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 long-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 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, like physical health, is crucial to economic productivity. Depression and anxiety, two of the most common conditions, cost the global economy an estimated USD 1 trillion annually (WHO, 2022). The rising demand for mental health services strains healthcare systems worldwide, underscoring the need to understand the root causes of mental health conditions to develop effective policies and interventions.

While the relationship between the biophysical environment and mental health remains underexplored (Kühn & Gallinat, 2024), recent medical research increasingly suggests a link between air pollution exposure and mental health outcomes (e.g., Braithwaite et al., 2019, Zundel et al., 2022). Numerous studies show 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 linked to 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, due to the complexity of mental health disorders and potential confounding factors, rigorous causal inference models are necessary 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). By using depression and anxiety diagnoses, along with antidepressant prescriptions and specialist visits, the paper offers detailed insights into the impact of air pollution on mental health outcomes. Our identification strategy rests on the staggered implementation of low-emission zones (LEZs) in German cities after 2008, which, by limiting access of emission-intensive vehicles 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, $PM_{2.5}$ by 3.1 percent, and NO₂ levels by 15.3 percent in the covered areas. These reductions in air pollution translate into significant and robust improvements in mental health outcomes. Specifically, LEZs are associated with a 3.8 percent decrease in the likelihood of receiving antidepressant prescriptions, a 8.3 percent decrease in specialist visits (psychotherapist or psychiatrist), and a 4.1 percent reduction in the likelihood of an anxiety diagnosis. Our mechanism analysis suggests that these 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 analyses reveal 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). Our cost-benefit analysis suggests that LEZs in Germany prevent around 28,000 antidepressant prescriptions annually, saving $\notin 80$ to $\notin 140$ million per year in public health expenditures for our study's age group in large cities.

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 wellbeing. 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 Providing evidence from a European city, Beshir and Fichera (2022) examine the effects of London's 2019 Ultra Low Emission Zone (ULEZ) on well-being, finding improvements in reported feelings of happiness, worthiness, and satisfaction in the year after the introduction. Besides not being able to estimate effects beyond the short-term, a key limitation of the literature has been the reliance on self-reported wellbeing measures, which may be vulnerable to social desirability bias (see, e.g., Paulhus, 1984). Administrative health data, besides offering a larger, more representative sample, provides a more objective and comprehensive picture of healthcare utilization, which is more directly tied to healthcare costs. 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 contribute a broad perspective on the causal effect of air pollution on mental health.

In addition, we add to the existing knowledge on the effectiveness of the German LEZs as an example of driving restriction policies that could be implemented elsewhere. 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). While various air pollutants pose risks to human health,³ fine particulate matter $(PM_{2.5})$ is increasingly recognized for its severe

¹For 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.

²Zheng et al. (2019b), using a happiness index derived from 210 million geo-tagged tweets on the Chinese microblog platform *Sina Weibo* (equivalent to X), 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.

³See Pestel and Wozny (2021) for an overview.

health impacts (European Environment Agency, 2024). $PM_{2.5}$ particles, due to their small size, can penetrate deeply into the respiratory system and enter the bloodstream, potentially affecting brain functions and neurodevelopment (e.g., Ye et al., 2023). Therefore, more knowledge on which policies effectively reduce $PM_{2.5}$ is 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 potentially due to restricted mobility. Given the strong link of mental health with both physical health and well-being and the opposing effects found in Sarmiento et al. (2023), 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 growing evidence on the health risks of air pollution in the early 2000s, the EU issued a series of Clean Air Directives, that set specific numerical limits for fine particles, coarse particles (PM₁₀), nitrogen dioxide (NO₂), and other ambient pollutants.⁴ PM₁₀ 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 that failed to meet EU air quality standards were required to develop "Clean Air Plans" outlining 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 widely adopted was the introduction of Low Emission Zones (LEZs), which restricted high-emitting vehicles, such as older diesel cars, from entering

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

⁵These 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 (NO₂, SO₂, PM₁₀, CO, and O₃). It is a revised version of Directives 1999/30/EC (EU, 1999), 2000/69/EC (EU, 2000), and Directive 2002/3/EC (EU, 2002).

certain areas, mainly 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 The police and public order offices enforce the restrictions, with violations resulting in fines of $\notin 100.^7$

LEZ implementation is decided at the regional level, involving city administrations, councils, and local stakeholders, although state governments can overrule local authorities. The necessity of a Clean Air Plan and LEZ depends on prior pollution levels and regional decision-making processes, which are shaped by various stakeholders. 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.1⁸). 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 2023^9 , 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 offers universal access to high-quality healthcare, ensuring that all residents receives necessary medical services. Public health insurance is mandatory for employees earning below a certain income threshold ($\in 69,300$ annually) and other groups, including 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).

⁶Stickers 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.

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

 $^{^{8}\}mathrm{All}$ appendix material can be found in the online appendix.

⁹One LEZ in Erfurt had been abolished earlier in 2021.

Mental health care in Germany follows a collaborative model involving psychiatrists, psychologists, psychotherapists, and general practitioners. Patients usually begin mental health care by consulting a general practitioner, who may refer them to specialized services. However, a shortage of psychotherapists, particularly in outpatient care, has led to excessive demand. An analysis by the Federal Chamber of Psychotherapists in 2019 found that, on average, people had to wait nearly five months to start therapy after a need for treatment was identified (Bundespsychotherapeutenkammer, 2021).¹⁰

2.3 Mechanisms linking LEZs to Mental Health

Medical research suggests that lower air pollution levels directly affect brain function (see Section 1), making this the primary mechanism through which LEZs influence mental health outcomes. We will provide suggestive evidence for the role of these mechanisms in Section 5.5.

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 reduce noise pollution by restricting heavy-duty vehicles and promoting newer, quieter models. 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 high-lighted the detrimental effects of air pollution on productivity in both low-skilled (Chang et al., 2016, 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

¹⁰Since 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)

retrofit these vehicles.

LEZs may also influence the socio-economic composition of neighborhoods by attracting individuals who prioritize cleaner air and a higher quality of life, potentially altering the local population. Although our analysis excludes individuals who relocate during the observation period, changes in the neighborhood's socio-economic makeup may still impact the mental health of remaining residents. Additionally, shifts in local businesses and employment opportunities driven by demographic changes could indirectly affect mental health outcomes.

3 Data

3.1 Administrative Health Insurance Data

Our primary data source consists of administrative health records for nine million individuals, representing 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. The dataset includes inpatient and outpatient health records, diagnoses, prescriptions, and medical billings, along with detailed individual-level characteristics such as age, sex, education and zip code of residence.¹¹ We consider working age individuals (15-65 years old) who were insured without interruptions between 2005 and 2019.¹² To address potential selection bias, we exclude individuals who change their county of residence during the sample period.¹³

Following Pestel and Wozny (2021) and Ahammer et al. (2023), we use the ICD-10-GM for diagnoses¹⁴ and the Anatomical Therapeutic Chemical (ATC) Classification System for prescriptions¹⁵ to analyze health outcomes. We also include specialist visits¹⁶ and specific outpatient billings¹⁷ 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)¹⁸ of prescriptions and specialists billings as a measure of the intensive margin. See Table 1 for a descriptive summary of our outcome variables.

¹¹Education 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.

 $^{^{12}\}mathrm{See}$ Figure A.2 for detailed information on age distribution.

¹³In Section 5.3 we show that our results are robust to including individuals that change their residence.

¹⁴We 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.

¹⁵In 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.

¹⁶Specialist 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."

¹⁷Outpatient 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.

¹⁸The assumed average maintenance dose per day for a drug used for its main indication in adults (WHO, 2024a).

	Outside LEZs			Inside LEZs				
Mental health outcomes	mean	sd	\min	max	mean	sd	\min	max
Extensive Margin								
Antidepressant probability	0.07	0.02	0	0.18	0.07	0.02	0	0.16
Specialist visit probability	0.06	0.03	0	0.23	0.06	0.03	0	0.35
Depression probability	0.07	0.03	0	0.2	0.07	0.03	0	0.23
Anxiety probability	0.06	0.02	0	0.18	0.06	0.02	0	0.14
Intensive margin								
Antidepressant prescriptions	0.25	0.1	0	0.67	0.26	0.1	0	0.63
Antidepressant DDD	17.77	8.31	0	64.38	18.28	7.94	0	50.06
Specialist visits	0.18	0.08	0	0.62	0.18	0.09	0	0.88
Specialist billings	1.75	0.89	0.03	9.32	1.6	0.84	0	6.34
Confirmatory and Placebo Outcomes								
Cardiovascular disease probability	0.32	0.08	0	0.63	0.31	0.07	0.03	0.56
Cardiovascular prescription probability	0.21	0.07	0	0.42	0.19	0.06	0	0.46
Cardiovascular prescriptions DDD	128.05	48.71	0	342.95	113.11	47.15	0	346.63
Injury probability	0.11	0.03	0	0.21	0.11	0.03	0	0.25
Observations (zipcode \times year)		10,7	767			11,2	226	

Table 1: Descriptive statistics: Outcomes

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 LEZ implementation history, stringency (e.g., bans on Euro 1–3 vehicles), and geographic coverage.¹⁹ 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 data comes from the German Federal Environment Agency's monitoring system. We use data from all stations measuring nitrogen dioxide (NO₂) and particulate matter (PM₁₀) concentrations between 2005 and 2018. We assign each zip code to the nearest monitoring station with valid pollution readings, aggregating data at the zip code-year level. To prevent cross-contamination, we ensure that monitoring stations inside LEZs are not linked to non-LEZ zip codes, and vice versa. 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 higher within LEZs compared to outside LEZs.

We supplement ground-based data with monthly satellite-derived fine particulate matter concentrations ($PM_{2.5}$) compiled by Van Donkelaar et al. (2021). While $PM_{2.5}$ is linked to severe health threats (see e.g., Feng et al., 2016), studies on the effectiveness of LEZs in reducing $PM_{2.5}$ in Germany remain limited due to data constraints (Klauber et al., 2024).

¹⁹Table A.1 lists the name, state, stringency, adoption and abolish dates as well as covered area and circumference of all LEZs in Germany.

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 grid-level data to the zip code level to align with outcome variables. We control for various socioeconomic factors, including the yearly average purchasing power per capita, unemployment rate, and the share of foreigners. 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 socioe-conomic and demographic characteristics, as LEZs are predominantly established in large cities and city centers (Pestel & Wozny, 2021). Additionally, Wolff (2014) shows that in a sample of large and relatively polluted German cities, the EU air pollution regulation of exceeding limits for 35 days in a given year introduced plausibly exogenous variation in treatment assignment. 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 21,993 zip code by year observations, inhabited by more than 2 million insured individuals.²⁰

Table 2 displays descriptive statistics for our time-varying zip code characteristics. There are only small socioeconomic differences between treatment and control group. Within LEZs, there is a slightly lower unemployment rate and higher purchasing power compared to the control group. Further, baseline pollution levels tend to be slightly higher within LEZs than in the

²⁰We 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.





Municipality <100k Municipality >100k (comparison group) Low Emission Zone (treatment group)

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

control areas.

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} (purchasing power per capita, unemploy-

	Outside LEZs			Within LEZs						
Controls	mean	sd	\min	max	n	mean	sd	min	max	n
Socioe conomic										
Purchasing power per capita	$22,\!492$	4,523	$11,\!934$	$42,\!257$	10,767	22,871	$4,\!417$	$12,\!362$	41,332	$11,\!226$
Unemployment rate	8.12	4.2	0.16	25.3	10,767	7.23	4.43	0.21	23.49	$11,\!226$
Share of foreigners	13.06	8.49	0.57	49.92	10,767	16.7	8.68	0.37	51.08	$11,\!226$
Cars per household	0.74	0.23	0.18	1.47	10,767	0.79	0.34	0.25	1.53	$11,\!226$
Number of inhabitants	$15,\!134$	7,186	610	$38,\!587$	10,767	$14,\!361$	7,416	1,028	$61,\!667$	$11,\!226$
Number of insured individuals	668	448	21	$7,\!103$	10,767	511	403	21	$6,\!388$	$11,\!226$
Weather										
Humidity	77.34	3.14	66.97	88.11	10,767	75.86	3.25	66.02	86.14	11,226
Precipitation	1.95	0.44	0.73	4.18	10,767	2.02	0.44	0.73	4.33	$11,\!226$
Temperature	10.24	0.97	4.17	17.32	10,767	10.51	1.14	4.14	17.8	$11,\!226$
Maximal temperature	14.5	1.23	7.77	23.05	10,767	15.04	1.22	7.75	23.54	$11,\!226$
Minimal temperature	5.95	0.97	0.19	12.28	10,767	6.06	1.32	-0.34	12.69	11,226
Vapor pressure	10.1	0.55	6.78	15.5	10,767	10.07	0.59	6.92	16.29	$11,\!226$
Wind speed	3.53	0.65	1.77	8.77	10,767	3.21	0.63	1.02	8.77	$11,\!226$
Sunny hours	4.74	0.53	2.58	7.68	10,767	4.91	0.53	2.39	7.54	11,226
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

Table 2: Descriptive statistics treatment and control group

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.

ment rate, and share of foreigners). 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.²¹

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

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

where EventTime^k_{it} 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'Hault-

²¹The same equation applies to air pollution as the outcome, with adjusted control variables.

fœuille, 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 "nonswitchers," 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).

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).

Data source:	Pollution	Cross-validated satellite estimates		
Dependent variables:	$\begin{array}{c} \log(\mathrm{PM}_{10}) \\ (1) \end{array}$	$ \begin{array}{c} \log(\mathrm{NO}_2) \\ (2) \end{array} $	$\begin{array}{c} \log(\mathrm{PM}_{2.5}) \\ (3) \end{array}$	
All Zip Codes				
ATT	-0.1036***	-0.1532^{**}	-0.0309***	
	(0.0314)	(0.0590)	(0.0092)	
Observations (zipcode \times year)	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)	
Observations (zipcode \times year)	11,819	11,819	7,493	
Socioeconomic controls	\checkmark	\checkmark	\checkmark	
Weather controls	\checkmark	\checkmark	\checkmark	
Year fixed effects	\checkmark	\checkmark	\checkmark	
Zip code fixed effects	\checkmark	\checkmark	\checkmark	

Table 3: LEZ on Air Pollution

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.

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 $0.4\mu g/m^3$. 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). Satellite-based $PM_{2.5}$ data capture regional pollution patterns, potentially diluting the localized effects of LEZs.²² Second, satellite measurements may not fully capture ground-level reductions in pollution, potentially underestimating the policy's impact with re-

²²Indeed, 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 ($0.01^{\circ} \times 0.01^{\circ}$), but do not fully resolve PM_{2.5} gradients at the gridded resolution due to influence by information sources at coarser resolution."

spect to $PM_{2.5}$ (Holloway et al., 2021).^{23,24}

In the lower part of Table 3 we focus on zip codes with large streets (≥ 3 lanes) as we expect larger effect sizes in areas with higher traffic volume.²⁵ As expected, estimates based on monitor data (Columns 1-2) become larger in magnitude and the statistical significance tends to increase. However, the effects are not statistically significantly different from one another. 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 (SO₂ and O₃) and find statistically significant reductions for SO₂.

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, 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 (Panel A) and on visiting a specialist, such as a psychotherapist or psychiatrist (Panel B). We find a statistically significant 3.8 percent reduction in the probability of being prescribed antidepressants. This translates into a reduction of the zip code incidence from 7.4 to 7.2 percent. For the probability of visiting a specialist, our estimated effect is a 6.6 percent reduction, which corresponds to a decrease in the zip-code level incidence from 6.2 to 5.8 percent. Moreover, we report the effects of LEZs on mental health diagnoses such as depression (Panel C, Table 4) and anxiety disorder diagnoses (Panel D). Our findings indicate that individuals residing in zip codes with LEZs have a 2.6 percent lower probability of being diagnosed with depression, however, the effect is not statistically significant at conventional significance levels. Further, the introduction of LEZs results in a statistically significant 4.1 percent reduction in the probability of being diagnosed with an anxiety disorder, which in turn translates into an incidence reduction from 6.3 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

²³The 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).

²⁴Using a subset of pollution monitor data due to data constraints, Klauber et al. (2024) find no effect of LEZ introduction on $PM_{2.5}$.

²⁵We 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.

(2021) and Pestel and Wozny (2021).

Figure 3 illustrates the dynamic treatment effects for our mental health outcomes at the extensive margin, corresponding to Panels A to D 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

Model:	(1)	(2)	(3)	(4)
Dependent variables in log:				
Panel A	Antide	pressant pres	scription prob	oability
ATT	-0 0474***	-0.0512**	-0.0542**	-0 0377***
	(0.0178)	(0.0233)	(0.0246)	(0.0122)
Mean	0.074	0.074	0.074	0.074
Observations (zipcode \times year)	19,345	19,345	19,345	19,345
Panel B		Specialist vis	it probability	/
АТТ	-0.0878**	-0.0851**	-0.0885**	-0.0661**
	(0.0339)	(0.0376)	(0.0395)	(0.0267)
Mean	0.062	0.062	0.062	0.062
Observations (zipcode \times year)	19,323	19,323	19,323	19,323
		_		
Panel C		Depression	probability	
АТТ	-0.0167	-0.0285	-0.0333	-0.0256
	(0.0196)	(0.0244)	(0.0246)	(0.0172)
Mean	0.068	0.068	0.068	0.068
Observations (zipcode \times year)	19,333	19,333	19,333	19,333
Panel D		Anxiety p	probability	
АТТ	-0.0644***	-0.0730***	-0.0741***	-0.0407**
	(0.0208)	(0.0257)	(0.0268)	(0.0173)
Mean	0.063	0.063	0.063	0.063
Observations (zipcode \times year)	19,338	19,338	$19,\!338$	19,338
Socioeconomic controls	_	\checkmark	\checkmark	\checkmark
Weather controls	_	_	\checkmark	\checkmark
County×Year linear trends	_	_	_	\checkmark
Year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Zip code fixed effects	\checkmark	\checkmark	\checkmark	\checkmark

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

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. Panel A shows the estimated effects on the probability to be described antidepressants. 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 the probability of depression and anxiety diagnoses. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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.

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 mental health treatments. We present the intensive margin by including the average number of antidepressant prescriptions (Panel A). To improve interpretability, we also include the average defined daily doses (DDD) per individual (Panel B). This approach accounts for the intensity of each prescription, by weighting individuals according their clinical need. We find



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

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 Column (4) in Table 4. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

that LEZs reduce the number of prescriptions by approximately 5.1 percent and DDDs by about 4.4 percent. In other words, the average number of yearly prescriptions per individual is reduced from 0.26 to 0.25 and the DDDs from 18.64 to 17.83. Both estimates are significant at the one percent level. Similar to Panel B in Table 4, we also include an intensive measure for specialist visits (Panel C)²⁶. In Panel D, we include the number of specialist billings as an outcome, covering all available psychotherapy billings²⁷. The estimated effect of LEZs on specialist visits is a reduction of 8.3 percent, while the effect on specialist billings is a reduction of about 4 percent. Those effects translate into an average reduction of the number of specialist billings from 1.67 to 1.60. The estimate for specialist visits is significant at the one percent level, while the

²⁶Counting specialist visits in Germany is challenging because actual visits are not directly observable; researchers only observe quarterly cases.

 $^{^{27}\}mathrm{Billings}$ include different quantities of the rapy sessions.

Model:	(1)	(2)	(3)	(4)	
Dependent variables in log:					
Panel A	А	ntidepressan	t prescription	ns	
ATT	-0.0589***	-0.0602***	-0.0634***	-0.0505***	
	(0.0174)	(0.0223)	(0.0236)	(0.0132)	
Mean	0.263	0.263	0.263	0.263	
Observations (zipcode \times year)	19,345	19,345	19,345	19,345	
Panel B		Antidepres	ssant DDD		
ATT	-0.0501**	-0.0555**	-0.0587**	-0.0437***	
	(0.0191)	(0.0239)	(0.0252)	(0.0143)	
Mean	18.641	18.641	18.641	18.641	
Observations (zipcode \times year)	19,345	19,345	$19,\!345$	$19,\!345$	
Panel C	Specialist visits				
ATT	-0.0918**	-0.0892**	-0.0926**	-0.0829***	
	(0.0372)	(0.0411)	(0.0427)	(0.0263)	
Mean	0.182	0.182	0.182	0.182	
Observations (zipcode \times year)	19,323	19,323	19,323	19,323	
Panel D		Specialis	t billings		
ATT	-0.0657***	-0.0692**	-0.0732**	-0.0397**	
	(0.0223)	(0.0280)	(0.0292)	(0.0186)	
Mean	1.671	1.671	1.671	1.671	
Observations (zipcode \times year)	19,359	19,359	$19,\!359$	19,359	
Socioeconomic controls	_	\checkmark	\checkmark	\checkmark	
Weather controls	_	· —	\checkmark	\checkmark	
County×Year linear trends	_	_	_	\checkmark	
Year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	
Zip code fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	

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

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. Panels 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). Panel C 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). Panel D shows the estimated effects on the average number of prescriptions power per capita, unemployment rate, and share of foreigners. 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.

estimate for specialist billings is significant at the five 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: 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 psychotherapy (for detailed information on specialist billings see Appendix A.2). Specifications correspond to Column (4) in Table 5. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

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 7 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 anxiety diagnoses (Figure 3, Panel d), which become statistically significant three years after treatment. Specialist visits and billings tend to take the longest to decrease (Figure 3, Panel c, 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 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 Robustness Checks

In this section, we investigate the robustness of our estimations regarding spatial spillovers, confirmatory and placebo exercises, and alternative sample construction and estimators.

First, LEZs could impact the health of individuals living in zip codes just outside their borders. Theoretically, these areas could either benefit from improved air quality or suffer from increased pollution if drivers bypass the LEZ using emission-intensive vehicles. The latter scenario is particularly concerning as it could cause an overestimation of the treatment effects due to rising pollution levels in parts of the control group. To address these concerns, we exclude control group zip codes that intersect with 1km and 5km buffers around the LEZs. Table 6 displays the results of the spillover analysis. We find that the coefficients for the 1km buffer generally increase when excluding adjacent zip codes from the control group. This effect becomes more pronounced when excluding zip codes that intersect the 5km buffer. This suggests that zip codes adjacent to LEZs may benefit from air quality improvements generated by the LEZs. 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 indicate that our treatment effects are not overestimated due to negative spillovers from polluting traffic into the control group but rather represent a conservative estimate.

Second, 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). Table B.3 displays the effect of the introduction of LEZs on the probability of a prescription for cardiovascular diseases (Column 1). We find that LEZs reduce the probability of prescriptions by 2.7 percent, with the estimate being statistically significant at the five percent significance level. Moreover, the effect size falls 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 B.3. While finding a suitable placebo outcome is challenging, as air pollution affects many aspects of life, we test whether our empirical strategy detects effects on an outcome plausibly

Dependent variables in logs:	Antidepressant probability	Specialist Visit probability	Depression probability	Anxiety probability
Panel A		Buffer: 1	km	
ATT	-0.0477***	-0.0734***	-0.0332	-0.0522*
	(0.0173)	(0.0249)	(0.0235)	(0.0292)
Observations (zip code \times year)	$17,\!591$	$17,\!572$	$17,\!579$	$17,\!584$
Panel B		Buffer: 5	km	
ATT	-0.0617***	-0.0709***	-0.0374**	-0.0426
	(0.0159)	(0.0217)	(0.0149)	(0.0583)
Observations (zip code \times year)	15,011	$14,\!999$	$14,\!999$	$15,\!004$
Dependent variables in logs:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
Panel C		Buffer: 1	km	
ATT	-0.0561***	-0.0434*	-0.0889***	-0.0474**
	(0.0177)	(0.0222)	(0.0260)	(0.0181)
Observations (zip code \times year)	$17,\!591$	$17,\!591$	$17,\!572$	$17,\!605$
Panel D		Buffer: 5	km	
ATT	-0.0663***	-0.0547***	-0.0931***	-0.0520**
	(0.0140)	(0.0181)	(0.0238)	(0.0199)
Observations (zip code \times year)	15,011	$15,\!011$	$14,\!999$	$15,\!025$
Socioeconomic controls	\checkmark	\checkmark	\checkmark	\checkmark
Weather controls	\checkmark	\checkmark	\checkmark	\checkmark
County× year linear trends	\checkmark	\checkmark	\checkmark	\checkmark
Year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Zip code fixed effects	<u> </u>	1	\checkmark	\checkmark

Table 6: Accounting for Spillovers

Note: This table displays the average treatment effect on the treated of Low Emission Zones on different average probabilities in logs. The estimates report outcomes at the extensive and intensive margin, see Tables 4 and 5. All variables are on the zipcode-year level. In Panel A to D, zip codes that intersect with a 1km or 5km buffer around the LEZs are dropped from the control group. Socioe-conomic controls include purchasing power per capita, unemployment rate, and share of foreigners. 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.

unrelated to pollution. For this purpose, we identify ICD codes related to injuries²⁸ and estimate the effect of LEZ introduction on their probability. We find that the introduction of LEZs did not affect the probability of injuries (Figure 5, Panel b and Table B.3, Column 2).

Third, 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.4 displays the estimation without excluding any individual that moves their residence during the sample period. The coefficients remain qualitatively similar. We interpret these findings as further evidence that compositional changes are not driving the results.

²⁸ICD-Chapter S: This chapter specifically covers injuries to specific body parts.



Figure 5: Event Studies Confirmatory and Placebo Exercise

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

Fourth, 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. The stacked DiD 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 wave of LEZ introductions 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. Figure 6 displays the dynamic treatment effects for three alternative estimators. The event studies display a similar pattern, independent of the estimation method used.

Finally, we conduct a retrospective design analysis to assess the plausibility of our effect sizes, presented in Section C in the Appendix. Overall, the estimated effects of LEZs on mental health remain stable when accounting for potential spatial spillovers, and across variations in sample construction and estimators.

5.4 Heterogeneity

In this section, we examine whether our findings vary across age groups, building on previous research showing that age groups differ in their vulnerability to air pollution (e.g., Bishop et al., 2023, Currie & Neidell, 2005, Ju et al., 2023). Figure 7 presents results for three age groups: 15 to 29, 30 to 49, and 50 to 65 years old. A general pattern emerges across outcomes: the effects are more pronounced for the youngest group, 15 to 29 years old, which also has the highest baseline depression rates (see, e.g., Hapke et al., 2019).



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. Following Klauber et al. (2024), the stacked difference-in-differences approach additionally includes event time by treatment wave fixed effects and treated unit by treatment wave fixed effects. Standard errors are clustered at the county level. Estimates are shown including 95% confidence intervals.

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 effects of early exposure to air pollution (e.g., Chay & Greenstone, 2003, Currie



Figure 7: Event Studies Age Heterogeneity

♦ Age 15 - 29 ▲ Age 30 - 49 🗰 Age 50 - 65

_4

-2

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Years relative to LEZ introduction

6

6

_4

-2

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Years relative to LEZ introduction

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). Specifications correspond to Column (4) in Table 4. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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.

& 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.

5.5 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 cardio-vascular 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 noise²⁹, 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 effects 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.³⁰

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

²⁹Although 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.

³⁰One 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.

main findings.³¹

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.³²

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 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.

6 Cost-benefit Analysis

Our analyses demonstrate that policy measures targeting reductions in air pollution have farreaching 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 costeffectiveness 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 mental health disorders. In our sample (15-65 year old individuals living in large cities), an average of 7.4 percent of the population is prescribed antidepressants each year. We chose to focus on antidepressant prescriptions, as they represent the broadest outcome, including, among others, prescriptions for depression, anxiety, and sleep disorders. Since the administrative health insurance data is broadly representative of the German population, we can approximate the yearly number of individuals with antidepressant prescriptions 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 10 million individuals from our age cohort reside in zip

³¹Nonetheless, 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.

³²Specifically, 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.

codes with (future) LEZs, resulting in approximately 740,000 individuals with antidepressant prescriptions each year. To determine the number of antidepressant prescriptions prevented by implementing LEZs, we start with the average number of antidepressant prescriptions in (future) LEZ areas and multiply it with the average reduction in individuals with antidepressant prescriptions found in our study (3.8 percent). This calculation results in approximately 28,000 fewer antidepressant prescriptions annually. To estimate the avoided health costs, we multiply the number of prevented mental health cases by the average health costs associated with depression. 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 mental health issues translate into €84 million to €140 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 and antidepressant prescriptions. 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 approximately $\notin 2,500$ per month, this equates to an annual WTP of $\notin 1,800$ per person. For 28,000 cases of antidepressant prescriptions prevented, this amounts to approximately \notin 50 million annually. Furthermore, mental health issues 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 approximately $\notin 1.000$ per employee per year in 2014. Eßl-Maurer et al. (2022) estimate that sick leave costs for moderate to severe depressive symptoms amounts to approximately $\notin 2,200$, compared to sick leave costs for those with no to mild symptoms. Using the average of these estimates, preventing 28,000cases of mental health disorders could result in an additional saving of approximately €45 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.³³ Even without accounting for potential tax revenue losses, the direct and indirect monetary benefits of LEZs in reducing depression amount to approximately \notin 179 to \notin 235 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\$1.1 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.

³³Occupational 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 trafficrelated 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. 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 anxiety diagnoses 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 due to the policy. Second, our results emphasize that younger populations may 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). While previous research by Bishop et al. (2023) emphasized neurodegenerative impacts of air quality on older adults, our results indicate that policies such as Germany's LEZs yield substantial mental health co-benefits, broadening the policy relevance of air quality interventions across age groups. 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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Supplemental Appendix

A Descriptives

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	В	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	$_{\rm BW}$	Green	01.01.2010 - 01.03.2023	31	30
Pforzheim	$_{\rm BW}$	Green	01.01.2009	2	9
Regensburg	BY	Green	15.01.2018	1	7
Remscheid	NW	Green	01.01.2013	1	6
Reutlingen	$_{\rm BW}$	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	$_{\rm BW}$	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

Table A.1: LEZs in Germany



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 of observations over time.

Table A.2:	GOP -	Codes
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Code	Description
Psuchiatric a	and asuchatheraneutic fee schedule items (asuchiatrists)
21220	Conversation consultation discussion clarification (individual treatment)
21220	Psychiatric treatment (group treatment)
21221	i sychaetic etcaeniche (group etcaeniche)
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
Developth	···· · · · · · · · · · · · · · · · · ·
Psychotherap	peutic jee scheaule 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 acco	ording to the psychotherapy quideline (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 acco	ording to the neuchotherany guideline - Individual theranies
35401	Depth psychological psychotherapy (short-term therapy 1 individual treatment)
35402	Depth psychological psychotherapy (short-term therapy 1, 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)
<i>a</i>	
Services acco	runng to the psychotherapy guiaeline - 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)
30033 - 30039	Complex for group therapies (analytical therapy, long-term therapy)
35552 25552	Complex for group therapies (behavioral therapy, short-term therapy)
35703 - 30009 35703 - 35700	Complex for group therapies (vertagic therapy, short term therapy)
35713 - 35719 35713 - 35710	Complex for group therapies (systemic therapy, short-term therapy)
30119 - 30119	complex for group inclusion (systemic inclusivy, long-term inclusivy)
Psychodiagn	ostic 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

S90-S99

Depression (F32-F33) F32 Depressive episode F33 Recurrent depressive disorder Anxiety (F40-F41) F40Phobic disorder F41Anxiety disorder Chapter I - Diseases of the circulatory system (I00-I99) I00-I09Acute rheumatic fever I10-I15 Hypertensive diseases I20-I25 Ischemic heart diseases I26-I28Pulmonary heart disease and diseases of pulmonary circulation I30-I52 Other forms of heart disease I60-I69 Cerebrovascular diseases I70 - I79Diseases of arteries, arterioles, and capillaries I80-I89 Diseases of veins, lymphatic vessels and lymph nodes, not elsewhere classified I95 - I99Other 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 Injuries to the abdomen, lower back, lumbar spine, pelvis and external genitals S30-S39 S40-S49Injuries to the shoulder and upper arm S50-S59Injuries to the elbow and forearm S60-S69 Injuries to the wrist, hand and fingers S70-S79Injuries to the hip and thigh S80-S89 Injuries to the knee and lower leg

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.

Injuries to the ankle and foot

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
- C08 Calcium channel blockers

Table A.4 continued from previous page

ATC	Description
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 - A	gents 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 - La	ipid modifying agents
C10A	Lipid modifying agents, plain
C10B	Lipid modifying agents, combinations

B Additional Analyses

All zipcodes k with streets (>2 lanes)

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.

Dependent variables in log:	Antidepressant probability	Specialist Visit probability	Depression probability	Anxiety probability
ATT	-0.0408***	-0.0803***	-0.0359*	-0.0536***
	(0.0133)	(0.0219)	(0.0207)	(0.0199)
Observations (zipcode \times year)	14,306	14,284	$14,\!298$	$14,\!297$
Dependent variables in log:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
ATT	-0.0560***	-0.0469***	-0.0973***	-0.0527**
	(0.0145)	(0.0141)	(0.0215)	(0.0205)
Observations (zipcode \times year)	14,306	14,306	14,284	14,318
Socioeconomic controls	\checkmark	\checkmark	\checkmark	\checkmark
Weather controls	\checkmark	\checkmark	\checkmark	\checkmark
County×Year linear trends	\checkmark	\checkmark	\checkmark	\checkmark
Year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Zip code fixed effects	\checkmark	\checkmark	\checkmark	\checkmark

Table B.1: Main Results:	Only Zip Codes without Main Street	is $(\leq 4 \text{ lanes})$
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Note: This table displays the average treatment effect on the treated of Low Emission Zones on different average probabilities in logs. The estimates in the top panel of the table report outcomes at the extensive margin while the bottom panel reports outcomes measured at the intensive margin. All variables are on zipcode-year level. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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

 \blacklozenge All zipcodes \blacklozenge with streets (>2 lanes) Note: This figure displays dynamic effects of Low Emission Zones on yearly particulate matter (PM₁₀) and nitrogen dioxide (NO₂) 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.

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. Socioeconomic 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

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. Besides the zipcode and year fixed effects, regressions control for the number of inhabitants and county-specific trends. 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

🔶 Cardiovascular diagnosis 🔺 No cardiovascular diagnosis

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). Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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.

Model	Main specification	Excluding large streets	
Dependent variables in log:	Sleep disorder probability	Sleep disorder probability	
ATT	-0.0477***	-0.0445***	
	(0.0170)	(0.0150)	
Observations (zipcode \times year)	19,327	14,289	
Socioeconomic controls	\checkmark	\checkmark	
Weather controls	\checkmark	\checkmark	
State×Year linear trends	\checkmark	\checkmark	
Year fixed effects	\checkmark	\checkmark	
Zip code fixed effects	\checkmark	\checkmark	

Table B.2:	Sleep	Disorders
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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. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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.

Dependent variables in log:	Cardiovascular prescriptions probability	Injury probability
Model:	(1)	(2)
ATT	-0.0266**	0.0025
	(0.0129)	(0.0165)
Socioeconomic controls	\checkmark	\checkmark
Weather controls	\checkmark	\checkmark
County×Year linear trends	\checkmark	\checkmark
Year fixed effects	\checkmark	\checkmark
Zip code fixed effects	\checkmark	\checkmark
Mean of dependent variable	0.212	0.105
Observations (zipcode \times year)	$19,\!350$	$19,\!353$

Table B.3: Effect of LEZ Introduction on Cardiovascular Diseases and Injuries

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. Columns (1) and (2) show estimated effects on outcomes related to Cardiovascular diseases. Column (1) in terms of prescription probability and Column (2) in terms of defined daily dosage. Column (3) shows the estimated effects on the probability of a diagnosis related to an injury. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. Weather controls include information on humidity, vapor pressure, wind speed, 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.

Dependent variables in log:	Antidepressant probability	Specialist Visit probability	Depression probability	Anxiety probability
ATT	-0.0377***	-0.0661**	-0.0256	-0.0407**
	(0.0122)	(0.0267)	(0.0172)	(0.0173)
Observations (zipcode \times year)	19,345	19,323	19,333	19,338
Dependent variables in log:	Antidepressant prescriptions	Antidepressant DDD	Specialist visits	Specialist billings
ATT	-0.0505***	-0.0437^{***}	-0.0829***	-0.0397**
	(0.0132)	(0.0143)	(0.0263)	(0.0186)
Observations (zipcode \times year)	$19,\!345$	$19,\!345$	19,323	19,359
Socioeconomic controls	\checkmark	\checkmark	\checkmark	\checkmark
Weather controls	\checkmark	\checkmark	\checkmark	\checkmark
Demographic controls	\checkmark	\checkmark	\checkmark	\checkmark
County×Year linear trends	\checkmark	\checkmark	\checkmark	\checkmark
Year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark
Zip code fixed effects	\checkmark	\checkmark	\checkmark	\checkmark

Table B.4: Main Results including Movers

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. Socioeconomic controls include information on purchasing power per capita, unemployment rate, and share of foreigners. 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.

C 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.

Prob. antidepressant prescription (extensive) Ar			Antidepress	Antidepressant prescriptions (intensive)			
Effect size	Power	Type S	Type M	Effect size	Power	Type S	Type M
Plausible hypothetical effect sizes							
0.01	0.1298	0.0210	2.9940	0.01	0.1179	0.02789	3.2234
0.02	0.3744	0.0004	1.6176	0.02	0.3285	0.0008	1.7264
0.03	0.6911	0	1.2073	0.03	0.6228	0	1.2684
0.04	0.9064	0	1.0563	0.04	0.8578	0	1.0866
0.05	0.9838	0	1.0101	0.05	0.9662	0	1.0205
0.06	0.9985	0	1.0010	0.06	0.9952	0	1.0031
0.07	0.9999	0	1.0000	0.07	0.9996	0	1.0003
0.08	1.0000	0	1.0000	0.08	1.0000	0	1.0000
Estimated effect sizes							
0.0377	0.8708	0	1.0783	0.0505	0.9690	0	1.0189

Table C.1: Retrospective Design Analysis

Note: This table displays the results of a retrospective power analysis for two mental health outcomes, probability of antidepressant prescription (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 the probability of antidepressant prescription the coefficient and standard errors are based on Panel A of Tab. 4 while estimate and standard error for antidepressant prescriptions are sourced from Panel A Tab. 5.

Table C.1 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 0.88, with an exaggeration rate of 1.08. This suggests that we may be overestimating the true effect size by a factor of 1.08 on average (Timm, 2024). Turning to the estimate and standard error of antidepressant prescriptions, the overestimation error is even smaller. To conclude, while some coefficients may be slightly exaggerated, we conclude that power issues and exaggeration errors do not seem to be a major problem in our analysis.