and the number of inhabitants. The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

Figure B.5: Effect of LEZ Introduction Depending on Cardiovascular Health



Note: This figure displays dynamic effects of Low Emission Zones on different average probabilities in logs for sub samples depending on having a cardiovascular diagnosis in our study period. The effects are estimated using estimators proposed by Sun and Abraham (2021). All variables are on zipcode-year level. Panel (a) shows the estimated effects on the probability to be described antidepressants (for detailed information on ATCs see Appendix A.4). Panel (b) shows the estimated effects on the probability of a specialist visit (for detailed information on how a specialist visit is defined see Section 3). Panels (c) and (d) show estimated effects on Depression and Anxiety diagnosis (for detailed information on ICDs see Appendix A.3). Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. Estimators are shown including 95% confidence intervals.

Table B.2: Sleep Disorders

Model	*Main specification*	*Excluding large streets*
Dependent variables in log:	Sleep disorder probability	Sleep disorder probability
ATT	-0.0474***	-0.0511***
	(0.0129)	(0.0132)
N	17,894	13,319
Socio-economic controls	✓	✓
Weather controls	✓	✓
County×Year linear trend	✓	✓
Year fixed effect	✓	✓
Zip code fixed effect	✓	✓

Note: This table displays the average treatment effect on the treated of Low Emission Zones on the average probability of sleep disorder diagnoses in logs. Colum (1) displays the ATT for the entire sample while Column (2) excludes those zip codes with large streets (see Table B.1 for details). The variable is measured zipcode-year level. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

Table B.3: Main Results including Movers

Dependent variables in log:	Antidepressant probability	Specialist Visit probability	Depression probability	Anxiety probability
ATT	-0.0394***	-0.0626***	-0.0343***	-0.0394***
	(0.0085)	(0.0195)	(0.0107)	(0.0118)
N	17,929	17,930	17,925	17,921
Dependent variables in log:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
ATT	-0.0554***	-0.0511***	-0.0791***	-0.0400***
	(0.0098)	(0.0124)	(0.0215)	(0.0148)
N	17,929	17,929	17,930	17,938
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓

Note: This table displays the average treatment effect on the treated of Low Emission Zones on different outcomes (for details, see Tables 4 and 5) without excluding individuals that moved in the observation period. All variables are on zipcode-year level. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). The effects are estimated using estimators proposed by Sun and Abraham (2021). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

Table B.4: Main Results with Alternative Estimators

	Extensive margin			
Dependent variables in log:	Antidepressant prescription probability	Specialist visit probability	Depression probability	Anxiety probability
TWFE				
ATT	-0.0276**	-0.0491*	-0.0364*	-0.0499**
	(0.0131)	(0.0253)	(0.0196)	(0.0192)
N	17,896	17,886	17,894	17,893
Stacked DiD				
ATT	-0.0407**	-0.0411	-0.0558**	-0.0632**
	(0.0155)	(0.0294)	(0.0241)	(0.0250)
N	84,501	84,493	84,493	84,512

	Intensive margin			
Dependent variables in log:	Antidepressant prescriptions	Antidepressant prescriptions DDD	Specialist visits	Specialist billings
TWFE				
ATT	-0.0452***	-0.0425***	-0.0585**	-0.0333*
	(0.0128)	(0.0136)	(0.0255)	(0.0179)
N	17,896	17,896	17,886	17,910
Stacked DiD				
ATT	-0.0641***	-0.0597***	-0.0508*	-0.0464**
	(0.0151)	(0.0165)	(0.0300)	(0.0214)
N	84,501	84,501	84,493	84,580
Socio-economic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
County×Year linear trend	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓
Zip code fixed effect	✓	✓	✓	✓
Event time×treatment wave fixed effects	(✓)	(✓)	(✓)	(✓)
Treated unit×treatment wave fixed effects	(✓)	(✓)	(✓)	(✓)

Note: This table displays the average treatment effect on the treated of Low Emission Zones on different outcomes (for details, see Tables 4 and 5). Rows 1 and 3 use the TWFE estimator, Rows 2 and 4 use the stacked DiD approach (see e.g., Cengiz et al. 2019) including estimator specific fixed effects (event time × treatment wave and treated unit × treatment wave). All variables are on zipcode-year level. Socio-economic controls include information on education, and purchasing power per capita. Weather controls include information on humidity, vapor pressure, wind speed, sunshine duration, precipitation, and temperature (mean, minimum, and maximum). Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

Table B.5: Retrospective Design Analysis

Depression diagnosis (extensive)				Antidepressant prescriptions (intensive)			
Effect size	Power	Type S	Type M	Effect size	Power	Type S	Type M
Plausible hypothetical effect sizes							
0.01	0.1102	0.0340	3.4235	0.01	0.1434	0.0155	2.8053
0.02	0.2979	0.0012	1.8097	0.02	0.4247	0.0002	1.5264
0.03	0.5725	0	1.3257	0.03	0.7564	0	1.1617
0.04	0.8151	0	1.1133	0.04	0.9429	0	1.0344
0.05	0.9464	0	1.0311	0.05	0.9931	0	1.0013
0.06	0.9900	0	1.0073	0.06	0.9996	0	0.9980
0.07	0.9988	0	0.9998	0.07	0.9999	0	1.0006
0.08	0.9999	0	0.9999	0.08	1.0000	0	0.9993
Estimated effect sizes							
0.035	0.7054	0	1.1945	0.057	0.9990	0	1.0021

Note: This table displays the results of a retrospective power analysis for two mental health outcomes, depression diagnosis (extensive margin) and antidepressant prescriptions (intensive margin). We use the R package *retrodesign* by Timm (2024) to calculate the power as well as type s (sign) and m (magnitude) errors. For depression diagnosis the coefficient and standard errors for this analysis are based on Column 1 of Tab. 4 with degrees of freedom df = 16,351, while estimate and standard error for antidepressant prescriptions are sourced from Column 1 Tab. 5 with the corresponding df = 16,353.