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Exploring Transition Processes in Germany with Environmental Data

Empirical essays on International Trade and the Environment, Regulation by Information and Spatial Environmental Data

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Contents

List of Figures

List of Tables

Table of Abbreviations

Table 0.1: Table of Abbreviations

Abbreviation	German Name Description/Translation	English Name Description/Translation
2SLS	(2-stufige) Instrumentvariablenschätzung	Two Stage Least Squares Regression
a	Jahr	Year
ADH	Autor, Dorn & Hanson	Autor et al. (2013)
ATE	Durchschnittlicher Behandlungseffekt	Average Treatment Effect
ATT	Durchschnittlicher Behandlungseffekt (auf die Behandelten)	Average Treatment Effect on the Treated
AVG	Mittelwert	Average
BA	Bundesagentur für Arbeit	German Federal Employment Agency
BBR	Bundesamt für Bauwesen und Raumordnung	German Federal Office for Building and Regional Planning
BBSR	Bundesinstitut für Bau-, Stadt- und Raumforschung	German Federal Institute for Research on Building, Urban Affairs and Spatial Development
BHP	Betriebs-Historik-Panel (IAB)	(IAB) Establishment History Panel
BKG	Bundesamt für Kartographie und Geodäsie	German Federal Agency for Cartography and Geodetics
BMBF	Bundesministerium für Bildung und Forschung	German Federal Ministry of Education and Research
BRD	Bundesrepublik Deutschland	Federal Republic of Germany
CAAA	US Gesetz zur Reinhaltung der Luft	Clean Air Act Amendments (US)
CDC	-	Climate Data Center (DWD)
CDSE	-	Center for Doctoral Studies in Economics, Mannheim
CLC	-	CORINE Land Cover Project (EU)
CLRTAP	Übereinkommen über weiträumige grenzüberschreitende Luftverunreinigung	Convention on Long-Range Transboundary Air Pollution
CO_2	Kohlenstoffdioxid	Carbon Dioxide
COMEAP	-	Committee on the Medical Effects of Air Pollutants
COMTRADE	-	International Trade Statistics Database of the United Nations
COPD	Chronisch obstruktive Lungenerkrankung	Chronic Obstructive Pulmonary Disease
CORINE	(EU) Koordinierung von Informationen über die Umwelt	(EU) Coordination of Information on the Environment
DFS	Dauth, Findeisen & Suedekum	Dauth et al. (2014)
DGNB	Deutsche Gesellschaft für Nachhaltiges Bauen e.V.	German Sustainable Building Council
DDR / GDR	Deutsche Demokratische Republik	(Former) German Democratic Republic
DWD	Deutscher Wetterdienst	National Meteorological Service (Germany)
EC	Europäische Kommission	European Commission
ECB	Europäische Zentralbank	European Central Bank
E[ast][ern]E	Osteuropa	Eastern Europe (used in Graphs and Tables)
EEA	Europäische Umweltagentur	European Environment Agency

Table 0.2: Table of Abbreviations (cont.)

Abbreviation	German Name Description/Translation	English Name Description/Translation
EKC	-	Environmental Kuznets Curve
EPER	Europäisches Schadstoffemissionsregister	European Pollutant Emission Register (predecessor to the E-PRTR)
E-PRTR	Europäische Schadstoff-Freisetzungs- und Verbringungsregister	European Pollutant Release and Transfer Register (successor of the EPER)
EPSG	-	European Petroleum Survey Group
EPA	Umweltschutzbehörde (USA)	Environmental Protection Agency
ΔEPA	Absolute Änderung im Exportvolumen pro Fläche	Export Exposure Change per area
ΔEPW	Absolute Änderung im Exportvolumen pro Arbeiter	Export Exposure Change per worker
ERE	-	Environmental and Resource Economics (Journal)
EU	Europäische Union	European Union
EURO[1-6]	Europäische Abgasnorm [1-6]	European emission standards [1-6]
EURO / €	Euro (Währung)	Euro (currency)
EU27	27 EU-Mitgliedstaaten	27 Member States of the European Union
EX	Exporte (in €)	Exports (in €)
FDI	-	Foreign Direct Investment
FED	Zentralbank der USA	US Federal Reserve
F&B	F+B Forschung und Beratung für Wohnen, Immobilien und Umwelt GmbH	F+B (housing data provider)
GDP	Bruttosozialprodukt (in € or $)	Gross Domestic Product (in € or $)
GESS	-	Graduate School of Social and Economic Sciences, Mannheim
GIS	Geoinformationssystem	Geographical Information System
GMM	Generalisierte Momentenmethode	Generalized Method of Moments
GRETA	-	Gridding Emission Tool for ArcGIS
GWR	-	Geographically Weighted Regressions
ha	Hektar	hectare
HPI	Häuserpreisindex (from F&B)	Housing Price Index (from F&B)
IAB	Institut für Arbeitsmarkt- und Berufsforschung (BA)	Institute for Employment Research (of the German BA)
IM	Importe (in €)	Imports (in €)
INKAR	INdikatoren und KARten zur Raum- und Stadtentwicklung in Deutschland und in Europa (BBSR)	Indicators and maps on spatial and urban development in Germany and Europe (BBSR)
IPCC	Zwischenstaatlicher Ausschuss für Klimaänderungen (UN)	Intergovernmental Panel on Climate Change (UN)
ΔIPA	Absolute Änderung im Importvolumen pro Fläche	Import Exposure Change per area
ΔIPW	Absolute Änderung im Importvolumen pro Arbeiter	Import Exposure Change per worker
ITC	-	International Trade Commission (US)
IV	Instrumentalvariable	Instrumental Variable

Table 0.3: Table of Abbreviations (cont.)

Abbreviation	German Name Description/Translation	English Name Description/Translation
LEZ	Umweltzone (im Verkehr)	Low-Emission Zone
LKS	Landkreis(e)	County (Germany)
MSA	US Metropolregion	Metropolitan Statistical Area
MCC	-	Mercator Research Institute on Global Commons and Climate Change, Berlin
NACE[1.1]	Nomenclature statistique des activités économiques dans la Communauté Européenne (Revision 1.1)	Statistical Classification of Economic Activities in the European Community (Revision 1.1)
NFR	-	Nomenclature for Reporting
NO_2	Stickstoff	Nitrogen Dioxide
O_3	Ozon	Ozone
OI[E]	Optimales Interpolationsraster (für Emissionen)	Optimal Interpolation (Emission) Raster
OLS	Methode der kleinsten Quadrate	Ordinary Least Squares Regression
$PM2.5$	Feinstaub (Durchmesser $\leq 2.5\mu m$)	Particulate Matter (Diameter $\leq 2.5\mu m$)
$PM10$	Feinstaub (Durchmesser $\leq 10\mu m$)	Particulate Matter (Diameter $\leq 10\mu m$)
PRC	Volksrepublik China	People's Republic of China
RCG	-	REM-CALGRID (Model)
RR	Relativer Risikofaktor	Relative Risk (factor)
SARAR	-	Spatial-autoregressive model with spatial-autoregressive errors
SE	Standardfehler	Standard Error
SEDAC	-	Socioeconomic Data and Applications Center
SITC [Rev. 3/4]	Internationales Warenverzeichnis für den Außenhandel, Revision 3/4	Standard International Trade Classification, Revision 3/4
SNAP	-	Selected Nomenclature for Air Pollution
SO_2	Schwefeldioxid	Sulfur Dioxide
STD	Standardabweichung	Standard Deviation
TREMOD	Emissionsberechnungsmodell (Verkehr)	Transport Emission Model
TRI	-	Toxics Release Inventory (US)
TTB	-	Temporary Trade Barriers
UBA	Umweltbundesamt	German Federal Environment Agency
VSL	Wert eines statistischen Lebens	Value of Statistical Life
UCB	-	University of California, Berkeley
UN	Vereinte Nationen	United Nations
UNECE	Wirtschaftskommission für Europa der Vereinten Nationen	United Nations Economic Commission for Europe
USA	Vereinigte Staaten von Amerika	United States of America
USD / $	-	US Dollar
UTM	-	Universal Transverse Mercator (System)
VAR	Varianz	Variance
WGS84	-	World Geodetic System 1984
WTO	Welthandelsorganisation	World Trade Organization
WZ93	Klassifikation der Wirtschaftszweige, Ausgabe 1993	German Classification of Economic Sectors, Revision 1993
ZSE	Zentrales System Emissionen	German National Emission Inventory

General Introduction

There is a growing awareness that human civilization and industrial activity interact with the environment and create negative externalities by deteriorating its quality for current and future generations. While greenhouse gas emissions change the composition of the atmosphere and have the power to impact the climate at a global scale, emissions of local pollutants directly impact the well-being of individuals close to the source. The rise in awareness is exemplified by international agreements such as the Paris Agreement signed in 2016 and recent EU air quality directives (e.g. 2008/50/EC - Directive on Ambient Air Quality and Cleaner Air for Europe). It is also accompanied by an increasing level of data availability and an increasing willingness of policy makers to monitor environmental data and share it with the public.

This makes research on environmental externalities and the policies addressing these externalities an important and promising endeavour. Not least because the various environmental threats and remedies are hotly debated in the public and novel environmental data allows environmental economists to accurately address previously unanswerable research questions.

While most advanced economies have nowadays implemented intricate environmental regulation, Germany presents a unique case study, as it is one of Europe's largest economies, at the center of international trade networks and the arena of an unprecedented energy and industrial transition process. The novel environmental datasets published by the German Environment Agency ("Umweltbundesamt", UBA) over the course of the past two decades have the power to highlight this transition process.

First of all, these two decades have seen a rapid shift in economic power at the international level. They have provided challenges to economies trying to adjust to technological change and financial turmoil. And they have been characterized by a growing exposure to globalized trade flows. As Germany continues to deepen its trade ties with Eastern Europe and China, it remains a relevant question whether the resulting shift in industrial production has been in line with Germany's alleged willingness to reduce local emissions. This research project can shed light on how advanced economies and terms of trade shape industrial production in times of growing environmental awareness and global interconnectivity.

Second, EU regulations enforce the reporting of pollution emissions and concentrations in an attempt to foster regulation by information through citizens using the data at their disposal for community action. One prime example are the point source emissions from industrial facilities via the European Pollutant Release and Transport Register (E-PRTR). The publication of German raw emission data in the year 2009 and the resulting real estate price dynamics are a testing ground for the question of public awareness and uptake of such information.

My dissertation aims to answer both questions and is structured as follows: Chapter 1 presents the main findings regarding the effect of trade openness on local air quality in Germany by combining adapted trade shock data with spatial grid data on pollution concentrations. Chapter 2 explores the effect of publicly available pollution emission reports from industrial facilities (via the E-PRTR) on real estate prices in Germany, thereby evaluating public awareness of environmental quality and public response to regulation by information. Chapter 3 synthesizes information on the spatial pollutant emission datasets available for researchers in the German context and provides insight on how to harness their potential. The Appendix (A) contains supplementary material for all Chapters.

First Chapter: Trade and the Environment

During recent elections in Europe and America, the growing trade interconnectivity has come under criticism and populists and media outlets have emphasized the negative impacts of trade exposure. On the other hand, there is rich empirical evidence highlighting the positive aspects of international trade and the German export industry may be one of the biggest beneficiaries.

According to recent research in trade and labor economics, the increasing trade flows with China and Eastern Europe since 1998 have stabilized aggregate employment and created new manufacturing job opportunities in the German labor market despite significant restructuring in industries under pressure.

This chapter evaluates, whether the restructuring processes resulting from trade opportunities also had a positive impact on emission profiles. A significant shift of production capacities towards cleaner and more modern facilities could be considered a beneficial windfall effect of trade openness and is potentially detectable using spatial environmental data. Demonstrating the potential of existing terms of trade for such environmental improvements may be an antidote against the populist notion that trade openness has predominantly negative effects for developed nations.

To this end, I study whether the increase in trade relationships towards China and Eastern Europe is tied to a reduction in local aerial pollution concentrations. The analysis in long differences exploits regional variation in trade exposure and pollution exposure over the time period from 1998 to 2008 coinciding with China's admission to the WTO in 2001 and subsequent EU accession waves. I observe regional pollution concentration changes for NO_2, SO_2 and $PM10$ and pair this data with changes in trade flows at the German county level over the same time period. Threats to identification are resolved through the implementation of exogenous variation in Chinese and Eastern European trade openness as instrumental variables. I find a positive effect of rising local import competition on environmental quality for NO_2 and $PM10$ concentrations, which survives robustness checks such as weighting trade exposure by area or controlling for initial dirtiness. These gains are not offset by the negligible contributions of export opportunities towards China or the minor increases in pollution levels caused by export scaling towards Eastern Europe. As emission increases tied to export opportunities are small in comparison to the savings from trade-induced restructuring, this yields a net reduction of $0.07\mu g/m^3$ in average concentration levels for NO_2 and of $0.24\mu g/m^3$ for $PM10$ over the observation period. These windfall effects of trade openness constitute an economically significant but minor contribution to the absolute reductions in both substances ($\sim 3\mu g/m^3$) over the observed time frame.

Second Chapter: Regulation by Information

This research project addresses a policy response to industry emission externalities which refrains from direct command-and-control regulation and instead promotes "regulation by information" by making environmental pollution data available to the public. The European Pollutant Release and Transfer Register (E-PRTR) is a web-based register established by EU regulations (i.e. Regulation (EC) No 166/2006 implementing the UNECE PRTR Protocol signed in 2003) and maintained by the European Environment Agency (EEA). It obliges industrial facilities within EU member states to report emitted pollutant quantities to the national environmental agencies if these exceed predefined thresholds. The German Environment Agency (UBA) compiles this information and has made the reports available to the public on a yearly basis since 2009. The research design in this chapter exploits the publication timing in a quasi-experimental approach based on differences-in-differences and event study tools in order to analyze whether such emission reports alter asset prices in the German housing market.

The event under study is the publication of the first wave of reported E-PRTR emission quantities in 2009. The analysis is based on quarterly housing prices at the German postal code level for the years 2007-2011 and provides the first evidence from Europe on the link between emission data and housing prices. Estimating a differences-in-differences model and controlling for observable differences in land use, housing type distribution, tax revenues and other postal code area characteristics by means of propensity score matching, the released emission information is found to have no effect on housing valuations in affected postal code areas. This result survives a number of robustness checks designed to assess whether the finding is due to data aggregation issues or the treatment definition. It leads to the conclusion that on an aggregate level the 2009 publication of E-PRTR data did not have an immediate and noticeable effect on housing prices in Germany.

Third Chapter: Spatial Environmental Data

This chapter provides an overview of the environmental datasets that enable the research projects presented above. It compares the characteristics of these datasets, evaluates their usefulness for different research questions and provides methodological insight on how to utilize the datasets and harness their potential for the research questions at hand. The summary focuses on data products provided by the German UBA and the industry emission dataset E-PRTR compiled for the EEA. The former mainly consist of spatial grid data based on the Optimal Interpolation (OI) methodology and advanced distribution models, which generate raster datasets for the evaluation of local immission concentrations of airborne pollutants such as NO_2, $PM10$ and SO_2 in lieu of underlying point source measurements. More recent raster products rely on the Gridding Emission Tool for ArcGIS (GRETA) to distribute emissions onto a finer spatial grid and attribute emission quantities to source sectors. The E-PRTR contains obligatory reports of pollutant releases from industrial facilities exceeding predefined thresholds and covers a broad selection of chemical agents [1].

A lot of relevant information regarding the more technical aspects of data preparation behind my empirical research has been compiled in this chapter and has been referenced throughout the document. The chapter also highlights some of the advantages and inherent limitations entailed by the usage of various datasets and can therefore serve as a practical guide on how to utilize the data for subsequent empirical projects or related research questions. Last but not least, the chapter provides justification for the use of individual datasets in the context of my research and tests their validity for the research questions under study.

[1] While chemical agents and particles released from a point source are defined as emissions, local aerial concentrations resulting from the dispersion and travel of such emissions may occur in areas far from the source and constitute the so-called immisions. Thus, Chapter 1 utilizes immission concentrations for its empirical analysis, while Chapter 2 analyzes the public response to emission reports.

Chapter 1

Did Globalization help Germany become cleaner? - The effect of increasing Import/Export Exposure on local air pollution

1.1 Introduction

The past decades have seen a remarkable change in the structure of the world economy as both the World Trade Organization (WTO) and the European Union (EU) have expanded towards the states of the former Soviet Union and have fully integrated the People's Republic of China into their vast trade network. This development has affected Western economies on many levels and recent literature has attempted to quantify and evaluate its effects on local labor markets, regional industry structures and society as a whole. While the increasing trade integration is sometimes perceived as a challenge to the existing status quo and has been shown to create social and economic pressure, it provides access to foreign markets, opportunities for renovation and incentives for innovation.

One important aspect of exposure to the world markets is the impact on local environmental quality within the countries involved. Due to the complexity of trade relationships and the countervailing nature of observed effects, it remains an empirical question, whether the environmental situation in a given country benefits or suffers from increasing trade links. Seminal papers such as Antweiler et al. (2001) and Copeland and Taylor (2004) have highlighted the possibility for positive effects of free trade on environmental quality. They have identified several channels as drivers of the relationship between trade exposure and environmental quality such as scale of production, technological change and the composition of the production spectrum. While Shapiro and Walker (2018) have recently disentangled the effects of environmental regulation, productivity and trade on aerial pollution in the United States manufacturing sector, empirical evidence for the aggregate effect of Globalization on environmental quality in developed economies remains sparse.

This chapter explores the effect of rising trade openness on the local environmental quality in Germany by linking changes in trade exposure towards rising economies in the East between 1998 and 2008 to spatial concentration measures of aerial pollution. In doing so, it conducts the first empirical analysis of this aspect with a focus on Germany as one of the world's leading exporters and one of the pivotal economies in the European Union. For the empirical analysis, local concentrations of nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and particulate matter with a diameter of $10\mu m$ or less ($PM10$) are obtained at high spatial resolution from geocoded datasets provided by the German Environment Agency (UBA). They are combined with trade exposure measures at the German county level. This allows for the exploitation of regional variation in both trade intensity and local air quality for the sake of empirically identifying causal effects between trade openness and emission patterns[2].

An efficient methodology for distributing trade volumes onto the regional level has been developed by Autor et al. (2013) (henceforth ADH), who evaluate domestic US labor market responses by assigning trade flows to commuting zones according to proportional industry employment shares. While their exposure measures reveal a negative impact of increasing trade

[2]The pollutants under study are known for their detrimental effects on the respiratory and the cardiovascular system resulting in severe short term and long term health risks associated with exposure. They are by-products of industrial production processes and described in more detail in Appendix A.1.1.

ties with China on US manufacturing workers, Dauth et al. (2014) (henceforth DFS) find contrasting evidence for the German manufacturing sector by adopting the same framework for the computation of variables at the German county level. Trade ties between Germany and both China and the former members of the Soviet Union in Eastern Europe have increased significantly since the fall of the Iron Curtain. By exploiting cross-county variation in trade shock severity, DFS demonstrate that the German manufacturing sector has been capable of harnessing export opportunities especially towards Eastern Europe. This is evidenced by the sector securing a high employment share above trend through the creation of up to 442,000 additional jobs. By conducting an extensive study of worker flows in Germany, Dauth et al. (2021) demonstrate, however, that the overall positive employment effect requires individual worker mobility to mitigate adverse impacts of import shocks on careers in industries suffering from import competition. Despite significant structural changes, the dominating influence of expanding export opportunities towards Eastern Europe has rendered Germany a positive singularity in the international context. This becomes particularly evident when comparing the labor market effects with the adverse developments in the US market. The magnitude of both trade expansion[3] and labor market responses gives rise to the question, whether this restructuring process also has the capacity to effectively shape and enhance industry emission profiles.

1.2 Contribution

I contribute to the existing literature by expanding the research on the effects of trade openness on local stakeholders to local emission profiles by making use of (i) the regional trade exposure framework and (ii) the identification

[3]According to Dauth et al. (2014), this expansion amounts to a rate of 1608% in imported goods from China to Germany between 1988 and 2008 and a growth rate of 900% in German exports to China. The growth rate for imported goods from Eastern Europe amounts to a rate of roughly 900% and is slightly exceeded by the growth rate of German exports to this region. Their definition of Eastern Europe (EasternE) has been adopted for this chapter and encompasses Bulgaria, the Czech Republic, Hungary, Poland, Romania, Slovakia and Slovenia as well as former members of the Soviet Union (Russia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan).

strategy introduced by ADH and DFS, which resolves endogeneity issues through the use of exogenous variation in Chinese and Eastern European trade openness. With respect to potentially beneficial environmental impacts, Germany is an excellent case study as documented by DFS. This is because (i) Germany allows for an analysis beyond trivial emission savings due to a shrinking manufacturing sector and because (ii) it represents a major trade hub economy in Europe that has also implemented costly environmental regulation. Environmental benefits in this scenario may therefore be the result of restructuring and modernization instead of a pure liquidation of manufacturing capacities. The empirical approach is designed to evaluate, whether the net effect of Germany's rising trade exposure towards China and Eastern Europe has been a reduction in local pollution concentration levels. It also allows for the quantification of such net effects.

First of all, the estimates from my long differences instrumental variable (IV) regressions suggest that import competition from both China and Eastern Europe has lowered NO_2 and $PM10$ levels in Germany, while emerging export opportunities have not caused level increases of comparable magnitude. The resulting net effect of increased trade exposure on local air quality in Germany is therefore a reduction in concentration levels of $-0.07\mu g/m^3$ for NO_2 and of $-0.24\mu g/m^3$ for $PM10$.

Second, robustness checks incorporating initial county-level heterogeneity reveal that air quality in initially dirtier counties benefits more from import exposure than air quality in cleaner counties. Initially polluted counties also experience stronger scale effects due to export opportunities, however.

Finally, I demonstrate that the overall savings represent economically significant improvements when translated into mortality benefits but a small contribution to the overall long-term trends, which yield pollution exposure reductions of approximately $-3\mu g/m^3$ for NO_2 and of $-2.84\mu g/m^3$ for $PM10$ over the same time period (1998-2008). Since Germany has experienced beneficial manufacturing employment effects as a result of the new trade routes, demonstrating the existence of meaningful pollution concentration benefits in the presence of related scale effects is a strong empirical finding[4].

[4]Average reductions across all German counties are the result of back-of-the-envelope

1.3 Literature and Historical Background

1.3.1 Existing empirical evidence

The works by Autor et al. (2013) and Dauth et al. (2014) provide the empirical methodology for dissecting trade exposure at the local level used within this chapter. They also provide ample evidence for the significant impact of increased trade volumes on local labor markets and the restructuring pressure in non-competitive industries. Autor et al. (2014) for example demonstrate that rising import competition with China drove workers out of affected US industries and lowered wages especially for low-skilled manufacturing workers. Dauth et al. (2021) confirm the pattern for Germany that rising import penetration induces workers to leave the exposed industries and that industry sorting has been an effective form of adjustment for absorbing the trade shocks in Germany. Non-competitiveness may be due to the fact that affected industries rely on technologically obsolete facilities or suffer from a competitive disadvantage due to higher environmental regulation. Their restructuring therefore constitutes a plausible impact channel for environmental improvements[5].

Consequently, empirical research by Naughton (2010) conducted with aggregated data from several European countries indicates that variables capturing the degree of trade intensity are positively linked to reductions in SO_2 and nitrogen oxide (NO_X) emissions per capita over the time period from 1980 to 2000. Furthermore, Managi et al. (2009) demonstrate that trade openness as a major aspect of Globalization has allowed OECD countries like Germany to improve their environmental footprint between 1972 and 2000 but that non-OECD countries have experienced detrimental effects with respect

calculations based on the regression coefficients from my preferred IV specification presented in Table 1.3 of Chapter 1.5.2. Chapter 1.5.3 describes this back-of-the-envelope methodology in more detail and contains a simple Value of Statistical Life (VSL) estimation which assesses the economical impact of savings through the mortality channel.

[5]Anecdotal evidence (e.g. The New York Times, 2007) suggests that obsolete and dirty German facilities have been dismantled in their entirety and reassembled in China, where their operation is still profitable.

to SO_2 and carbon dioxide (CO_2) emissions over the same time period.

On the other hand, de Sousa et al. (2019) find positive effects of trade integration for local Chinese SO_2 concentrations as a result of increased processing trade activities. These reductions are mainly driven by trade with developed countries and imply the possibility of positive environmental effects within developing economies if trade openness raises the technological level of operations. Milner and Xu (2009) also discuss the environmental impact of trade liberalization on China and find contradictory evidence depending on the model assumptions. When taking pollution content into account, the impact of trade openness on China's domestic environmental quality becomes negative making China a net exporter of embodied pollutants. By constructing export shocks at the Chinese prefecture level, Bombardini and Li (2016) find that trade shocks with respect to dirty industries affect local pollution and child mortality. A one standard deviation increase in polluted exports raises SO_2 concentrations by $5.4\mu g/m^3$ between 1990 and 2010 according to their analysis. However, they also find that higher domestic incomes drive demand for clean environments. Furthermore, Lin et al. (2014) argue that China has become one of the world's largest emitters of anthropogenic air pollution and that pollution from export-oriented industries is contributing to sulfate pollution and ozone levels on the US West Coast. This implies that growing Chinese industrial production causes environmental damages affecting air quality far from the point of origin. Outsourcing this production, however, retains the potential for domestic environmental benefits on the part of the developed trade partners.

A recent paper by Shapiro and Walker (2018), investigates the role of trade, productivity and environmental regulation on aerial pollutant abatement in the US manufacturing sector between 1990 and 2008. They find that the largest portion of reductions can be traced back to stricter regulation and that the remaining effect of trade exposure is rather small. This implies that regulation in Germany may lead both to direct local abatement and simultaneous outsourcing of production in order to avoid costly compliance with environmental regulation. Consequently, rising import competition and pollution reductions may be directly correlated and estimations may be subject to simultaneity bias. This reinforces the need for an identification strategy via instrumental variables based on exogenous variation in trade openness demonstrated by the foreign trading partners.

1.3.2 Impact channels of trade exposure on environmental quality

The seminal paper by Antweiler et al. (2001) argues that free trade globally reduces pollution emissions through production scaling, technology effects and changes in product mix. Their empirical analysis reveals that a rise in production and income by 1% reduces pollution concentrations by 1%. Estimates for SO_2 indicate that rising global trade openness creates small but measurable reductions in pollution concentrations by reducing the pollution intensity of domestic production. Copeland and Taylor (2004) examine the relationship between international trade, economic growth and the environment and review prior empirical and theoretical works. They highlight the role of comparative advantages through environmental regulation and the interaction of trade policy and environmental policy, which can manifest itself in deregulated "pollution havens" attracting industry production from environmentally regulated countries. A recent review by Dechezlepretre and Sato (2017) reveals that strict environmental regulation represents a comparative disadvantage for affected industries. While small compared to overall trends in production and mitigated by innovation in clean technologies, this disadvantage can have significant impacts on pollution- and energy-intensive sectors in the short run. Wagner and Timmins (2009) for example find statistically and economically significant evidence for an outsourcing to "pollution havens" within the German chemical industry. Their empirical panel regression analysis demonstrates that stringent environmental regulation acts as a deterrent for foreign direct investment (FDI) in this sector .

While the outsourcing of highly pollution intensive manufacturing from developed economies through trade liberalization will lead to environmental benefits within the outsourcing countries, it may conversely lead to detrimental environmental effects in developing economies if these fail to implement this industrial production at a much higher technological standard. The outsourcing economies then become cleaner domestically but remain net importers of embodied ecological footprints from countries with a comparative advantage in producing environment-intensive goods as demonstrated by Dam et al. (2017). This means that by outsourcing dirty production and re-importing the products a country does not necessarily change its domestic emission consumption profile, as it implicitly re-imports and consumes the emissions released abroad[6].

On the other hand, restructuring pollution and energy intensive manufacturing globally does offer opportunities for improvement. Koren et al. (2019) demonstrate that Hungarian machine operators benefit from exposure to imported machines and that importing advanced machinery increases skill and wage levels. Trade openness therefore yields beneficial productivity and environmental effects for developing nations if they experience additional trade exposure in high-skill technologies. The empirical correlation between high productivity and environmentally friendly production is well documented. Cui et al. (2015) as well as Forslid et al. (2018) provide theoretical models justifying this relationship by demonstrating that successful exporters are likely the most productive firms as well as the earliest adopters of new technologies and new pollution abatement methods. This is supported by an empirical analysis utilizing US and Swedish firm-level data, which demonstrates that export opportunities increase environmental quality via the internal technology adoption channel. Facilities from both developed and developing countries already operating at high productivity levels or in export markets are prone to enter a "virtuous circle" that makes such facilities ever more competitive

[6]This has also been shown by Aichele and Felbermayr (2012) and Aichele and Felbermayr (2015) in the context of CO_2 footprints and formal commitment to the Kyoto Protocol. My analysis focuses on locally active pollutants and evaluates the potential for domestic abatement, thereby abstracting from fairness aspects in a potential zero-sum game. The importance of emission leakage aspects becomes apparent, though, when considering outsourcing as a simple relocation of emission sources and has been studied thoroughly with respect to green house gases (see e.g. Jakob et al., 2014). The severity of this leakage effect depends on several factors and can be rather small if domestic emission intensity is able to respond to a rising demand for export goods (see e.g. Barrows and Ollivier (2018b)).

on global markets, more productive and therefore cleaner and more energy efficient[7]. Holladay (2016) highlights the relationship between productivity and emission intensity at the firm level and argues that import competition leads to the exit of pollution intensive establishments. Theoretical models and empirical evidence from this strand of literature thus emphasize that trade liberalization has the capacity to reduce local or even global pollution levels by reinforcing overall productivity, technological standards and the shift towards cleaner and more energy efficient industries.

A popular concept mirroring these aspects is the Environmental Kuznets Curve (EKC), which describes the relationship between a nation's wealth and its pollution levels. Stern (2004) revisits the theory and argues that the inverted-U-shaped relationship between the wealth of a nation and its pollution levels may be driven by a country's ability to dictate its terms of trade. Developed economies in such a framework start outsourcing their dirtiest production to developing economies. As environmental regulation creates financial constraints for polluting domestic industries, it incentivizes shifting production with costly compliance to less regulated countries (i.e. "pollution havens"). This research project seeks to analyze to what extent such impacts of import competition and export opportunities on environmental quality can be detected at the German county level, as the strict regulation in Germany is seen as a powerful catalyst in the context of existing frameworks (such as the EKC[8]).

While the impact of trade liberalization on pollution concentrations can be attributed to three principal channels according to Antweiler et al. (2001) and Copeland and Taylor (2004) and decomposed into a pure scale effect, a composition effect and a technique component, it is beyond the scope of this

[7]There is ample anecdotal evidence from Germany that manufacturing companies invest into the sustainability and emission intensity of modern facilities built after 1998 (e.g. Mitteldeutscher Rundfunk, 2019). This pertains to energy consumption as well and is partly driven by the desire to generate long-term savings, to improve the brand image and to achieve certification from independent bodies and testing institutes such as the German Sustainable Building Council ("Deutsche Gesellschaft für Nachhaltiges Bauen", DGNB).

[8]For a more detailed analysis of the role of free trade in the context of the Environmental Kuznets Curve refer to Appendix A.1.2.

research project to carry out such a decomposition[9]. Instead, I analytically focus on the compounded effect at the German county-level and provide a summary of the literature on potential impact channels as well as their decomposition in Appendix A.1.3 and Appendix A.1.4.

1.3.3 Trade exposure, labor markets and related research

ADH and DFS provide ample evidence for the significant impact of increased trade volumes on local labor markets. While ADH demonstrate that rising import competition with China has driven workers out of affected US industries and affected wages negatively, DFS demonstrate a much smaller detrimental effect for German industries exposed to Chinese import competition and a positive employment effect from rising export exposure, especially with respect to new export opportunities in Eastern Europe. They estimate that growing trade ties with these two trade partners have saved up to 442,000 German manufacturing jobs over trend between 1988 and 2008. This is in line with findings presented in Benedetto (2012), who argues that Germany has been able to exploit export opportunities with China. There is a concentration of export flows in mechanical and electrical intermediate goods, in investment goods for the Chinese exporting industry and in luxury cars according to his analysis. While this suggests that recent trends in globalization have yielded overall positive employment effects in Germany, restructuring and adjustments in industry production lead to foreclosures and frictions within less competitive sectors as documented by Dauth et al. (2021). A multi-sector gravity model with heterogeneous workers developed by Galle et al. (2018) quantifies the distributional welfare effects of the Chinese trade shock on US workers. They estimate that the most negatively affected groups suffer welfare losses up to five times the size of the positive average welfare gain. According

[9] A supplementary analysis relying on E-PRTR data at the industry-level is presented in Chapter 3.4.2. The limited availability of data precludes causal identification but the descriptive analysis verifies that key industries affected by trade exposure in DFS also drive pollution patterns.

to Marin (2017), the extent of aggregate employment gains through trade renders Germany a singularity in the international context, however, which can be explained by a predominantly decentralized management style and high product quality.

While restructuring from industries under pressure to exporting industries may yield environmental benefits, the perceived and actual welfare losses of affected workers have played a major role in recent political debates. Utilizing the data sources and the methodological approach popularized by DFS and linking voting behavior to localized trade exposure in Germany, Dippel et al. (2015) demonstrate that import competition has fueled the rise of right-wing populism. Utilizing results from the US congressional elections in 2002 and 2010, Autor et al. (2016) find a trend towards ideological polarization in districts exposed to import competition shocks, which end up electing either very conservative Republican candidates or very liberal Democrats. A shift towards cleaner production through import competition may therefore be accompanied by attrition effects and social frictions in affected regions, which require political attentiveness and can potentially be addressed through fiscal interventions and transfers.

Sectors and industries under pressure from import competition, however, can apply for Temporary Trade Barriers (TTB) via the EU or the International Trade Commission (ITC) in the US in order to defend their products and workers against supposedly unfair or insurmountable competition. Trimarchi (2019) shows that affected industries in the United States have been partially successful at doing so and have put non-tariff protection measures in place over the past two decades that have effectively protected employees. He estimates that negative employment effects from import competition in the United States are halved when accounting for successful protection measures[10]. Protectionist measures therefore have the capacity to slow down transformation processes and to delay welfare losses for domestic workers.

[10] A recent EU example are the anti-dumping and anti-subsidy measures against Chinese solar panels implemented in 2013 and terminated in 2018. Since this chapter is designed to evaluate the impact of actual trade flows, trade barriers potentially limiting such flows do not have to be accounted for.

1.3.4 German Timeline of Globalization

The most important catalysts for the trade expansion towards China and Eastern Europe are certainly the fall of the Iron Curtain after the collapse of the Soviet Union and China's accession to the WTO on December 11th, 2001. The post Cold War enlargement of the EU began in the mid nineties and was foreshadowed by Austria, Finland, and Sweden joining the EU on January, 1st, 1995, which marked its fourth enlargement phase. Eight Central and Eastern European countries (the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia) along with two Mediterranean ones (Malta and Cyprus) joined on May, 1st, 2004. Romania and Bulgaria were deemed ineligible for this wave of Eastern European Enlargement but admitted on January, 1st, 2007[11].

Figure 1.1 depicts the rise in absolute volumes of manufacturing goods between Germany and the new partners in the East during this time period and plots these against the overall trends in German manufacturing trade [12]. The trade flows with China and Eastern Europe exhibit a significant increase from less than €50bn each in 1998 to an already significant share of Germany's global manufacturing trade in 2008 with Eastern European exports exceeding €100bn by the end of 2008.

[11] An official summary of the EU accession history can be found on the official website (https://ec.europa.eu/neighbourhood-enlargement/policy/from-6-to-27-members_en).

[12] All real trade volumes are restricted to the manufacturing sector, denoted in 2005 currency and have been extracted from official UN trade data (COMTRADE). Total manufacturing trade figures are scaled according to the secondary axis. The selection of manufacturing industries follows DFS and is described along with the aggregation procedure in Chapter 1.4.1.1 and Appendix A.1.6.

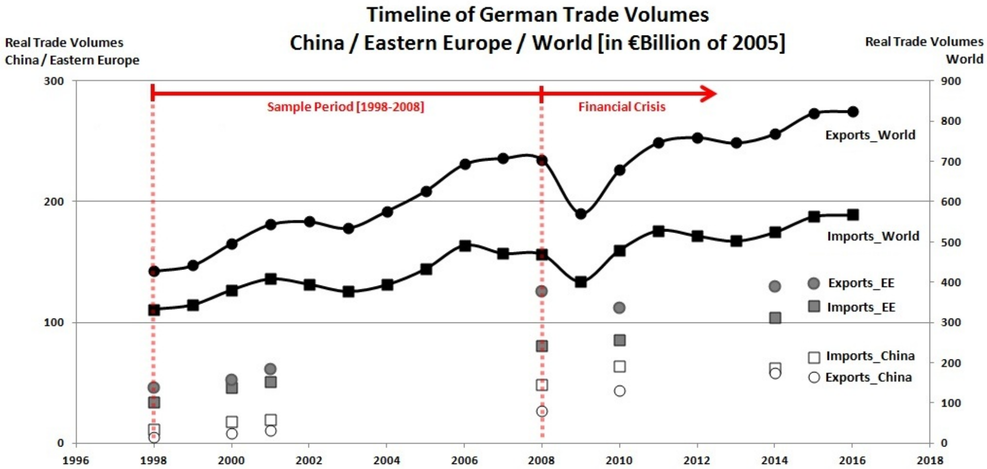

Figure 1.1: Timeline of German Trade Volumes (restricted to Manufacturing)

Figure A.6 in Appendix Chapter A.1.5 presents a timeline of the main accession events and compares them to the time series of available data sources for the empirical analysis in this chapter.

The deepening economical ties with Eastern European countries after the end of the Cold War are the outcome of a longer convergence process. DFS narrow down its hot phase to the period between 1998 and 2008, however, as it encompasses both the opening of German markets towards China and the main expansion waves of the European Union towards Eastern Europe. There is evidence (e.g. Xianbai, 2015) that the introduction of the EURO, which is included within the period of observation, has allowed the German exporting industry to further flourish due to the subsequent lack of currency appreciation. The empirical analysis in this chapter focuses on the same time frame as it encompasses all of these events and avoids the potentially confounding influence of the Financial Crisis after 2008.

1.4 Research Design

1.4.1 Data

1.4.1.1 Import/Export Exposure

This study relies on the changes in export and import exposure provided by DFS. These measures have been computed based on raw firm-level data obtained from the Institute for Employment Research ("Institut für Arbeitsmarkt- und Berufsforschung", IAB) of the German Federal Employment Agency ("Bundesagentur für Arbeit", BA) and have been compiled at the county level. The measures represent absolute changes in €1,000 per worker over the main time frame (1998-2008) for each respective county (i)[13]. The subscripts $j \in [1, ..., J]$ indicate NACE1.1 three-digit industries and the superscripts $X \in [China, EasternE, Pooled]$ indicate the trade partner. If no index (X) is given, then the variable represents the pooled trade exposure (with $X = Pooled$ denoting the aggregate of both). The variables have been computed by the authors according to the following formulas and can be abbreviated by ΔIPW (Import Exposure Change per worker) and ΔEPW (Export Exposure Change per worker):

$$\begin{aligned} & \mathit{\Delta} IPW_i^X \\ = \; & \mathit{\Delta}_{1998 \to 2008} ImportExposurePW_i^X \\ = \; & \sum_{j=1}^{J} \left[\frac{Employees_{ij1998}}{Employees_{j1998}} \cdot \frac{\mathit{\Delta}_{1998 \to 2008} Import_j^{GER \leftarrow X}}{Employees_{i1998}} \right] \end{aligned} \tag{1.1}$$

[13]In total, there are 413 counties ("Landkreise", LKS) in Germany in the reference year 2008 of this analysis.

$$
\begin{aligned}
& \Delta EPW_i^X \\
= \; & \Delta_{1998\rightarrow 2008} ExportExposurePW_i^X \qquad (1.2) \\
= \; & \textstyle\sum_{j=1}^{J} \left[\frac{Employees_{ij1998}}{Employees_{j1998}} \cdot \frac{\Delta_{1998\rightarrow 2008} Export_j^{GER\rightarrow X}}{Employees_{i1998}} \right]
\end{aligned}
$$

The variables $\Delta_{1998\rightarrow 2008}Import_j$ and $\Delta_{1998\rightarrow 2008}Export_j$ represent changes in absolute trade balances measured in 1.000€ between $t_0 = 1998$ and $t_1 = 2008$ that have been extracted from the United Nations Commodity Trade Statistics Database (COMTRADE)[14]. The employment shares responsible for the allocation of exposure values within the DFS methodology pertain to the initial time period $t_0 = 1998$. They distribute absolute changes in trade volumes within a given industry code onto the regional level according to national employment shares. Aggregating these industry-specific absolute changes measured in €1,000 per worker in the county over all manufacturing sectors present in the given county produces explanatory variables capturing how exposed the workers in a given county have been to shifts in manufacturing-related trade volumes.

Dividing the absolute changes by the county size $Area_i$ (measured in m^2) instead of by the number of workers in the county provides area-weighted explanatory variables controlling for the spatial density of exposure. Using these measures of trade intensity is intuitive because they can be directly related to pollution concentration averages (in $\mu g/m^3$) due to the comparable distribution of absolute quantities onto the shared spatial dimension ($1/m^2$). The resulting variables are therefore of the dimension 1,000€$/m^2$ and represent absolute changes in trade exposure per square meter. Regressions are performed for both types of exposure changes and the area-weighted measured

[14]Trade volumes are transformed into real values (€ of 2005) via publicly available exchange and inflation rates provided by the German "Bundesbank". The countries representing Eastern Europe are Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, Russia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan. All trade data is restricted to the manufacturing sectors selected by DFS. Please refer to Appendix A.1.6 for more information on the data generation process. The trade exposure changes computed by DFS have been used for the regression analysis in this chapter and the same weighting and transformation schemes underlying these variables have been used for my own calculations.

can be abbreviated by ΔIPA (Import Exposure Change per area) and ΔEPA (Export Exposure Change per area). Utilizing county size and the manufacturing employment figures in $t_0 = 1998$ provided by DFS, area-weighted exposure changes can be computed as follows:

$$
\begin{aligned}
& \Delta IPA_i^X \\
= \; & \Delta_{1998 \rightarrow 2008} ImportExposurePA_i^X \\
= \; & \Delta_{1998 \rightarrow 2008} ImportExposurePW_i^X \cdot \frac{Employees_{i1998}}{Area_i} \\
= \; & \sum\nolimits_{j=1}^{J} \left[\frac{Employees_{ij1998}}{Employees_{j1998}} \cdot \frac{\Delta Import_j^{GER \leftarrow X}}{Area_i} \right]
\end{aligned}
\tag{1.3}
$$

$$
\begin{aligned}
& \Delta EPA_i^X \\
= \; & \Delta_{1998 \rightarrow 2008} ExportExposurePA_i^X \\
= \; & \Delta_{1998 \rightarrow 2008} ExportExposurePW_i^X \cdot \frac{Employees_{i1998}}{Area_i} \\
= \; & \sum\nolimits_{j=1}^{J} \left[\frac{Employees_{ij1998}}{Employees_{j1998}} \cdot \frac{\Delta Export_j^{GER \rightarrow X}}{Area_i} \right]
\end{aligned}
\tag{1.4}
$$

1.4.1.2 Pollutant Concentrations and Air Quality

Pollutant immission data is available through the various distribution channels of the UBA. The agency routinely compiles fine-grid raster data for aerial pollutants including NO_2, $PM10$ and SO_2 concentrations. Time series of annual pollutant concentrations are therefore available for the year 1995 and continuously since 2000. This data is used to compute average changes in concentration levels across individual Germany counties ("Landkreise", LKS) in order to pair this information with the import and export exposure changes at the county level computed by DFS. The underlying hypothesis is that counties with strong increases in import exposure are subject to industry restructuring and in turn benefit from decreased local pollutant concentrations in the air. Although export opportunities result in increased production ("scale effect"), they are also predicted to benefit technologically advanced sectors and highly productive firms or non-polluting job profiles in the tertiary sector as discussed in Appendix A.1.4.

Pollutant concentration rasters for the year 1995 and the years 2000 to 2014 have been obtained containing yearly averages (in $\mu g/m^3$) for the aerial pollutants NO_2, $PM10$ and SO_2. They provide me with time series containing yearly averages of pollution concentrations measured in $\mu g/m^3$ for a total of 10332 rectangular grid cells, which individually represent an area of approximately $57km^2$. The UBA datasets used in this analysis combine advanced scientific methods to carefully approximate local immission concentrations. The underlying emission fields are derived from a top-down modeling approach with respect to local emission quantities and distributed according to meteorological parameters and the REM-CALGRID (RCG) model developed in Yamartino et al. (1992), which simulates the transport of chemical substances in various media. The resulting hourly emission concentrations are readjusted locally through hourly station measurements using the Optimal Interpolation (OI) framework developed by Flemming and Stern (2004).

Concerns such as the influence of temporary weather anomalies are addressed by averaging raw emission concentrations at the county-level over several years. Appendix A.1.8 describes the aggregation process in detail and Appendix A.1.9 discusses the properties of the dataset for the analysis at hand, while Chapter 3.3.2.2 presents correlations between the individual pollutants and various aggregation methods. The Germany-wide averages of these measures across all 413 counties are depicted in Figure 1.2.

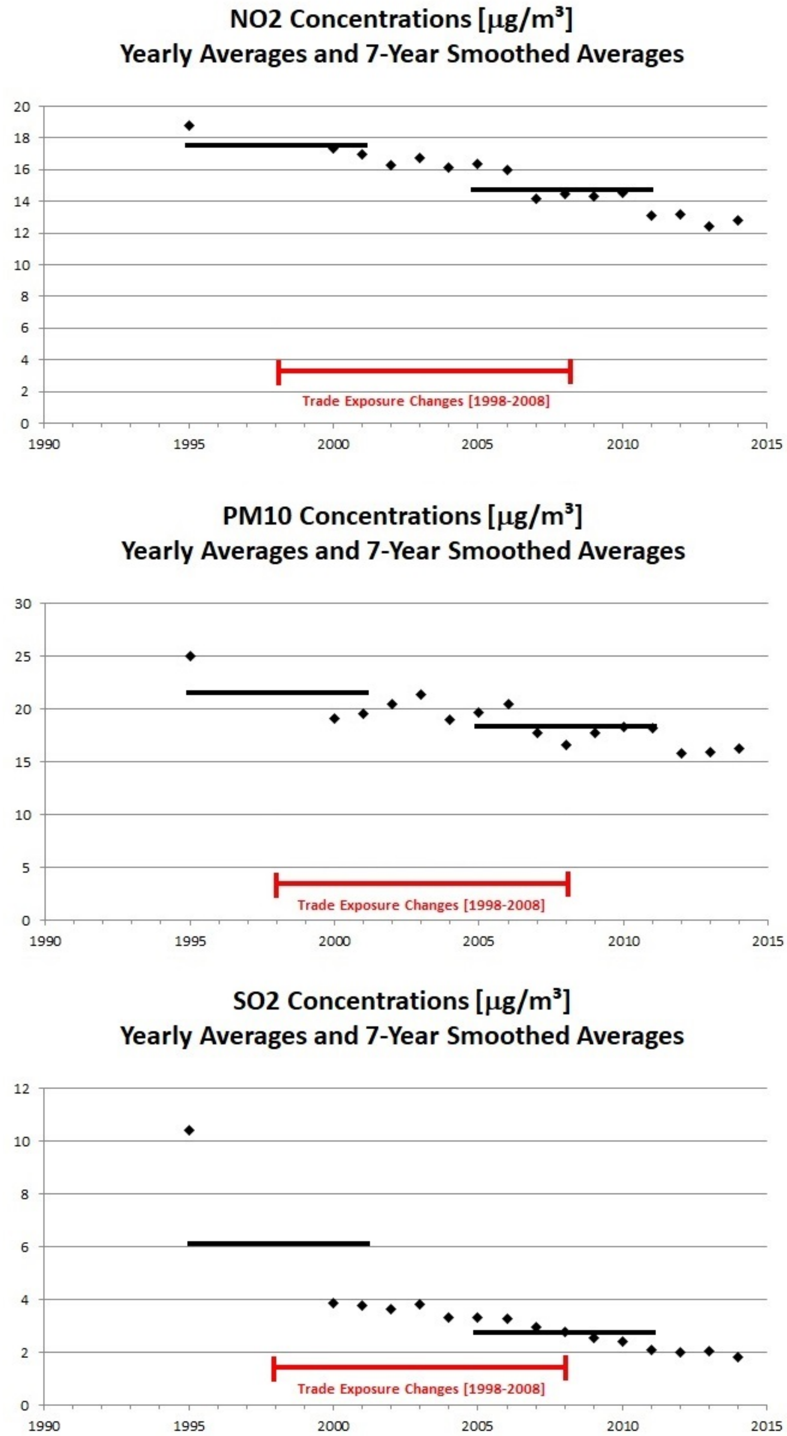

Figure 1.2: Averages of pollutant concentrations over time

1.4.2 Regression Model

This chapter's analytical approach is based on a first (long) differences model with continuous treatment. Its aim is to test, whether the hypothesis that increasing trade openness tends to have beneficial impacts on local pollution concentrations in Germany holds true. Its dependent variables are therefore the developments in pollutant concentration (Y_{it}) over time (t) and across 413 German counties (i) in the cross-section. The year $t_0 = 1998$ is the initial time period and $t_1 = 2008$ is the end-of-sample period marking the end of the treatment process, which is captured by the differences in trade flow exposure. The model is designed to evaluate aggregate effects of regional trade exposure on local environmental quality as a net expression of the underlying channels discussed in Appendix A.1.4.

The model can be applied to pollution concentrations measured in $\mu g/m^3$ for the three individual pollutants $Y_{it} \epsilon \,[NO2_{it}, PM10_{it}, SO2_{it}]$ and utilizes the first differences between smoothed averages over the years 1995-2001 and the years 2005-2011 across 413 counties in the cross-section[15]. The main explanatory variables are the changes in import and export exposure measured in €1.000 per worker or per area unit (i.e. m^2) as described in Chapter 1.4.1.1. Standard errors are clustered at the level of the German federal states ("Bundesland") to capture differences in legislation between federal states. A set of control variables pertaining to the initial time period in order to minimize endogeneity concerns can be added via the vector X_{i1998}. This yields the following model, which can be restricted to an individual trade partner $X \epsilon \,[China, EasternE]$ or the pooled trade flows ($X = Pooled$) and modified to include any larger subset of explanatory variables :

$$\begin{aligned} \Delta_{1998\rightarrow 2008} Y_i = \quad \alpha_1 \quad &+ \quad \alpha_2 \Delta_{1998\rightarrow 2008} ImportExposure_i^X \\ &+ \quad \alpha_3 \Delta_{1998\rightarrow 2008} ExportExposure_i^X \\ &+ \quad X'_{i1998} \cdot \overrightarrow{\beta} + \varepsilon_i \end{aligned} \tag{1.5}$$

[15]See Appendix A.1.8 for details on the aggregation procedure.

The standard set of controls contains regional dummies ($RegionNorth_i$, $RegionSouth_i$, $RegionEast_i$), which define separate large-scale labor markets as suggested by DFS and capture different trends in these macro regions[16]. The main coefficients of interest are α_2 and α_3 as they capture the effects of changes in export/import exposure with a given trade partner on the environmental quality within counties. The regressions can be modified to focus on individual trade partners only and the control set is tailored to capture prevailing trends in emission concentrations unrelated to trade exposure. The standard set of pre-sample controls includes the unemployment rate in 1998, the share of employees in the manufacturing sector in 1998, the share of votes received by the Green party ("Bündnis 90 / Die Grünen") during the parliamentary elections in 1998 as well as an additional control variable capturing the nature of traffic within a given county[17]. Thus, the trade exposure coefficients α_2 and α_3 capture the region-specific dispersion of emission responses caused by differences in the individual severity of trade shocks above or below the general trend component comprised of $X'_{i1998} \cdot \overrightarrow{\beta}$ and the intercept α_1.

[16]The first region covers the Northern German states Hamburg, Bremen, Lower Saxony and Schleswig-Holstein, while the second region covers Bavaria and Baden-Württemberg and the Eastern Region covers all states belonging to the former German Democratic Republic (GDR) along with West-Berlin.

[17]Since the aerial pollutants under study are also byproducts of the combustion of vehicle fuels, it is important to control for regional differences in transportation. However, trade opportunities have a direct effect on the labor market as shown by DFS and can therefore change commuting patterns and local traffic density. The same is true for local environmental quality as shown by Banzhaf and Walsh (2008). This implies the need for a pre-sample control variable capturing traffic density and the distribution of vehicle types in t_0. I use the number of traffic-related accidents per 100,000 inhabitants in 1998 as a proxy for the traffic conditions in a given county as these are likely indicative of traffic policies over the subsequent decade without being related to trade exposure. Including the change in traffic-related accidents between 1998 and 2008 does not change the results but potentially introduces another source of endogeneity. It should be noted that the research design does not account for changes in local emission profiles resulting from employees sorting into different counties in response to trade shocks other than through their contribution to manufacturing output and emissions. Refer to Appendix A.1.10 for further information on available control variables.

1.4.3 Identification Strategy

The estimates for the main coefficients α_2 to α_3 yield the causal average treatment effects of €1.000 increases in trade exposure on concentration levels under a number of conditions. Most importantly, pollution concentrations and trade exposure should not be endogenously related. Environmental regulations and domestic policies, however, may simultaneously be correlated with both exposures[18]. There is a possibility for reverse causality between emission figures and trade opportunities if local emissions a-priori create a desire for outsourcing and trade. In order to address these issues, an instrumental variable (IV) approach based on changes in world-wide trade flows between selected countries and China or Eastern Europe is employed. This identification approach has been introduced by ADH and refined for the German context by DFS. They suggest an IV strategy based on changes in trade volumes between China (or Eastern Europe) and other nations that do not share a border with Germany but are sufficiently large without having highly interconnected trade patterns. They argue that these trade flows should not be affected by German labor market movements or policy decisions and should instead capture the intrinsic motivation of China and Eastern European countries to expand their trade networks.

ADH further argue that until the early 2000s China's export growth has largely been the result of internal supply shocks and of obtaining WTO membership status. In their paper on Chinese trade flows and innovation pressure, Bloom et al. (2016) follow a similar reasoning and instrument trade flows with the abolishment of quotas on textiles and apparel after China's accession to the WTO. In the German case, DFS consider unobserved supply and demand shocks, which simultaneously affect trade exposure and regional economic performance, as the main threats to identification. They construct instrumental variables for their trade exposure measures based on global trade

[18] Strict regulations within Germany can incentivize firms to both outsource dirty productions abroad and at the same time abate pollution emissions in domestic plants. This biases the coefficients between trade flows and pollution exposure upwards in absolute terms as the coefficients do not capture the pure causal treatment effect anymore. The simultaneity bias consequently dilutes the causal relationship between trade openness and environmental quality.

flows between China (or Eastern Europe) and other nations, which are chosen to ensure that the instruments are independent of German emission levels.

The resulting set of economically relevant and influential but sufficiently distant countries includes Australia, Canada, Japan, Norway, NZ, Sweden, Singapore and the UK. The trade shock allocation procedure utilizes the formulas in Chapter 1.4.1.1 with lagged employment figures from the previous decade ($t_{-1} = 1988$) if available[19] to rule out the contemporaneous influence of trade flows on employment shares.

I obtain area-weighted instruments for the exposure changes per square meter by multiplying the worker-weighted instruments with lagged employment figures and dividing them by the county area. According to DFS, these trade flows between other countries and China (or Eastern Europe) are then able to isolate the exogenous component of Chinese or Eastern European competitiveness and attractiveness as export markets. The instruments are therefore constructed following the notation presented in Chapter 1.4.1.1 and eliminate the impact of shocks, which simultaneously affect German trade flows, regional industrial performance and pollution abatement:

$$\begin{aligned} & \mathit{\Delta}_{1998\rightarrow 2008} IVImportExposurePW_i^X \\ = \quad & \textstyle\sum_{j=1}^{J} \left[\frac{Employees_{ijt_{-1}}}{Employees_{jt_{-1}}} \cdot \frac{\mathit{\Delta}_{1998\rightarrow 2008} Import_j^{Other\leftarrow X}}{Employees_{it_{-1}}} \right] \end{aligned} \tag{1.6}$$

$$\begin{aligned} & \mathit{\Delta}_{1998\rightarrow 2008} IVExportExposurePW_i^X \\ = \quad & \textstyle\sum_{j=1}^{J} \left[\frac{Employees_{ijt_{-1}}}{Employees_{jt_{-1}}} \cdot \frac{\mathit{\Delta}_{1998\rightarrow 2008} Export_j^{Other\rightarrow X}}{Employees_{it_{-1}}} \right] \end{aligned} \tag{1.7}$$

[19] The instruments for the 87 Eastern German counties have to be computed using employment shares from $t_0 = 1998$ as older employment data is unavailable. This motivates the robustness checks in Chapter 1.6.1 testing for systematic differences by excluding Eastern German counties.

$$
\begin{aligned}
&\Delta_{1998\rightarrow2008} IV ImportExposurePA_i^X \\
= \quad &\textstyle\sum_{j=1}^{J} \left[\frac{Employees_{ijt_{-1}}}{Employees_{jt_{-1}}} \cdot \frac{\Delta_{1998\rightarrow2008} Import_j^{Other\leftarrow X}}{Area_i} \right]
\end{aligned} \tag{1.8}
$$

$$
\begin{aligned}
&\Delta_{1998\rightarrow2008} IV ExportExposurePA_i^X \\
= \quad &\textstyle\sum_{j=1}^{J} \left[\frac{Employees_{ijt_{-1}}}{Employees_{jt_{-1}}} \cdot \frac{\Delta_{1998\rightarrow2008} Export_j^{Other\rightarrow X}}{Area_i} \right]
\end{aligned} \tag{1.9}
$$

In order to obtain instruments satisfying the exclusion restriction, the policy regimes in all countries of the instrument group have to be sufficiently independent from German policy decisions. Out of the chosen set of countries (Australia, Canada, Japan, Norway, NZ, Sweden, Singapore and the UK), only Sweden and the UK have close ties due to their EU membership during the observation period. It can be argued, however, that the UK has traditionally been the most independent member of the EU and that Sweden exhibits vastly different trade patterns than Germany due to its industry composition and geographical location.

Another concern is that German policies affect the exporting patterns of Eastern European EU members as Germany has the ability to influence EU regulation[20]. With respect to Eastern Europe, the instruments may therefore be weaker than in the Chinese case due to the violation of the exclusion restriction stemming from EU regulations possibly introducing a simultaneity bias. As the only country among the Eastern European trade partners, Slovenia has introduced the Euro in 2007, which creates a presumably negligible source of endogeneity between German and Slovenian trade patterns.

The measures constructed above are used as instruments for the trade exposure measures in the regression model presented in Chapter 1.4.2 but it is not possible to include more than two instrumented explanatory variables at once without severely impeding the computation of First Stage regressions.

[20]One example are environmental regulations supported by German diplomats at the European level, which affect abatement strategies within both German industries and Eastern European exporting industries.

This is partly the case because the explanatory variables are positively correlated across counties to varying degrees. While some counties exhibit similar patterns with respect to both exports and imports over the observation period, there is enough variation to warrant the evaluation of several individual trade exposures in regression setups[21].

1.4.4 Descriptive Analysis

1.4.4.1 Summary Statistics

Descriptive statistics at the German county level are presented in Table 1.1. The corresponding exact variable definitions can be found in Table A.5 in Appendix A.1.10. All variables based on IAB raw data have been provided by DFS. The smoothed pollution concentration values for the years 1998 and 2008 are computed as unweighted averages over the 7 years around the year of interest and all reported statistics are unweighted Germany-wide averages over the 413 counties in existence on December 31st, 2008. Changes in Trade Exposure are pooled across both trade partners. In order to control for initial heterogeneity across counties, a normalized dirtiness indicator has been constructed that captures the relative pollution burden of counties in the year 1998 (see Appendix A.1.10 and Chapter 1.6.3 for the exact formula and the results of the robustness check).

[21] Examples for counties with similar trends in both imports and exports are the car manufacturing regions, which likely saw a rise in both export flows and import flows due to the exchange of intermediate and finalized goods. Exporting industries are also unlikely to discriminate against either China or Eastern Europe, so the patterns should be positively correlated. See Table A.2 of Appendix A.1.7 for an overview of the correlations.

Table 1.1: Summary table of mean characteristics at the county level

	Entire Germany			
Variables from INKAR Database	Mean	SD	Min	Max
Unemployment rate (1998)	10.94	4.67	4.04	23.63
Traffic Accidents per 100,000 inhabitants (1998)	650.46	111.94	380.00	1077.26
Green party votes in the 1998 general election (1998)	5.86	2.69	2.3	24.1
Variables from IAB Database	Mean	SD	Min	Max
E. Share in manufacturing of Tradable Goods (1998)	27.42	12.69	3.705	70.50
Percentage of college-educated employees (1998)	7.093	3.758	2.325	25.93
Percentage of foreign-born employees (1998)	5.858	4.263	0.167	18.10
Percentage of women (1998)	40.41	13.35	18.01	84.68
Percentage of employment in routine jobs (1998)	36.42	4.410	24.21	52.68
Variables from DFS/IAB Database	Mean	SD	Min	Max
ΔExportExposure per Worker in 1,000€ (1998-2008)	+4.75	3.00	+0.30	+21.09
► China only	+1.04	0.82	-0.06	+5.84
► Eastern Europe only	+3.71	2.27	-0.19	+15.62
ΔImportExposure per Worker in 1,000€ (1998-2008)	+3.75	2.65	+0.36	+17.70
► China only	+1.90	1.88	+0.19	+15.01
► Eastern Europe only	+1.85	1.30	-0.39	+9.55
Yearly Averages (Smoothed) from UBA OI Raster	Mean	SD	Min	Max
NO_2Concentration ($\mu g/m^3$) (1998)	17.70	5.45	7.45	37.34
ΔNO_2 Concentration ($\mu g/m^3$) (1998-2008)	-3.00	1.51	-7.87	+3.34
NO_2 Initial Dirtiness Indicator (1998)	0.47	0.15	0.20	1
$PM10$ Concentration ($\mu g/m^3$) (1998)	21.21	3.07	14.79	35.09
$\Delta PM10$ Concentration ($\mu g/m^3$) (1998-2008)	-2.84	1.60	-8.95	+2.05
$PM10$ Initial Dirtiness Indicator (1998)	0.60	0.09	0.42	1
SO_2 Concentration ($\mu g/m^3$) (1998)	6.02	2.45	1.94	17.31
ΔSO_2 Concentration ($\mu g/m^3$) (1998-2008)	-3.24	1.64	-10.53	+0.62
SO_2 Initial Dirtiness Indicator (1998)	0.35	0.14	0.11	1
Variables from Geodatenzentrum Shapefiles	Mean	SD	Min	Max
County Size (km^2) (2008)	865.8	637.7	35.5	3074.0
Number of counties ("Landkreise")			413	

Note: Table reports unweighted averages over 413 counties.

The spatial extents of counties reflect the status quo of territorial definitions as of December 31st, 2008. All files for the mapping of spatial data have been obtained from official sources and have been prepared for the subsequent analysis with Geographical Information System (GIS) tools according to the procedures described in Appendix A.1.11.

1.4.4.2 Maps of Trade Exposure

The following maps depict pooled changes in export and import exposure measured in €1.000 per worker between 1998 and 2008. The first map shows absolute changes in export exposures, while the second map shows changes in import exposures. The two variables appear to be highly correlated (see Figure 1.3) and large increases are concentrated on industrial centers in Western Germany such as the Ruhrgebiet, Baden-Württemberg (with more than €10.000 in additional import exposure per worker in car manufacturing dominated counties around Stuttgart) and Wolfsburg (with approximately €21.085 in additional export exposure per worker due to the Volkswagen headquarters)[22]. The area-weighted measures obtained from dividing the absolute changes by spatial area instead of workers demonstrate a slightly different pattern. The corresponding maps in Figure 1.4 demonstrate that increases in area-weighted import and export exposures are concentrated on large urban centers ("Kreisfreie Städte") and highly industrialized cities while exhibiting similar overall trends. This is to be expected given that more workers are concentrated in a smaller area in such production hubs. It demonstrates the usefulness of this alternative measure, however, as additional export opportunities for a single facility should have a smaller relative impact on average emissions in a large county with wide open spaces than in a concentrated urban area that is affected in its entirety by the emission output of each facility.

There is a noticeable amount of spatial correlation in both these maps and the ones in Chapter 1.4.4.3, which can be addressed by the use of spatial autoregression methods as suggested by Auffhammer et al. (2013). I corroborate my empirical results by estimating spatial autoregression models in Chapter 1.6.2.

[22]Pooled trade exposures combine Chinese and Eastern European trade flows. Maps for the split exposure measures exhibit similar general patterns.

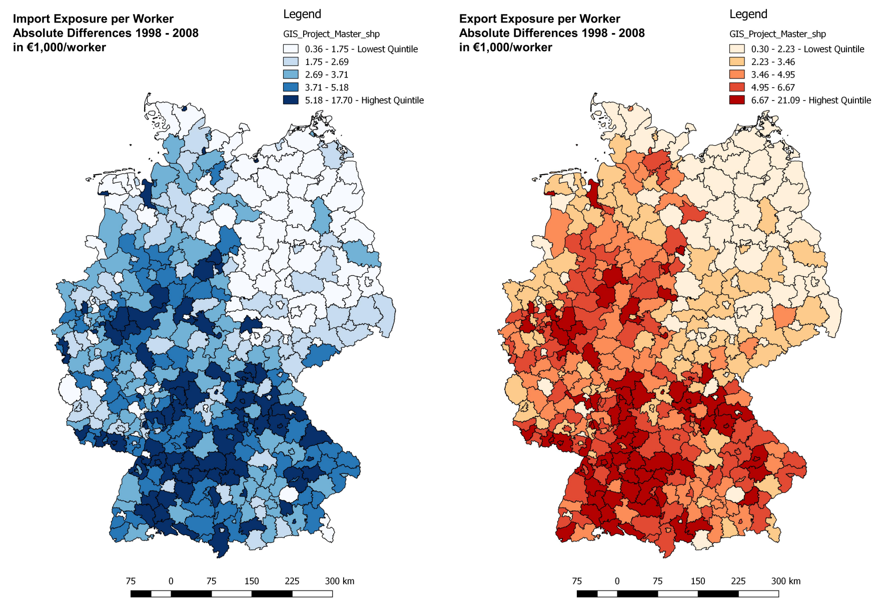

Figure 1.3: Absolute Changes in Trade Exposures per Worker (1998-2008)

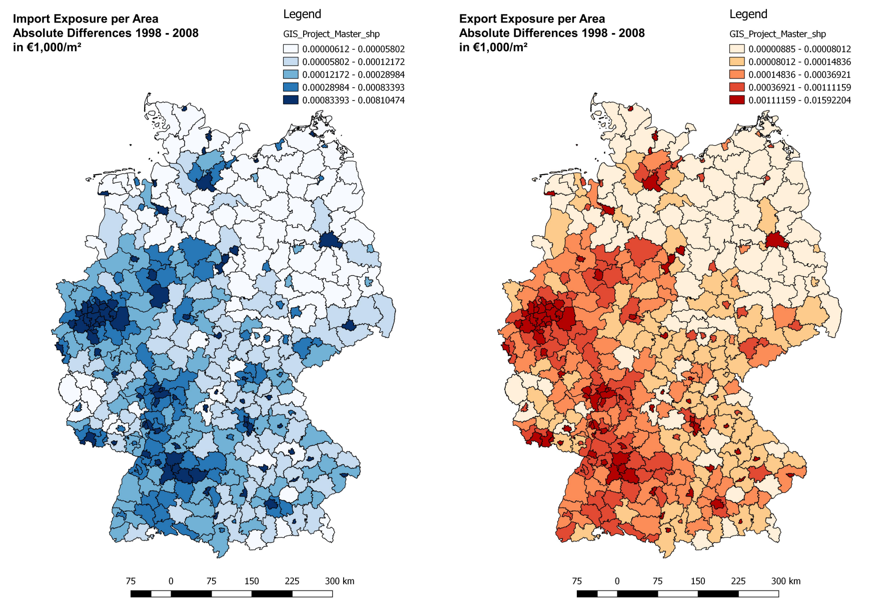

Figure 1.4: Absolute Changes in Trade Exposures per m^2 (1998-2008)

1.4.4.3 Maps of Pollutant Concentrations

The following maps depict developments in local pollutant concentrations between the years 1998 and 2008 through either percentage changes in Figure 1.5 or quantiles of absolute changes in Figure 1.6. The relative and absolute changes are computed based on the smoothed concentration levels in 1998 and 2008 as discussed in Chapter 1.4.1.2. They demonstrate that well-known industrial areas such as the Ruhrgebiet can experience significant increases in NO_2, whereas the majority of counties and especially rural areas in the former German Democratic Republic (GDR) have experienced a significant decline (top-left panel).

Increases in $PM10$ concentrations are also found in well-known urban and metropolitan areas but there is a noticeable increase in Eastern German counties possibly due to reverse catch-up effects in the wake of the Reunification (top-right panel). Increases in SO_2 concentrations are found in coastal and urban areas, while overall significant reductions of up to -78.5% dominate the pattern especially in Eastern Germany (bottom center panel).

There is enough variation across counties to warrant regressions of concentration level changes on trade exposure changes at the county level. The specific patterns found for SO_2 and $PM10$ (Eastern Germany) hint towards systematic regional differences[23]. Excluding Eastern German counties (see robustness check in Chapter 1.6.1) or coastal counties does not significantly alter the obtained empirical results.

SO_2 profiles, however, are likely affected by the rising container ship traffic as well as a potential bias arising from smoothing over the high concentration values in 1995. Empirical results for this pollutant consequently have to be interpreted with more caution.

[23]Increases in coastal regions and around the Nord-Ostsee-Kanal can be explained by a rising volume in cargo shipping (e.g. from China). This may introduce a serious bias as soon as trade exposure in landlocked counties causes emission increases in coastal regions, which are not necessarily recipients of the trade flows. If they are the recipients, then environmental benefits of the additional trade exposure are offset by increases in traffic-related pollution. Trade exposure coefficients are then expected to be biased towards the positive end of the scale as cargo shipping emissions introduce a positive correlation between locally consumed trade flows and shipping-related pollutants (e.g. SO_2).

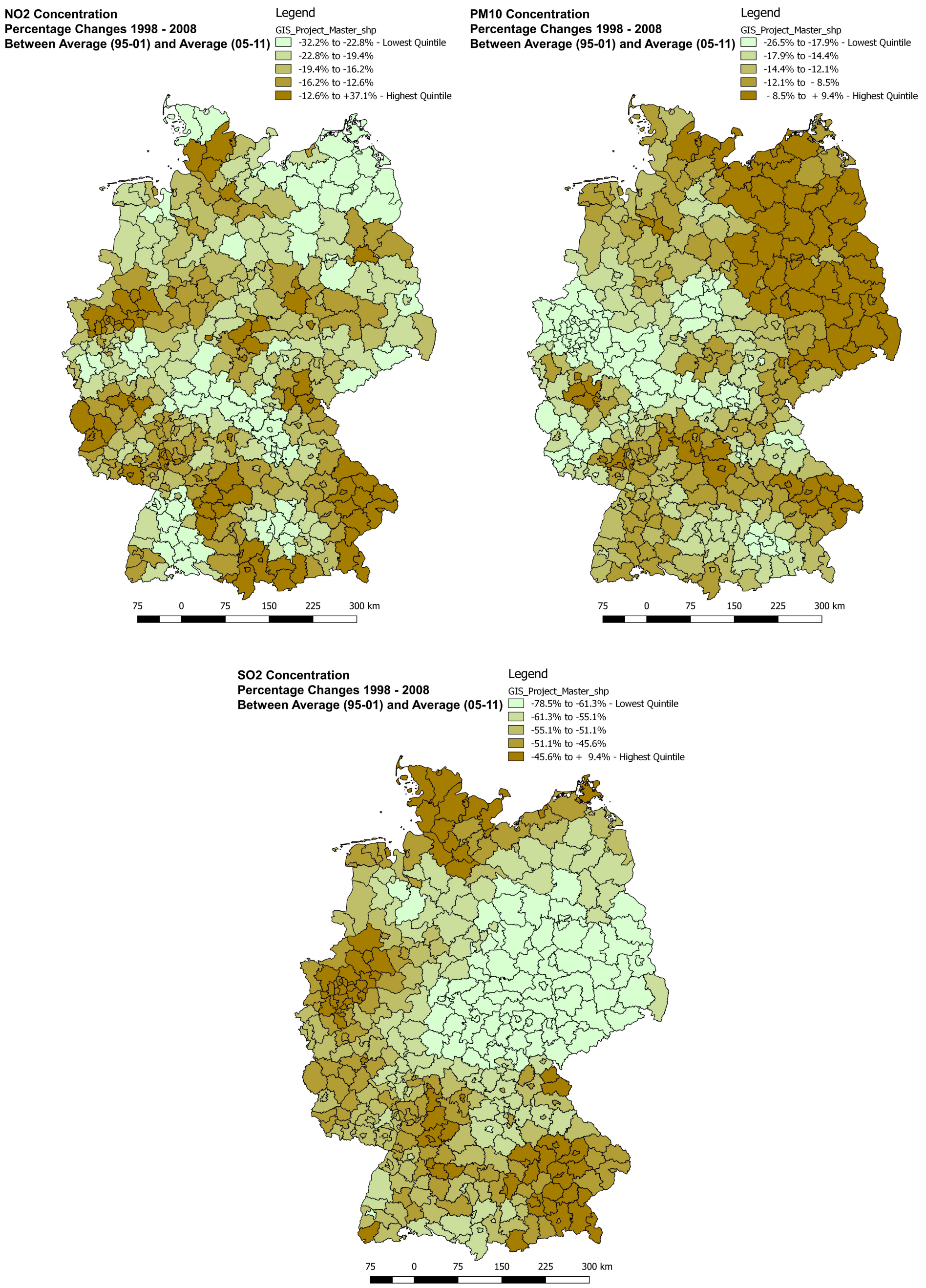

Figure 1.5: Percentage Changes in Pollutant Concentrations (1998 - 2008)

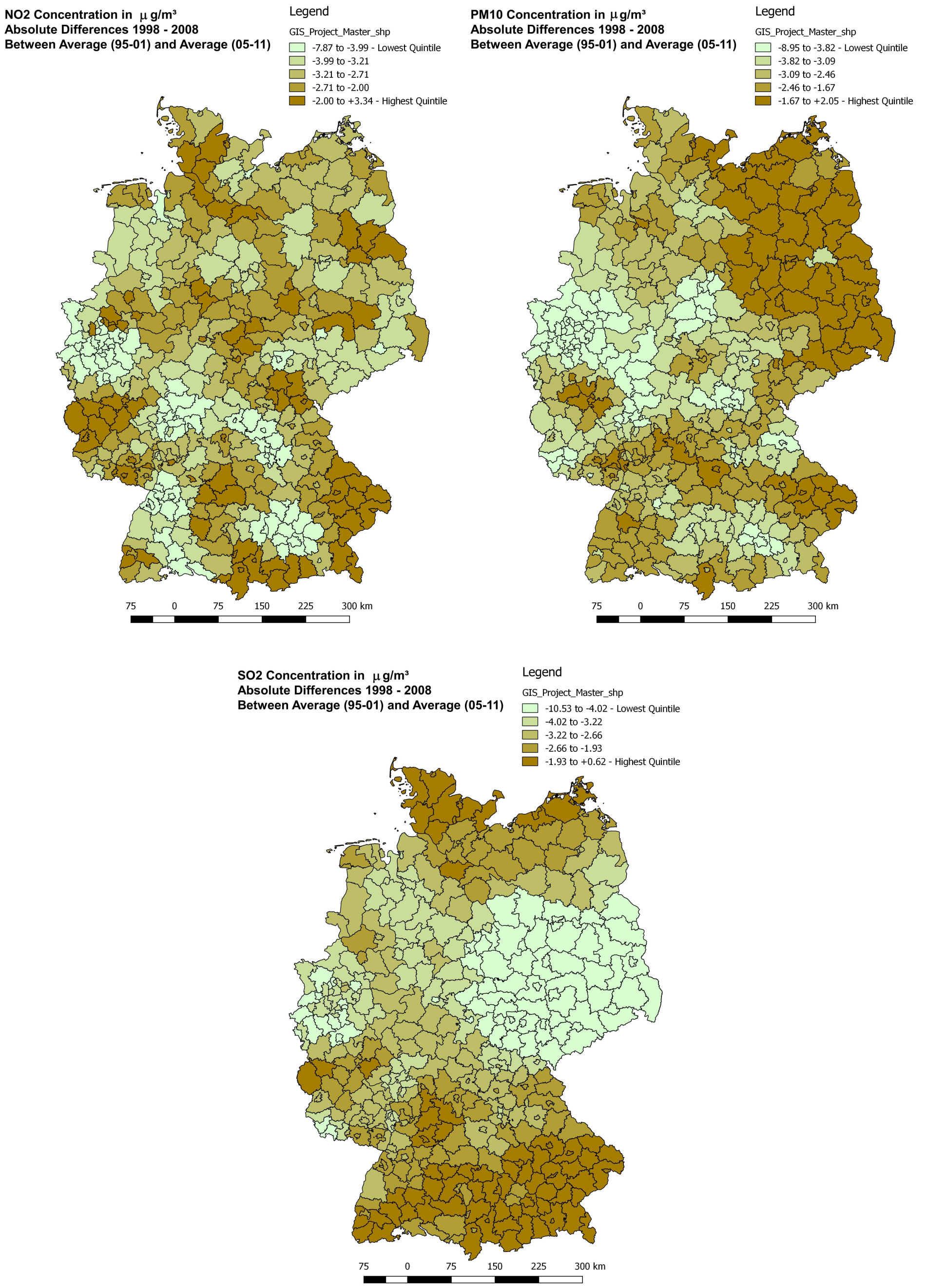

Figure 1.6: Absolute Changes in Pollutant Concentrations (1998 - 2008)

1.5 Empirical Results

1.5.1 Preliminaries

The empirical analysis employs the baseline model presented in Chapter 1.4.2 and either uses pooled trade exposure changes (*Pooled*) or the exposure changes restricted to one of the trading partners (*China* / *EasternE*)[24] as explanatory variables. The coefficients reported within a given column constitute the entire set of explanatory variables in the respective model (m) and the regression analysis in first differences is based on the complete set of 413 county-level observations. While the dependent variables are absolute differences in smoothed concentration levels between 1998 and 2008, the independent variables are the differences in trade exposure denoted by ΔEPW (Export Exposure Change per worker), ΔIPW (Import Exposure Change per worker), ΔEPA (Export Exposure Change per m^2) and ΔIPA (Import Exposure Change per m^2).

My baseline set of controls contains the 1998 employment share in manufacturing of tradable goods provided by DFS, the initial level of unemployment in 1998, the share of Green party votes in the general election ("Bundestagswahl") of 1998, the regional dummies described in Chapter 1.4.2 and the number of traffic accidents per 100,000 inhabitants in 1998. The inclusion of additional pre-sample traffic controls or additional labor market controls included by DFS (such as the share of female workers in manufacturing or the share of skilled workers) does not alter the empirical results. Standard errors (SE) are clustered at the level of the 16 German federal states ("Bundesland").

Following the discussion of impact channels in Appendix A.1.4, it seems reasonable to expect negative coefficients with respect to import competition

[24] Regressions performed with all four trade exposure changes as explanatory variables at once lead to extreme values and non-convergence in IV regressions because their high degree of collinearity impedes the computation of non-singular matrices. Regression models are computed using the estimators by Correia (2016) and Baum et al. (2002).

(ΔIPW, ΔIPA) due to product mix changes, foreclosures, layoffs or less invasive extensive margin reallocation, whereas coefficients for export opportunities can either be positive if production scale effects dominate or negative if productivity, core competency and technology effects dominate at the intensive margin (see Table A.1 in Chapter A.1.4). All models are estimated following the IV strategy outlined in Chapter 1.4.3 and the coefficients are derived from standard two-stage least squares (2SLS) procedures. For the preferred specification including the baseline control set and area-weighted exposure measures, refer to Table 1.3.

1.5.2 Basic Instrumental Variable Regressions

The 2SLS regressions are performed with the intrinsic trade expansion measures (for China and Eastern Europe) as instrumental variables, which have been computed on the basis of COMTRADE data by DFS. The table also reports the F-statistics from tests on the excluded instruments within the First Stage regressions. Negative coefficients of interest imply positive environmental effects, so the significant coefficient for ΔEPW^{China} in column (2) implies a reduction of $1.650\mu g/m^3$ (SE: $0.342\mu g/m^3$) in NO_2 levels for a €1,000 increase in export opportunities towards China per worker in a given county. For a county like Wolfsburg with €$5,470$ in additional exports per worker towards China, this yields a net reduction of $9.03\mu g/m^3$ between 1998 and 2008 tied to the additional export revenues[25].

According to columns (2) and (5), €1,000 per worker in additional import competition from China lowers NO_2 concentration levels significantly by $0.141\mu g/m^3$ (SE: $0.072\mu g/m^3$) and $PM10$ concentration levels by $0.242\mu g/m^3$ (SE: $0.082\mu g/m^3$) through emission savings in affected industries. The $\Delta IPW^{EasternE}$ coefficient in column (6) implies that €1,000 per worker in additional import competition from Eastern Europe lowers $PM10$ concentration levels by $0.331\mu g/m^3$ (SE: $0.088\mu g/m^3$). For a representative county like Stuttgart with €$2,473$ in additional Eastern European imports per worker,

[25]Wolfsburg represents an outlier due to the local Volkswagen headquarters.

this yields a net reduction of $0.82\mu g/m^3$ in $PM10$ concentrations. Table 1.2 therefore demonstrates positive environmental effects of import competition especially for China and to some extent for Eastern Europe. The reduction in NO_2 emissions due to export opportunities with respect to China in column (2) seems fairly high in comparison to initial NO_2 levels in Germany, though. As explained in Chapter 1.4.4.3 and Appendix A.1.8, the lack of significant and consistent results for SO_2 concentrations may be due to several biases[26].

Table 1.2: IV Regression (2SLS) with Worker-Weighted Exposures

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPW	-0.0142			-0.0684			-0.0126		
	(0.0625)			(0.0503)			(0.0220)		
ΔEPW	-0.00191			-0.0575			-0.00697		
	(0.0987)			(0.0906)			(0.0652)		
China									
ΔIPW		-0.141*			-0.242***			-0.0245	
		(0.0719)			(0.0817)			(0.0464)	
ΔEPW		-1.650***			-2.055			-0.176	
		(0.342)			(1.280)			(0.455)	
EasternE									
ΔIPW			-0.295			-0.331***			-0.153
			(0.293)			(0.0875)			(0.0992)
ΔEPW			0.0297			0.115			0.0781
			(0.119)			(0.0844)			(0.0914)
Const	-2.689**	-5.404***	-2.857***	-5.107***	-8.198***	-4.920***	-3.984***	-4.240**	-3.905***
	(1.187)	(1.181)	(0.830)	(1.520)	(2.946)	(1.176)	(1.424)	(1.835)	(1.319)
First Stage	F-Tests of excluded instruments								
ΔIPW	12.032	6.191	36.839	12.032	6.191	36.839	12.032	6.191	36.839
ΔEPW	65.567	3.321	43.292	65.567	3.321	43.292	65.567	3.321	43.292
Controls	Standard Set plus Region Dummies								
Uncentered R^2	0.813	0.786	0.812	0.839	0.762	0.841	0.905	0.904	0.905
F-Statistic	2.348	84.24	11.17	46.09	202.6	4.607	41.08	66.62	57.21
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

[26] Although the coefficient for Eastern European import competition in column (9) of Table 1.2 demonstrates the expected sign at a low p-value, I abstain from interpreting SO_2 coefficients in the subsequent chapters and only report them for the sake of completeness.

All first stage regressions feature highly significant coefficients for the most relevant instrument and high F-statistics, which is not surprising given that trade openness within China and Eastern Europe has likely increased somewhat indiscriminately towards all potential trade partners and given the successful application of these instruments by DFS and ADH. The weakest instruments are those for export opportunities towards China, which implies that patterns in German-Chinese trade flows differ from the trade patterns between China and the country sample behind the instruments.

In order to account for the impact of facility density and county size on the relationship between trade volumes and dispersed pollution concentrations, the IV regressions are repeated with area-weighted explanatory variables. These can be instrumented by the modified instruments described in Chapter 1.4.3 but the interpretation of the resulting coefficients is not as straightforward. Nevertheless, the area-weighting modification seems highly plausible as explained in Chapter 1.4.4.3 and offers the opportunity for convenient back-of-the-envelope calculations. I therefore consider the regression models presented in Table 1.3 to be my preferred specifications. With respect to back-of-the-envelope benefit calculations, the coefficients in Table 1.3 also yield the more conservative estimates.

First of all, it is noticeable that the IV strategy based on area-weighted variables yields much higher F-statistics in the respective first stage regressions, which are far above any threshold indicating weak instruments according to Stock and Yogo (2005). On the other hand, the regressions highlight the environmentally beneficial effect of import competition and imported intermediary goods, which is robust across specifications for both trade partners and both well-constructed pollutant measures (NO_2 and $PM10$). The impact of Chinese import competition on NO_2 and $PM10$ levels is documented by columns (2) and (5) and accompanied in column (6) by a prominent negative effect of Eastern European imports on $PM10$ levels in excess of -1303.9$\mu g/m^3$ (SE: 592.3$\mu g/m^3$) per €1,000/m^2. All coefficients for SO_2 are insignificant and indistinguishable from zero. While coefficients related to export opportunities tend to be slightly positive, they are not significantly different from zero either. In contrast to Table 1.2, this pattern holds for export opportunities towards China and the positive effect of export revenues vanishes[27].

Overall, this means that the scale effects from export opportunities do not outweigh the emission savings from growing import exposure, even though they outweigh negative effects of import competition on domestic production and employment figures on the labor market as demonstrated by DFS. While the effects of export opportunities on local emission concentrations are negligible, the significant coefficients for $\mathit{\Delta} IPA^{China}$ in columns (2) and (5) imply that every additional €1,000 per m^2 in Chinese import competition significantly reduces NO_2 concentrations by about $674.7 \mu g/m^3$ (SE: $293.9 \mu g/m^3$) and $PM10$ concentrations by $650.4 \mu g/m^3$ (SE: $204.5 \mu g/m^3$). Combining the coefficients from columns (2), (3), (5) and (6) in Table 1.3 with aggregated COMTRADE trade volumes allows for the computation of tangible net effects in the following chapter.

[27] Appendix A.1.12 contains the results for the area-weighted regressions without control variables for comparative purposes. Almost all pivotal coefficients are robust to slight modifications in model specification and particularly the omission of controls. I therefore refrain from reporting the results for a sequence of different control sets.

Table 1.3: IV Regression (2SLS) with Area-Weighted Exposures

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-491.1**			-544.6***			33.39		
	(236.3)			(202.1)			(86.48)		
ΔEPA	123.1			117.5			-37.30		
	(114.4)			(184.7)			(55.04)		
China									
ΔIPA		-674.7**			-650.4***			49.31	
		(293.9)			(204.5)			(120.4)	
ΔEPA		13.52			-215.8			-145.6	
		(211.0)			(563.5)			(118.8)	
EasternE									
ΔIPA			-477.7			-1303.9**			93.14
			(837.5)			(592.3)			(538.8)
ΔEPA			-78.01			266.8			-43.70
			(319.2)			(264.2)			(313.2)
Const	-3.595***	-3.554***	-3.906***	-6.030***	-6.087***	-6.332***	-4.060***	-4.111***	-3.962***
	(0.552)	(0.601)	(0.479)	(1.434)	(1.549)	(1.286)	(1.459)	(1.425)	(1.506)
First Stage	F-Tests of excluded instruments								
ΔIPW	1043.013	166.482	222.271	1043.013	166.482	222.271	1043.013	166.482	222.271
ΔEPW	385.752	38.162	185.482	385.752	38.162	185.482	385.752	38.162	185.482
Controls	Standard Set plus Region Dummies								
Uncentered R^2	0.821	0.820	0.820	0.849	0.848	0.849	0.905	0.905	0.905
F-Statistic	5.140	7.029	5.013	9.746	12.55	7.263	81.57	87.25	113.1
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

1.5.3 Net Effect of Trade Exposure

Multiplying the coefficient estimates from the area-weighted exposure IV regressions in Table 1.3 with COMTRADE trade volumes broken down onto the same spatial units allows for the computation of a "back-of-the-envelope" net effect. The coefficients are multiplied with the Germany-wide total manufacturing trade volumes (in $k€$) divided by the German state territory of $357,376km^2$ as the area-weighted trade exposures are measured in 1,000$€/m^2$.

Adding up the absolute reductions in NO_2 concentrations across both trade partners and both directional exposures yields a combined net effect of

(-0.070+/-0.030)$\mu g/m^3$ as most of the coefficients are indistinguishable from zero.

Adding up the absolute reductions in $PM10$ concentrations of $(-0.067 \pm 0.021)\mu g/m^3$ and $(-0.169 \pm 0.077)\mu g/m^3$ yields a combined net effect of approximately $-0.24\mu g/m^3$ due to the additional Chinese and Eastern European import flows observed in 2008[28].

These reductions have to be seen in the context of the much larger overall decline in NO_2 and $PM10$ concentrations visible in Figure 1.2 and contained as averages over all counties in Table 1.1. These reductions amount to roughly $-3.00\mu g/m^3$ for NO_2 and to $-2.84\mu g/m^3$ for $PM10$. Despite being mostly a windfall gain of trade liberalization, the trade-related reductions do constitute a significant contribution to these savings accounting for 8.3% of the overall reductions in $PM10$ concentrations between 1998 and 2008.

Table 1.4: Back-of-the-Envelope Net Effects of Trade Exposure

	(1) Pooled	(2) China	(3) Eastern Europe	(4) World
Import Exposure				
Absolute Difference in Trade Volumes (in million€)	83,353.35	37,081.88	46,271.46	137,356.06
Difference in Trade Volumes per area (in $k€/m^2$)	0.00023	0.00010	0.00012	0.00038
NO_2 Coefficient	-491.1	-674.7	≈ 0	-
NO_2 Back-of-the-Envelope Reduction (in $\mu g/m^3$)	-0.11454	-0.07001		
$PM10$ Coefficient	-544.6	-650.4	-1303.9	-
$PM10$ Back-of-the-Envelope Reduction (in $\mu g/m^3$)	-0.12702	-0.06749	-0.16882	
Export Exposure				
Absolute Difference in Trade Volumes (in million€)	101,187.26	21,287.86	79,899.40	277,017.10
Difference in Trade Volumes per area (in $k€/m^2$)	0.00028	0.00006	0.00022	0.00078
NO_2 Coefficient	≈ 0	≈ 0	≈ 0	-
NO_2 Back-of-the-Envelope Reduction (in $\mu g/m^3$)				
$PM10$ Coefficient	≈ 0	≈ 0	≈ 0	-
$PM10$ Back-of-the-Envelope Reduction (in $\mu g/m^3$)				
Combined Net Effect				
Overall NO_2 Reduction (in $\mu g/m^3$)	-0.11	-0.07		-
Overall $PM10$ Reduction (in $\mu g/m^3$)	-0.13	-0.24		

Note: All coefficients are taken from the the IV regressions with area-weighted exposure measures.
All monetary values are real values in € of 2005.

[28] The ranges given in parentheses represent the 68.2% confidence intervals for these estimates under standard normality assumptions. They are the result of multiplying aggregate trade volumes with the standard errors in Table 1.3.

The savings in NO_2 emissions can be translated into a long-term effect on mortality rates and into Value of Statistical Life (VSL) gains associated with these environmental benefits. This is achieved by employing the concentration-response function and methodology derived by Carozzi and Roth (2019) and Fowlie et al. (2019), which links changes in pollution exposure to changes in mortality via pollutant-specific relative risk (RR) factors and baseline mortality incidence rates. COMEAP (2018) and Atkinson et al. (2018) recommend using a relative risk factor of 1.023 per 10 $\mu g/m^3$ for NO_2, which implies that a permanent $10\mu g/m^3$ increase in NO_2 concentrations scales up annual all-cause mortality by 2.3%. The German population reached a value of 82.06million ($Population_{1998}$) in 1998 with a baseline mortality incidence rate of 10.683 per 1,000 inhabitants[29] ($MortalityRate_{1998}$). Plugging these into the following formula yields an estimate of the avoided deaths through NO_2 reductions relative to initial conditions:

$$\begin{aligned} \Delta Deaths = \quad & Population_{1998} \cdot MortalityRate_{1998} \\ & \cdot \left[1 - e^{-ln(1.023)/[10\mu g/m^3] \cdot \Delta NO_2}\right] \end{aligned} \tag{1.10}$$

The back-of-the-envelope reductions in Germany-wide NO_2 concentrations of $0.070\mu g/m^3$ (see Table 1.4) are then associated with 140 human lives saved per year. While it is difficult to arrive at a universally accepted valuation of human lives, VSL estimates represent a widely used method of monetarizing the number of avoided deaths. Viscusi and Masterman (2017) provide an income-adjusted VSL estimate for Germany of \$7.9million (in \$ of 2017), which corresponds to a VSL of €4.31million per avoided death (in € of 2008) according to time series provided by the German “Bundesbank”. Multiplying this figure with the above estimate yields an annual mortality premium of €603.77million purely due to the NO_2 reductions obtained as windfall gains from trade liberalization across German counties[30].

[29]Source: https://www.macrotrends.net/countries/DEU/germany/death-rate.

[30]In addition to this mortality premium, there is a mortality premium related to $PM10$ reductions that is more difficult to compute due to the limited availability of relative risk factors for particulate matter concentrations of higher diameter. The premium presented in this paragraph is therefore a lower bound estimate in terms of VSL benefits.

1.6 Robustness Checks

1.6.1 Robustness Check: Western Germany

The high explanatory power of trade exposure changes for $PM10$ and NO_2 developments conjures up the question whether confounding factors drive these results. One possible confounder with respect to $PM10$ are pollutant emissions from Eastern Europe swapping over into Eastern German counties close to the border. On the one hand, rising production volumes outside of Germany could manifest themselves in systematic spillover effects and rising $PM10$ concentrations in Eastern Germany. Stagnating import exposures in Eastern Germany, on the other hand, would then lead to biased regression coefficients and negative values caused by a channel that should not be interpreted as a causal link between domestic trade exposure and domestic industry emissions. Concerns that systematic developments specific to Eastern Germany (such as catch-up effects in the wake of the Reunification) drive estimates are further motivation for a robustness check restricting the observations to Western German counties. The regressions preserve the significant coefficients for $PM10$ and NO_2 within the reduced 326 county sample. Standard errors for the Eastern European trade flows are slightly increased due to the reduced sample size and the most noticeable divergence is a barely significant positive coefficient for export exposure in column (1). Column (6) deserves special attention as it contains the model for $PM10$ with respect to Eastern European trade flows and does preserve sign and magnitude of the estimated coefficients when compared to column (6) in Table 1.3. If Eastern German counties were to absorb pollution effects from Eastern European manufacturing, this would be the coefficient most likely affected by bias. The robustness of coefficients despite the exclusion of 87 counties rules out concerns that results are driven by confounding factors within Eastern German observations. Taking special precaution with Eastern German observations is therefore unnecessary reinforcing my choice of models in Table 1.3 as benchmark specifications[31].

[31] Regressions for Eastern German counties only suffer from the small sample size of 87 observations and are not reported.

Table 1.5: WGermany: IV Regression (2SLS) with Area-Weighted Exposures

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-614.7***			-446.3**			-53.77		
	(204.3)			(193.5)			(50.05)		
ΔEPA	169.6*			78.63			34.31		
	(93.95)			(183.4)			(42.40)		
China									
ΔIPA		-833.4***			-520.8**			-53.19	
		(253.3)			(204.4)			(77.46)	
ΔEPA		62.89			-259.1			52.59	
		(166.0)			(560.1)			(109.7)	
EasternE									
ΔIPA			-580.7			-1173.4**			-160.2
			(900.8)			(569.4)			(420.4)
ΔEPA			-80.12			238.2			74.42
			(353.4)			(265.9)			(251.5)
Const	-4.299***	-4.242***	-4.718***	-6.124***	-6.189***	-6.439***	-2.580***	-2.588***	-2.605***
	(0.416)	(0.497)	(0.292)	(1.754)	(1.916)	(1.567)	(0.599)	(0.578)	(0.620)
First Stage	F-Tests of excluded instruments								
ΔIPW	856.676	137.223	198.455	856.676	137.223	198.455	856.676	137.223	198.455
ΔEPW	339.1951	34.022	176.031	339.1951	34.022	176.031	339.1951	34.022	176.031
Controls	Standard Set plus Region Dummies and Traffic Accidents								
Uncentered R^2	0.807	0.805	0.806	0.879	0.878	0.879	0.943	0.943	0.944
F-Statistic	581.4	213.3	174.2	614.4	2884.9	58.54	7998.2	8066.7	682.1
Observations	326	326	326	326	326	326	326	326	326

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

1.6.2 Robustness Check: Spatial Autocorrelation

As demonstrated by the maps in Chapter 1.4.4.2 and Chapter 1.4.4.3, there is a visible amount of spatial correlation in both pollution concentration patterns and trade exposure due to agglomeration effects. Auffhammer et al. (2013) argue that spatial climate and weather data is typically affected by spatial autocorrelation and suggest the usage of spatial weighting matrices in regression designs to account for systematic spatial variation.

Following Drukker et al. (2013a), I generate a spatial contiguity matrix that assigns spatial weights to counties based on direct proximity. Choosing the "queen" criterion ensures that any counties that touch or share a border with each other are modeled as correlated. This weighting matrix is plugged into the spatial-autoregressive model with spatial-autoregressive errors (SARAR) implemented by Drukker et al. (2013b), which can also account for endogenous variables through the inclusion of instruments. This type of model is able to accommodate a weighted average of the dependent variable as a spatial lag component and allows the error term to depend on a weighted average of the disturbances from neighbouring counties.

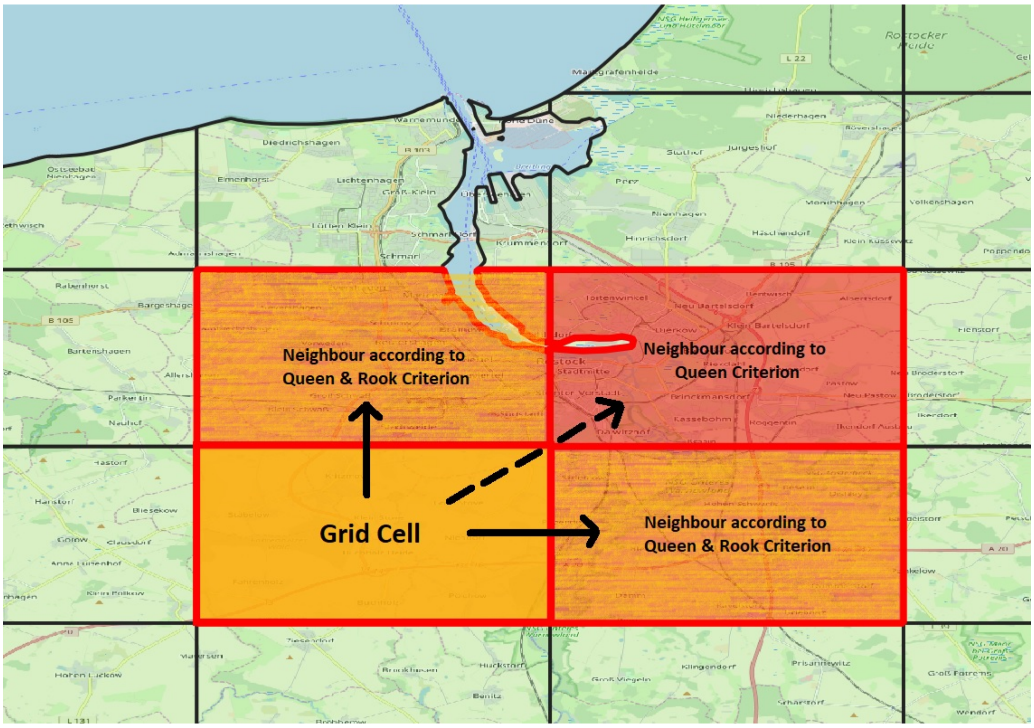

Figure 1.7: Queen and Rook Criteria in Contiguity Weighting

Figure 1.7 illustrates the different selection criteria for neighbouring counties using a grid cell example. Most German counties connected via the "queen" criterion are also connected via the "rook" criterion due to a common border. The SARAR model incorporates contiguity by means of the computed spatial weighting matrix W and is given by:

$$\vec{y} = \lambda \cdot W \cdot \vec{y} + X \cdot \vec{\beta} + Z \cdot \vec{\gamma} + \rho \cdot W \cdot \vec{\nu} + \vec{\varepsilon} \qquad (1.11)$$

The specification used in this robustness check contains spatial lags of the dependent variable $W \cdot \overrightarrow{y}$ as well as a spatial autoregressive error component $W \cdot \overrightarrow{\nu}$ capturing spillover effects and dispersion patterns of pollution concentrations across the adjacent county borders. X is a set of exogenous variables and Z is a set of instrumented endogenous variables.

The econometric analysis reveals that the signs of the preferred IV results from Table 1.3 are robust to the accommodation of such spatial autocorrelation. The import competition coefficients in columns (1), (2), (4) and (5) are nearly halved in magnitude and lose a portion of their significance but preserve the overarching patterns. The only meaningful divergence is that export exposure towards China reaches a noticeable level of influence in column (5). In light of the pervasiveness of spatial patterns demonstrated in Chapters 1.4.4.2 and 1.4.4.3, I consider this level of conformity to be a strong finding lending credibility to the prevailing effects.

Table 1.6: SPIVREG Regressions with Area-Weighted Exposures and Spatial Autocorrelation

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-248.9*			-368.0***			109.1		
	(129.5)			(113.4)			(103.6)		
ΔEPA	8.560			27.88			-68.16		
	(97.85)			(84.93)			(77.74)		
China									
ΔIPA		-336.1**			-312.4**			110.7	
		(152.5)			(135.6)			(123.4)	
ΔEPA		-266.4			-591.7**			-121.7	
		(269.2)			(239.7)			(213.7)	
EasternE									
ΔIPA			60.78			-556.3			399.7
			(396.5)			(359.1)			(327.6)
ΔEPA			-255.7			-45.62			-181.8
			(219.2)			(196.8)			(179.7)
Const	-2.373***	-2.466***	-2.568***	-4.285***	-2.865***	-4.469***	-3.924***	-3.931***	-3.857***
	(0.659)	(0.672)	(0.666)	(0.562)	(0.611)	(0.568)	(0.518)	(0.530)	(0.525)
SARAR				Estimated autoregression parameters					
λ	0.023***	0.022***	0.020***	0.028**	0.044***	0.030**	-0.006	-0.006	-0.007
	(0.007)	(0.007)	(0.007)	(0.012)	(0.010)	(0.012)	(0.013	(0.013	(0.013
ρ	0.252***	0.251***	0.249***	0.134***	0.197***	0.134***	0.147***	0.147***	0.147***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.015)	(0.008)	(0.006)	(0.006)	(0.006)
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors are an outcome of the SARAS estimation procedure.
The reported autoregression parameters demonstrate the level of autocorrelation.

1.6.3 Robustness Check: Dirtiness Indicator

Due to the likely existence of catch-up effects in pollution abatement across counties over the past decades (as documented for the US by Bento et al., 2014), initially dirty counties may benefit from larger trend reductions unrelated to trade exposure than initially cleaner counties. It is also possible that initially dirty counties react differently to trade exposure due to their industrial or social structure. To address this initial county-level heterogeneity, I run an IV regression including interactions with a continuous dirtiness indicator to test for such phenomena. Initial immission concentrations are readily available via the computed smoothed averages for the year 1998. Normalizing these averages by the maximum concentration found among all counties yields the following indicators with values between 0 and 1:

$$\begin{aligned}
Dirty_{i1998}^{NO2} &= \frac{\bar{Y}_{i1998}^{NO2}}{\max_i(\bar{Y}_{i1998}^{NO2})} \\
Dirty_{i1998}^{PM10} &= \frac{\bar{Y}_{i1998}^{PM10}}{\max_i(\bar{Y}_{i1998}^{PM10})} \qquad (1.12) \\
Dirty_{i1998}^{SO2} &= \frac{\bar{Y}_{i1998}^{SO2}}{\max_i(\bar{Y}_{i1998}^{SO2})}
\end{aligned}$$

There are individual initial dirtiness indicators for each pollutant and instruments for the interaction terms are computed as the product between former instrument and the appropriate dirtiness indicator. I restrict this analysis to the pooled explanatory variables for reasons of clarity and do not add control variables besides the regional dummies and the initial dirtiness indicator ($Dirty_{i1998}^{Y}$) as this indicator absorbs county-level characteristics in this setup. The underlying regression model then becomes:

$$\begin{aligned}
\Delta_{1998\rightarrow 2008} Y_i = \alpha_{10} &+ \alpha_{11} Dirty_{i1998}^{Y} \\
&+ \alpha_{20} \Delta_{1998\rightarrow 2008} ImportExposure_i^X \\
&+ \alpha_{21} \Delta_{1998\rightarrow 2008} ImportExposure_i^X \cdot Dirty_{i1998}^{Y} \\
&+ \alpha_{30} \Delta_{1998\rightarrow 2008} ExportExposure_i^X \\
&+ \alpha_{31} \Delta_{1998\rightarrow 2008} ExportExposure_i^X \cdot Dirty_{i1998}^{Y} \\
&+ X_{i1998}' \overrightarrow{\beta} + \varepsilon_i
\end{aligned} \qquad (1.13)$$

The coefficients of the interaction terms (α_{21} and α_{31}) capture the moderating or accelerating effect of initial air quality. Heterogeneous county-level trends and catch-up effects are captured by the coefficient α_{11} of the dirtiness indicator. I focus on aggregated trade flows first ($X = Pooled$) and report coefficients for worker-weighted exposure changes in Table 1.7 because their interpretation is straight-forward.

Table 1.7: Dirtiness Indicator: IV Regression (2SLS) with Worker-Weighted Exposures (I)

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPW	0.422**		0.543***	0.0223		-0.633	-0.268		-0.138
	(0.192)		(0.111)	(0.296)		(0.831)	(0.181)		(0.169)
ΔIPW*Dirty	-1.027**		-1.376***	-0.162		0.888	0.719		0.273
	(0.469)		(0.266)	(0.446)		(1.333)	(0.527)		(0.558)
ΔEPW		0.232	-0.0875		0.338**	0.726		-0.233*	-0.147**
		(0.171)	(0.131)		(0.141)	(0.460)		(0.130)	(0.0739)
ΔEPW*Dirty		-0.400	0.376**		-0.535***	-1.089		0.649**	0.475**
		(0.303)	(0.188)		(0.199)	(0.758)		(0.307)	(0.221)
Dirty	-2.576***	-4.429***	-3.285***	-11.38***	-9.583***	-10.10***	-9.895***	-10.23***	-10.37***
	(0.670)	(1.048)	(0.778)	(2.007)	(1.296)	(1.674)	(2.826)	(2.577)	(2.749)
Const	-1.214**	-0.765	-1.190**	3.658***	2.202**	2.610**	0.658	0.718	0.802
	(0.569)	(0.657)	(0.581)	(1.307)	(0.860)	(1.134)	(0.914)	(0.863)	(0.910)
First Stage	F-Tests of excluded instruments								
ΔIPW	54.716		103.731	56.305		183.357	33.627		141.098
ΔIPW*Dirty	43.079		115.411	54.163		357.487	9.439		134.682
ΔEPW		176.310	214.231		75.152	60.040		60.946	89.636
ΔEPW*Dirty		336.925	435.180		59.517	41.278		91.632	104.776
Controls	Regional Dummies only (dirtiness indicator used instead of controls to capture county heterogeneity)								
Uncentered R^2	0.865	0.857	0.862	0.918	0.915	0.916	0.955	0.958	0.957
F-Statistic	22.33	6.089	35.68	101.2	149.2	190.0	44.00	20.68	60.80
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the smoothed averaged difference in concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

First of all, the dirtiness indicator now absorbs much of the overall trends previously contained in the controls and the negative constant. This is especially visible for $PM10$ and SO_2, for which the dirtiest county (with an indicator value equal to 1 by construction) experiences a catch-up effect of roughly 9.6-11.4$\mu g/m^3$ unrelated to trade exposure. The coefficients in columns (1) and (3) identify initial dirtiness as a catalyst that lets dirty countries experience more beneficial NO_2 emission impacts through trade exposure ($\Delta IPW \cdot Dirty$). Clean counties experience much smaller NO_2 and $PM10$ concentration reductions due to pooled import exposure since their dirtiness indicator interactions are offset by positive ΔIPW coefficients. Initially clean counties therefore benefit less from import exposure and contribute less to overall beneficial net effects. Column (5) demonstrates a similar pattern ($\Delta EPW \cdot Dirty$) for $PM10$. An overall negative effect, however, exists only for the dirtiest counties with an indicator close to 1. Column (3) even exhibits a significantly positive coefficient for the export exposure interaction ($\Delta EPW \cdot Dirty$) regarding NO_2. This implies that dirty counties benefit the most from import competition in terms of air quality but experience dominant scale effects with respect to export opportunities[32]. Table 1.9 demonstrates that initially dirtier counties are not associated with much smaller trade flow increases but conversely tend to have stronger ones when looking at NO_2 exposure. This reinforces the claim that dirtier counties experience the most beneficial or most severe pollution effects from import and export scaling due to the significant interaction coefficients in Table 1.7.

Regressions with $X \in [China, EasternE]$ in Table 1.8 demonstrate that the accelerating or inhibiting effects of initial dirtiness in column (1) and (3) of Table 1.7 are mostly due to increased trade exposure towards China. Dirty and industrialized counties that expand their trade networks with China apparently drive the NO_2 emission savings through import competition. However, their scaling up of production for the Chinese market is also a major factor inhibiting emission reductions according to column (10).

In the German case, high levels of initial dirtiness and catch-up effects in Eastern Germany can be attributed to restructuring and modernization in the wake of the Reunification. Other counties with high levels of pollution in 1998 have introduced local policy measures to target particulate matter emissions along with other pollutants and have then experienced additional bonus effects through trade exposure. Dissecting the effect of trade openness further requires better micro data and attributing the benefits to individual channels beyond the above analysis is highly speculative. This robustness check does, however, address the existence of different pre-trends, as these trends are often related to catch-up effects stemming from varying levels of initial dirtiness (e.g. Bento et al., 2014). An additional robustness check evaluating the role of pre-trends is performed below.

[32] It should be noted that the regressions for area-weighted exposures produce less significant coefficients. See Appendix A.1.13. It is difficult to ascertain, whether the current specification represents the optimal implementation of initial dirtiness. The indicator depends heavily on the most unreliable pollutant averages from the year 1995 and is therefore likely biased. Although the inclusion of the indicator in lieu of socio-economic controls absorbs some of the significance in the area-weighted models, I conclude that it is reasonable to omit the dirtiness indicator from my preferred specifications in Table 1.3 and Table 1.5 but concede that doing so potentially inflates the coefficients of interest.

Table 1.8: Dirtiness Indicator: IV Regression (2SLS) with Worker-Weighted Exposures (II)

Regression	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔSO2	ΔSO2
Model	(10)	(11)	(12)	(13)	(14)	(15)
China						
ΔIPW	1.051***		-1.098		0.261*	
	(0.233)		(0.943)		(0.156)	
ΔIPW*Dirty	-2.546***		1.656		-1.157**	
	(0.471)		(1.501)		(0.507)	
ΔEPW	-1.631		4.204***		-2.746***	
	(1.088)		(0.904)		(0.852)	
ΔEPW*Dirty	3.839**		-6.201***		7.982***	
	(1.530)		(1.228)		(1.709)	
EasternE						
ΔIPW		-0.903		0.585		-1.531***
		(1.118)		(0.836)		(0.430)
ΔIPW*Dirty		1.378		-1.428		4.273***
		(2.648)		(1.336)		(1.181)
ΔEPW		0.654*		0.161		0.528***
		(0.363)		(0.247)		(0.127)
ΔEPW*Dirty		-1.141		-0.0457		-1.495***
		(0.858)		(0.390)		(0.414)
Dirty	-6.472**	-4.591***	-8.745***	-9.045***	-12.74***	-10.04***
	(2.605)	(0.803)	(1.610)	(1.915)	(2.704)	(2.494)
Const	0.329	-0.452	1.519	1.987*	1.612*	0.620
	(1.663)	(0.402)	(0.996)	(1.167)	(0.838)	(0.792)
First Stage	F-Tests of excluded instruments					
ΔIPW	150.322	65.153	289.913	59.261	164.397	112.182
ΔIPW*Dirty	256.040	65.883	515.344	73.701	94.869	108.415
ΔEPW	15.357	194.854	5.165	146.434	18.588	536.874
ΔEPW*Dirty	19.707	267.249	5.136	170.807	28.800	472.546
Controls	Regional Dummies only (dirtiness indicator used instead of controls to capture county heterogeneity)					
Uncentered R^2	0.849	0.861	0.903	0.915	0.946	0.953
F-Statistic	1115.0	24.08	1641.6	462.6	34.58	41.95
Observations	413	413	413	413	413	413

Note: Dependent variable is the smoothed averaged difference in concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

Table 1.9: Correlation Matrix of Dirtiness Scores

	ΔIPW	ΔEPW
ΔIPW	1	-
ΔEPW	0.6475	1
$Dirty_{i1998}^{NO2}$	0.0692	0.1973
$Dirty_{i1998}^{PM10}$	-0.0046	0.0398
$Dirty_{i1998}^{SO2}$	-0.2133	-0.1842

Note: Correlations between Changes in Trade Exposure per Worker and Dirtiness Scores.

1.6.4 Robustness Check: Pre-Trends

The treatment can only be argued to be exogenous if county characteristics do not influence both treatment intensity and environmental performance simultaneously. If pre-trends in pollution concentrations differ significantly between counties highly affected by trade openness and less exposed counties, an interpretation of treatment effects as causal is precarious. Even more so if there is a credible risk of endogenous selection into treatment intensity. One way to test for such a confounding relationship is regressing the pre-trends in the outcome variable (i.e. the change in pollution concentrations) on treatment intensity to rule out the existence of such a correlation between important county characteristics and treatment. The lack of comprehensive pollutant concentration data before the year 1998 makes it difficult to construct convincing pre-trends[33]. Therefore, I have to rely on the changes between 1995 and 2000 as a proxy for pre-trends before the year 1998, which marks the initial time period of my main analysis.

The following tables report the main coefficients of interest from simple regressions with either no controls or the standard set of controls including region dummies. In each regression, the pre-trends are regressed on individual trade exposure changes. In an optimal scenario without a confounding relationship, neither of these regressions yield a significant coefficient between dependent and independent variable. Consequently, Table 1.10 confirms that there is no relationship between initial NO_2 trends and trade patterns, while pre-trends in $PM10$ are weakly related to trade exposure in setups with the baseline control set.

Overall, trade exposure changes after 1998 have little explanatory power for pre-treatment trends. This implies that there is only a weak link between treatment intensity and pre-trends and that sorting into trade patterns in response to pollution trends can be ruled out at least for NO_2. The robustness

[33]While sparse data from measuring stations does exist before 1998, no datasets or interpolation strategies can saturate the entire territory of Germany without introducing measurement errors as explained by Auffhammer et al. (2013). Constructing historical pre-trends for a small subset of counties with sufficient information and limiting the pre-trend analysis to these counties creates an unbalanced sample suffering from selection bias.

check does caution against a causal interpretation of effects related to $PM10$ values, though. Since initial trends in $PM10$ exhibit a negative correlation with trade openness, later emission reduction estimates with respect to this pollutant are not entirely attributable to the causal effect of trade exposure and likely biased downwards. Notwithstanding, the common trend assumption appears to hold for the vast majority of models and the apparent violations may also be precipitated by the use of imperfect pre-trend proxies.

Table 1.10: Pre-Trends on Trade Exposure Changes (Regression Coefficients)

	Pre-Trend NO_2 (1995-2000)							
ΔIPW	0.0481	0.0227						
	(0.0694)	(0.0313)						
ΔEPW			-0.0252	-0.0511				
			(0.0841)	(0.140)				
ΔIPA					-229.4	-28.89		
					(246.3)	(126.3)		
ΔEPA							-148.3	45.12
							(194.8)	(138.1)
	Pre-Trend $PM10$ (1995-2000)							
ΔIPW	0.100	0.106						
	(0.116)	(0.0665)						
ΔEPW			0.0374	-0.212**				
			(0.106)	(0.0878)				
ΔIPA					-376.5	-438.6*		
					(369.3)	(228.1)		
ΔEPA							-285.7	-378.9**
							(251.8)	(169.8)
.	Pre-Trend SO_2 (1995-2000)							
ΔIPW	0.451*	0.0672						
	(0.224)	(0.0674)						
ΔEPW			0.451*	-0.0314				
			(0.227)	(0.147)				
ΔIPA					318.5	-90.02		
					(302.2)	(183.0)		
ΔEPA							154.6	-150.0
							(207.7)	(133.4)
Controls	None	Standard	None	Standard	None	Standard	None	Standard
Observations	413	413	413	413	413	413	413	413

Note: Pre-Trends are concentration differences between 1995 and 2000. Regressions are performed without controls and with the baseline set plus regional dummies. This table reports only the main coefficient from each regression.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.

A recent discussion has developed revolving around the use of so-called Bartik instruments. According to Goldsmith-Pinkham et al. (2019) and Borusyak et al. (2018), ADH use a shift-share instrumental variable design to estimate the causal effect of rising import penetration on labor markets. These variables represent Bartik instruments and Borusyak et al. (2018)

argue that the approach can be viewed as a reasonable way of leveraging exogenous shock variation, while Goldsmith-Pinkham et al. (2019) use balance and overidentification tests to challenge the plausibility of these Bartik instruments.

Both DFS and ADH use lagged employment shares to construct the instruments and do not rely on temporal shifts in employment figures for their identification but on static employment shares. This circumvents a few pitfalls associated with Bartik instruments but Goldsmith-Pinkham et al. (2019) stress the importance of parallel trends for the plausibility of the instruments. While I am unable to provide pre-trend tests at the industry-level due to the necessary micro level data, the above robustness checks suggest the existence of parallel trends in NO_2 concentrations regardless of treatment severity, which lends credibility to NO_2 results obtained from the instrumental variable approach.

1.7 Conclusion

Utilizing the trade shocks and instruments from Dauth et al. (2014) along with spatial datasets of emission concentrations in Germany, I am able to confirm the hypothesis that increased trade volumes with China and Eastern Europe over the time period from 1998 to 2008 have impacted local air quality in Germany. The empirical analysis is based on an instrumental variable identification approach, exploits regional variation in pollution and trade exposure across German counties and yields a positive net benefit of rising trade exposure on environmental quality for both NO_2 and $PM10$ but mixed results for SO_2, possibly due to limitations in data availability at the beginning of the sample. These net reductions in pollution concentrations are driven by emission savings due to import competition and productivity benefits through imports, which are not offset by the scale effects associated with growing export opportunities towards China and Eastern Europe. While Dauth et al. (2014) demonstrate positive employment effects through these export opportunities of singular magnitude, this growth does not cause a comparable increase in pollution emissions. It is possible that the beneficial effects of export revenues on productivity and abatement technology prevalence neutralize any scale effects in the exporting industries or that cleaner and more efficient industries are the main beneficiaries of these export opportunities.

Following my preferred specification based on spatially dispersed trade exposure changes, I compute an estimate of the net effect of trade expansion. Due to the air quality improvements tied to import competition and the almost pollution-neutral additional export opportunities, trade liberalization with respect to China generates an average net reduction of approximately $0.070\mu g/m^3$ in NO_2 concentrations and of approximately $0.067\mu g/m^3$ in $PM10$ concentrations across German counties. Expanding the trade network with Eastern European countries lowers average $PM10$ concentrations by an additional $0.168\mu g/m^3$ mainly as a result of growing import exposure and despite their dominant role as export markets. While analyzing pre-trends and initial heterogeneity at the county-level reveals a potentially confounding relationship for $PM10$ regressions, it reinforces the credibility of NO_2 estimates. Since relative risk factors for this pollutant are readily available, I perform a basic estimation of the overall value of statistical life (VSL) preserved by NO_2 reductions and arrive at an annual benefit of €602.77million tied to the avoidance of emission-related mortality. The net benefits are economically meaningful because of their relevance for human health but small compared to overall trend reductions of roughly 3 $\mu g/m^3$ for NO_2 and 2.84 $\mu g/m^3$ for $PM10$ over the same time period. This implies that the contribution of trade exposure to air quality is small compared to the reductions achieved by regulation, technological progress and social norms unrelated to trade activity. These findings mirror recent results for the United States by Shapiro and Walker (2018). In light of the fact that Germany has experienced advantageous impulses for its manufacturing labor force through trade liberalization and has remained a net exporter, these small but robust savings should nevertheless be interpreted as a remarkable result.

The finding also provides an antidote against the well-documented populist strategy of framing international trade as a threat for the local populace in developed nations (e.g. Dippel et al., 2015, and Autor et al., 2016). My research contributes to the body of literature that emphasizes the ability of developed nations to harness the terms of trade, to outsource costly and environmentally harmful production and to collect windfall gains from trade liberalization beyond export revenues.

On the other hand, it has to be taken into account that Germany represents a singularity due to its ability to absorb a major fraction of EU trade flows and to avoid deindustrialization by seizing export opportunities. Thus, empirical findings for Germany may not be valid in other contexts. Furthermore, this analysis ignores potentially detrimental environmental effects for citizens abroad and explores only the domestic cross-sectional propensity to harness trade shocks for environmental benefits. Another caveat is that my research framework based on the seminal paper by Autor et al. (2013) focuses on aggregate effects and does not attribute environmental benefits to individual channels at the micro level. It would be interesting to evaluate, to what extent the emission reductions are due to restructuring at the extensive margin and to what extent they are caused by improvements in emission intensity along the intensive margin. In order to arrive at such a specification, measures of emission intensity and productivity have to be constructed that incorporate price dynamics in a correct manner as emphasized by De Loecker (2011). Last but not least, aggregate improvements in both job opportunities and environmental quality are tied to distributional inequalities and welfare is not increasing evenly across stakeholders. Galle et al. (2018) and Dauth et al. (2021) have explored these distributional concerns with respect to the labor market. My analysis of initial heterogeneity at the county-level reveals that dirty counties experience the largest improvements in air quality and drive aggregate effects. On the flipside, they also experience the strongest labor market pressures. Helm (2019) demonstrates that trade shocks induce spillover effects into connected industries in the vicinity due to agglomeration economies, which constitute up to 38% of total employment effects. My baseline research design ignores spatial spillovers and treats import competition shocks as county-specific, while in reality they affect workers and air quality in surrounding regions. The fact that aerial pollutant emissions exhibit powerful dispersion patterns (e.g. Lin et al., 2014) makes immission rasters an imperfect proxy. Accounting for spatial autocorrelation is therefore an important and expandable aspect of my analysis.

Altogether, my analysis provides robust evidence for domestic air quality improvements in Germany as a result of the trade liberalization process. I interpret these improvements as windfall gains from trade openness that can likely be replicated in other scenarios if terms of trade are favorable and supported by local environmental regulations, incentives for innovation and subsidies for abatement technologies. The magnitude of environmental benefits - between 2.3% of overall reductions between 1998 and 2008 for NO_2 and 8.3% for $PM10$ - makes them not immediately noticeable by everyone affected. Consequently, creating awareness for such environmental improvements and the positive aspects of global trade integration remains a challenge, while politicians need to make sure that social, economical and environmental benefits from Germany's focal position in international trade are distributed efficiently and fairly - even across national borders.

Chapter 2

The Effect of Emission Information on Housing Prices - Quasi-experimental evidence from the European Pollutant Release and Transfer Register

with Kathrine von Graevenitz and Daniel Roemer

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The Effect of Emission Information on Housing Prices:
Quasi- Experimental Evidence from the
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Notes

The following subchapters are identical to the published version except for the formatting and the inclusion of an erratum. This erratum was added in order to replace a flawed map in the original version and is available on the Springer website "Erratum to: The Effect of Emission Information on Housing Prices: Quasi-Experimental Evidence from the European Pollutant Release and Transfer Register"[34]. The following subchapters therefore represent the final version of the paper accepted for publication with slight modifications regarding the numbering of the subchapters, the placement of the appendix and the inclusion of the erratum for the convenience of the reader.

Abstract

In this paper, we study whether the release of pollutant emission information has an effect on housing prices. The event under study is the publication of the first wave of emission quantity data from the European Pollutant Release and Transfer Register in 2009. Our analysis is based on quarterly housing prices at the German postal code level for the years 2007-2011 and provides the first evidence from Europe on this research question. Estimating a differences-in-differences model and controlling for observable differences in land use, housing type distribution, tax revenues and other postal code area characteristics by means of propensity score matching, we find no significant effect of the release of emission information on the value of houses in affected postal code areas. This result survives a number of robustness checks designed to assess whether our findings are due to data aggregation issues or the actual treatment definition. This leads to the conclusion that on an aggregate level the 2009 publication of E-PRTR data did not have an immediate and noticeable effect on housing prices in Germany.

[34] Figure A.16 in Appendix A.2.8 is the corrected version also found on the website (https://link.springer.com/article/10.1007%2Fs10640-016-0100-9).

2.1 Introduction

The first wave of data for Germany from the European Pollutant Release and Transfer Register (E-PRTR) was released in 2009 and reported on location and volume of pollutant emissions in 2007. The origin of this type of registry can be found in the American Toxics Release Inventory (TRI) that was introduced in 1989 and continues to publish U.S. emission information on a regular basis. The introduction of the E-PRTR was meant to provide information about local emissions to communities in Germany and other European countries, which previously did not have access to public information of such quality. The aim of this paper is to assess the impact of this event on the German housing market.

In general, the provision of information about pollutant emissions gives households the opportunity to adjust their behavior in response. If households react to the reports and re-evaluate locations according to the reported emissions, the housing market should reflect the resulting adjustments of preferences in the corresponding real estate values. To test this hypothesis, we look at the revelation of emission information tied to the first wave of E-PRTR data in Germany and evaluate possible impacts on aggregated housing prices. In doing so, we provide the first assessment of the impact of a large-scale publication of emission information on housing prices in a European context.

The idea that the mere provision of information can be an effective means of regulating polluters is popular among policymakers as it is relatively cheap to implement. The information provided to the public should then give rise to community pressure on polluters to reduce their emissions. As emissions are present before and after publication, only unexpected information about quantities or substances should lead to adjustments in behavior. The way in which households respond to such information depends on how they understand it and what their prior beliefs are, i.e. whether they perceive a change in the risk they are exposed to. There is evidence that households do respond to information on environmental amenities in a variety of situations and that they reduce their exposure to hazardous substances when learning about water quality (Graff Zivin et al., 2011) or ambient ozone pollution (Neidell, 2009, Moretti and Neidell, 2011). It is important to note that emission inventories only provide indirect information on environmental quality and do not convey exact measurements of health relevant variables such as local concentration of pollution. Nevertheless, recent empirical studies on the most prominent program established on the basis of this concept, the U.S.-American TRI, have confirmed its effectiveness by demonstrating significant market responses particularly in the context of housing prices (Sanders, 2014, Mastromonaco, 2015).

The E-PRTR covers emissions to three different media: air, water and soil, with approximately 60 pollutants in each group and some degree of overlap. We base our analysis on a quarterly House Price Index at the German postal code level for the years 2007-2011. Our identification strategy is based on a differences-in-differences model using the time of the announcement to identify varying developments in housing prices in the treatment and control group. Treatment status is assigned based on the number of emission reports affecting a given spatial entity. Our analysis relies on several assumptions concerning market extent and the identification of an appropriate control group. For the treatment effect to be accurately identified, the control group should be identical to the treatment group in the absence of treatment. Specifically, in this context, pre-treatment trends should be the same in both groups.

We are fortunate to have a comprehensive data set that provides detailed characteristics for all postal code areas in our sample and allows us to accurately construct comparable treatment and control groups. First of all, we are able to spatially assign socio-economic information at the municipal level to individual postal codes. Secondly, the use of Geographical Information Systems (GIS) allows us to collect data on the categories of land use within each postal code area including industrial land use, landfills, infrastructure and urban areas. Evidence from the hedonic literature emphasizes the importance of accounting for locally undesirable land use in assessing the impact of exposure to hazardous substances on house prices (Taylor et al., 2016). Since our data indicate substantial systematic differences between treated postal code areas and untreated areas in the full sample, a matching approach seems prudent. Based on land use and a list of other relevant observable characteristics we are able to match our treated postal code areas to suitable controls. For the matched sample, we do not find a significant effect on mean house prices in treated postal codes.

Subsequently, we carry out several robustness checks, predominantly based on our treatment definition. Our baseline treatment definition, assigning the treatment status to any postal codes with at least one emitter, may be too broad as small emissions are given the same weight as large emissions. To better capture the treatment intensity, we redefine the treatment variable to indicate quartiles of toxicity-weighted emission quantities by approximating toxicity through the reporting thresholds of the register. These thresholds are publicly available and send a distinct signal about the danger associated with the emission. An additional robustness check approaches treatment intensity from a different angle by factoring in the absolute number of reporting facilities. Moreover, we address the distance to emissions and narrow down the treatment definition to concern only those postal codes with urban area within 500 m of a point source. We estimate regression models with different sets of fixed effects, but also compute Average Treatment Effects on the Treated as in Muehlenbachs et al. (2015) for comparative purposes. None of these robustness checks indicate the existence of systematic, significant effects after nearest neighbor matching is performed. In sum, our results suggest that disclosing the first wave of E-PRTR emissions in 2009 had no significant impact on postal code average housing prices in Germany once we account for observable characteristics of these postal code areas.

2.2 Related Literature and Background

2.2.1 Empirical evidence on environmental amenities in the housing market

Following Tiebout's seminal paper on households voting with their feet (Tiebout, 1956), households' residential choice should reflect their preferences for public goods, including environmental amenities. Empirical evidence in support of this hypothesis has been provided by Banzhaf and Walsh (2008), who find that local changes in environmental quality are linked to local changes in community demographics. Such changes should be reflected in the housing market, and as a result housing markets are often used for non-market valuation purposes. There is a large literature on housing prices and environmental amenities using e.g. the hedonic model (Palmquist, 2006).[35] In the last decade, a number of papers on environmental valuation using a quasi-experimental approach have emerged (e.g. Chay and Greenstone (2005) on the Clean Air Act, Greenstone and Gallagher (2008) on Superfund sites and Davis (2004) on cancer clusters). As emphasized by Parmeter and Pope (2009), the use of treatment evaluation techniques aids in overcoming a number of issues concerning omitted variable bias, which is otherwise an inherent problem in most cross-sectional hedonic analyses. It should be noted, however, that hedonic models are designed to recover a marginal willingness to pay measure from the slope of the hedonic price function, whereas the quasi-experimental approach recovers a capitalization effect. Kuminoff and Pope (2014) emphasize that several assumptions are required to interpret the capitalized effect as an estimate of households' average marginal willingness to pay for an amenity.

There are several studies that look at the effect of providing information on environmental amenities on housing prices. While there are also examples using direct information on environmental quality,[36] empirical studies that deal with the effect of publishing indirect information on environmental amenities, in particular emission information via the Toxics Release Inventory in the United States, are the most relevant empirical counterparts to our analysis. The results are mixed.[37] Bui and Mayer (2003) find no significant effects of TRI releases on the housing market at the zip code level for more than two hundred zip codes in Massachusetts, while Sanders (2014) provides evidence of a negative non-linear impact of reported TRI emissions on housing

[35] Housing markets have also been used to evaluate changes in utility due to proximity to sex offenders (Linden and Rockoff, 2008), school quality, etc.

[36] Pope (2008) for example exploits the introduction of disclosure laws that require sellers to provide exact information about airport noise exposure to potential buyers.

[37] A list of scientific articles relying on TRI data can be found in the booklet Environmental Protection Agency (2013) released by the Toxics Release Inventory Program Division.

prices. Sanders conducts a nation-wide event-study at the postal code level and based on the 1998 extension of the TRI pollutant reporting definitions. His findings imply that only substantial deviations from previously reported emissions have a significant effect on real estate prices.

Moreover, there are papers based on micro-level data: Oberholzer-Gee and Mitsunari (2006) find a negative effect of emissions on predicted housing values within short distances (< 1 mile) of the emitter for a limited sample of five counties in the Philadelphia region. Using TRI and census data from the 1980s for the six New England states, Hanna (2007) finds estimates suggesting that being a mile closer to a polluting manufacturing plant reduces house values by 1.9 %. Mastromonaco (2015) uses a difference-in-differences specification and a change in the reporting requirements for several chemicals in 2000/2001 as a quasi-experiment to test for housing price changes in the San Francisco-Oakland-San Jose Metropolitan Area and finds that listing a firm in the TRI lowers housing prices in the vicinity by up to 11 %. Currie et al. (2015) look at both health effects from residing near polluting facilities and the effects of the opening and closing of facilities registered in the TRI on housing prices. Using micro data on individual transactions, they find a significant effect on house prices, albeit at the very local level within 0.5 miles of the facility. Thus, several existing studies find both statistically and economically significant effects of revealed emission information on housing prices but with mixed evidence on the magnitude and spatial range of the effect. As Currie et al. (2015) emphasize, many of the pollutants in the TRI are odorless, colorless and hence undetectable without technical equipment. The same holds true for many pollutants in the E-PRTR. For this reason, households are unlikely to accurately perceive the (spatial) extent of emissions from a nearby facility. Information announcements from the European register therefore have the potential to stimulate households to update their information sets and consequently their risk perceptions. To the best of our knowledge, this research project is the first to look at the effect of the E-PRTR on housing prices. We use Germany-wide housing data on the zip code level and provide first evidence on the effect of large-scale publication of emission information outside the U.S.

2.2.2 The quasi-experiment

The European register for emissions was established following the signing of the Aarhus Convention in 1998 by EU member states. The convention aims to increase democratic participation and grants the public the right to information about the environment. In 2000, the European Council decided to establish the European Pollutant Emission Register (EPER) based on Article 15(3) of Council Directive 96/61/EC. The main objective of the EPER was to fulfill the public's right to know about the releases of pollutants in their neighborhood. The EPER was a web-based register, which enabled the public to access data on emissions to water and air of 50 key pollutants from large and medium-sized industrial point sources in the European Union. The register was hosted by the European Environment Agency (EEA). In 2003, the UNECE Pollutant Release and Transfer Register protocol was signed resulting in the establishment of the European Pollutant Release and Transfer Register. The E-PRTR expands the coverage of the EPER to include additional substances and release media. The first round of data for the E-PRTR covers 2007 and was released in 2009 with the launch of the E-PRTR website. We downloaded the data in the summer of 2012. E-PRTR emissions data is collected annually with a delay of approximately 2 years. Since 2009, comprehensive data releases have taken place every year.

While the predecessor, the EPER, lived a relatively quiet life,[38] the launch of the E-PRTR in 2009 was heavily publicized. Several major German newspapers announced the launch of the German E-PRTR website and released short articles detailing the purpose and the scope of the register. In the period between 2006 and 2011, 43 articles were retrieved from a LexisNexis search for the keywords "E-PRTR" and "PRTR" in German newspapers. For the year 2009 alone, there were 34 entries.[39] The launch

[38]The EPER made Europe-wide emissions data for the year 2001 available in 2004 and emissions data for the year 2004 available in 2006. However, this register received very little public attention. A LexisNexis search involving German newspapers regarding the keyword "EPER" yielded only 7 hits for the time frame before 2009. Mentions of the term were largely concentrated in special interest journals regarding environmental topics or the waste treatment industry such as Entsorga (2004).

[39]Examples of comprehensive newspaper articles on the newly available E-PRTR data

was also accompanied by an official conference in Berlin and the introduction of a more professional and user-friendly website layout. The website itself is centered around a convenient database hosted on the servers of the EEA and was featured in a number of popular magazines. Furthermore, maps on the website containing the graphical depiction of all point sources made the information more accessible to people not familiar with the subject or not interested in filtering through extensive micro data.[40]

In addition, the number of pollutants was greatly expanded in the E-PRTR register to 91 substances in comparison to 50 EPER categories, leading to 4,727 reported point source releases in the first E-PRTR data wave compared to 3,413 reported releases in the last EPER data wave with respect to Germany alone. Analyzing the media impact of the old and the new register as well as the scope of the databases suggests that the release of the first wave of E-PRTR data had a much greater impact on the public perception of emission quantities in the local environment than previous reports including any EPER releases and publications. In fact, limiting the numerical analysis to facilities that were included in the 2009 E-PRTR release but did not report emissions under EPER in order to eliminate all observations for which prior high-quality information may have been available, did not reveal substantially different results. This suggests that the E-PRTR reports were not treated differently by the housing market with respect to potentially available EPER emission figures from 2004 or 2006 and that all information released in 2009 was equally new to the market. Since it seems reasonable to assume that the information released on June 3rd 2009 should be considered news to the German households, we treat the release of the E-PRTR information in the second quarter of 2009 as the pivotal event in our analysis. While households likely had beliefs about the level of pollutant emissions in their area, the release of E-PRTR data provided them with the opportunity to update their

include "Database of hazards" - Sueddeutsche Zeitung (2010), "Pollutant information now online"-Hamburger Abendblatt (2009), and "Interesting information on environmental sinners in the neighborhood"-TAZ (2009).

[40]Compared to the EEA website the localized website was fairly basic but also easier to use and has been updated substantially over the following years. The current German front-end application for private inquiries is available under: http://www.thru.de/search/

beliefs and adjust behavior if deemed necessary. To account for the possibility that large emitters might represent more obvious pollutant sources allowing for more precise beliefs on the side of the households, we provide a robustness check estimating treatment effects for different emission levels separately (see Chapter 2.6.1).

2.3 Method

Our analytical approach is based on a difference-in-differences model that focuses on the evolution of housing prices (Y_{ist}) over time (t, yearly quarters), and across different postal code areas (i) within different federal states (s). We restrict the data on housing prices to a time interval covering two years before and after the release of the data as suggested by Sanders (2014).[41] Given our quarterly data, we are left with 16 observations for each postal code area, starting in 2009Q2 and ending in 2011Q1. We include a shift dummy variable ($Post_t$), which is set to 1 for all quarters after the release of the emissions data, and a dummy variable for treatment ($Treated_i$). We estimate the following model with postal code fixed effects ($\alpha_{4,i}$) and state-by-time dummies ($\alpha_{5,st}$) for each state and quarter, allowing for time trend differences between the 16 German federal states:

$$Y_{ist} = \alpha_0 + \alpha_1 Post_t + \alpha_2 Treated_i + \alpha_3 Post_t Treated_i + \alpha_{4,i} + \alpha_{5,st} + \varepsilon_{ist} \quad (2.1)$$

When performing a fixed effects regression, the treatment dummy is dropped because of time invariance and the coefficient of interest is α_3. Its estimate will yield the average treatment effect of the release of emissions data on housing prices under four conditions.

First, the appropriate definition of treatment status ($Treated_i$) is crucial to our study and we test a number of different definitions. In the E-PRTR

[41] It is possible to obtain House Price Index values for a longer time horizon and E-PRTR emission data for the subsequent years (i.e. data from 2008 released in 2010, data from 2009 released in 2011 and so forth). However, the scope of this research project is to focus on the immediate impact of the initial data release. The following waves of E-PRTR information would allow inhabitants to continuously update their beliefs, which could potentially dilute the actual effect of interest.

dataset, the geographical coordinates of each emitter are provided along with a postal code. Hence, we define a postal code area as treated if it contains at least one emitter reporting emissions in the 2009 release. We refine these treatment definitions in section 6 in order to address the concern that the emitted quantity or the facility density may be important for the housing price response.

Second, the extent of the market is important in determining the appropriate capitalization effect if there is heterogeneity in preferences in different housing markets. While treating large geographic areas (e.g. the whole U.S.) as a single market is not unusual in the quasi-experimental hedonic literature (e.g. Greenstone and Gallagher (2008) and Sanders (2014)), Gamper-Rabindran and Timmins (2013) find that there is considerable heterogeneity in the capitalization of clean-ups of hazardous waste across the U.S. Their findings suggest that pooling data across regions may be misleading. Given the German history and the resulting very different economic conditions in Eastern and Western Germany, we estimate our model for each of these two regions separately with the former covering the previous territory of the DDR along with Berlin.

Third, we need to rule out systematic differences between control and treatment group and the prevalence of systematically different housing market trends in particular. If treatment status is determined at least in part by the value of an unobserved variable which is correlated with the general development of housing prices, the estimate of the treatment effect will be biased (e.g. Angrist and Pischke, 2009, p. 243). We address this concern by using propensity score matching techniques to secure comparable control and treatment groups. For this purpose, we carefully collect data on the characteristics of the postal code areas including land use and socio-demographic information useful in predicting the probability of finding emitters in the different areas. The market definition discussed in the previous paragraph can also be seen as an important step towards narrowing down the relevant control group to one that is highly comparable to treated postal code areas and as an important factor in our efforts to control for all relevant (regional) differences in terms of unobservable characteristics.[42]

Finally, we need to assume no other changes unique to the treatment group take place when the data is released. A potential threat might be the financial crisis that peaked around the time of the first E-PRTR publication. This would cause problems if treated postal code areas were systematically affected differently than the control areas. It could be the case for example that housing prices are less volatile in industrial areas due to less speculation as compared with urban housing and high quality living areas. We can address this concern by including the share of industrial areas within a postal code area in our matching procedure.

The observable characteristics that we use for the matching procedure are measured shortly before the event under observation. This ensures that control and treatment observations share similar properties at the time of the data release. Treatment and control groups then remain unchanged over all 16 time periods.[43]

Further, we follow Muehlenbachs et al. (2015) and compute Average Treatment Effects on the Treated (ATET) based on mean differences in housing prices pre and post treatment for comparative purposes. This setup abstracts from individual zip code characteristics and only takes state fixed effects for each German "Bundesland" into account to control for different evolutions in the housing markets across federal states. In general, the ATET measures a similar effect as the interaction term in the regression model but should be less sensitive to issues concerning the balancing of covariates for the matched samples.

[42] This point is made in a recent paper by Abbott and Klaiber (2013). They use matching to account for observable characteristics, but limit matching to potential controls within a certain radius (spatial proximity) to obtain comparable units in terms of unobservable characteristics. The procedure is intuitively similar to the use of fixed effects to capture neighborhood unobservable characteristics.

[43] In essence this corresponds to using matching as a non-parametric pre-processing of the data, see Ho et al. (2007). By limiting the analysis to a matched sample, the estimated models become less sensitive to misspecification as there is less implicit interpolation when the treatment and control group are balanced in terms of observable characteristics.

2.4 Data

2.4.1 Housing data

We use a hedonic House Price Index, the “F&B Wohn-Preis-Index”, on the postal code level with quarterly data for the 4 years surrounding the information release (2007Q2-2011Q1). This data was purchased from F&B GmbH, a private research and consulting institute in Hamburg, Germany, that specializes in the housing market. This hedonic price index is based on supply data from up to 20 million German real estate objects in the private sector such as family homes, condominiums and privately owned terraced houses. An adjustment is made to account for the differences between listing prices and actual transaction prices. The index uses aggregates computed on the basis of supply data from selected online and offline sources for housing and weighted by typical variables such as number of rooms, age of building, type of residency and location. With these adjustments, the index describes how the development in the price of an “average home” changes across time and postal code areas. Plausibility checks are performed for each entry and the aggregation process controls for regional and seasonal variation in types of homes available. Details can be found on the company website and have been summarized in F+B (2012).[44]

The baseline index is normalized to 100 in 2004Q2 for each of the 8,212 postal codes and describes the development in housing prices within each separate postal code relative to the House Price Index at this fixed point in time. We compared the aggregate long term trends with annual data obtained from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung, BBSR) and found fairly similar trends confirming the general validity of the obtained housing price data. Monthly data has been converted to quarterly data by assigning the index value from the latest month to the respective quarterly time series. Figure A.9 in Appendix A.2.4 shows that by 2009Q2

[44]www.f-und-b.de (F+B Forschung und Beratung für Wohnen, Immobilien und Umwelt GmbH, Hamburg). Accessed on 28-10-2013.

the index values had fallen by 5% on average across German postal codes. The subsequent recovery back to 99% in mean housing price values can be attributed to the Financial Crisis and the resulting lack of other attractive investment opportunities. The turnaround point roughly coincides with the publication of the first wave of E-PRTR data in 2009Q2 and divides our period of observation into two sub-periods exhibiting almost linear trends, which facilitates their interpretation and parts of the analysis but also stresses the necessity of a careful approach with respect to existing pre-treatment trends. All changes in House Price Index values are basis point changes relative to the level of housing prices within a certain postal code in 2004Q2.

2.4.2 Pollutant emissions data

2.4.2.1 Facility reports

Polluted emissions data has been taken from the website of the E-PRTR. The database itself is maintained by the European Environment Agency and lists pollutant emissions from point sources on the facility level for all European countries reporting to the E-PRTR in absolute quantities.[45] The database contains releases into air, water and soil as well as transfers to external waste treatment facilities. The reports differentiate between 96 pollutant categories including some aggregate classes and 91 individual pollutants, out of which 70 actually occurred in Germany in the reports for 2007. For the year 2007, there were 4,727 point source releases and 952 waste transfers reported for 1,976 individual facilities. All facilities engaging in at least one of 65 specified economic activities[46] are obliged to report their yearly emissions of those 91 specified substances that exceed a certain threshold defined for

[45]Database accessible via: http://www.eea.europa.eu/data-and-maps/data/member-states-reporting-art-7-under-the-european-pollutant-release-and-transfer-register-e-prtr-regulation-12

[46]All relevant economic activities are listed in the Annex (p. 8 et seq.) to the regulations published in European Union (2006b) in January 2006. Official information accessible via: http://prtr.ec.europa.eu/. The register includes information of about 29000 facilities in 32 countries (EU27, Iceland, Liechtenstein, Norway, Switzerland and Serbia).

each pollutant and release medium separately.[47] The specific thresholds were chosen to ensure that about 90% of industrial emissions are captured by E-PRTR reports.[48] The basis for this calculation was data accumulated by EU member states such as Germany, the Netherlands and the UK in years prior to the passage of regulation. We exclude reports on CO_2 for our analysis as this substance does not pose a local threat to nearby households and is not contained in the TRI.[49] Moreover, we exclude reports on transfers as their final destination is usually not close to the reporting site and transportation to another facility such as a waste treatment site should evoke fewer concerns within the local community than the direct release of pollutants into the local environment. Emissions from such a waste treatment site would be reported in the E-PRTR if they exceed the respective reporting threshold.

2.4.2.2 Facility locations

The E-PRTR database also contains Gauss-Krüger coordinates (WGS84) of each facility. We use geographic information systems (ArcGIS) to attribute the point source to the corresponding postal code area.[50]

The location of emissions by postal code areas is displayed in Figure 2.1, using a shape file that contains the full set of 8,212 German postal code areas as of January 2012, provided by GfK GeoMarketing GmbH.[51] The visual representation shows that point sources are not spread out evenly across Germany. Emissions are concentrated in well-known industrial areas such as the Ruhr valley, as well as in certain rural areas in the former German Democratic Republic. There are in total 1,118 postal code areas, which contain at least one point source according to the data set published in 2009.

[47] These thresholds will be used as weights to normalize emissions when calculating a weighted severity measure, see Appendix A.2.2 or Chapter 2.6.1. All pollutants and thresholds are listed under: http://prtr.ec.europa.eu/docs/Summary_pollutant.pdf.

[48] See question 5 on http://prtr.ec.europa.eu/#/faq.

[49] Including these reports does not qualitatively affect the results.

[50] Interestingly, using the geographic coordinates revealed that in more than 200 cases in 2007 alone, the postal code in the E-PRTR reflected the location of a firm's main office rather than the location of the actual emission.

[51] This shape file has also been used for the remaining maps displayed in this paper.

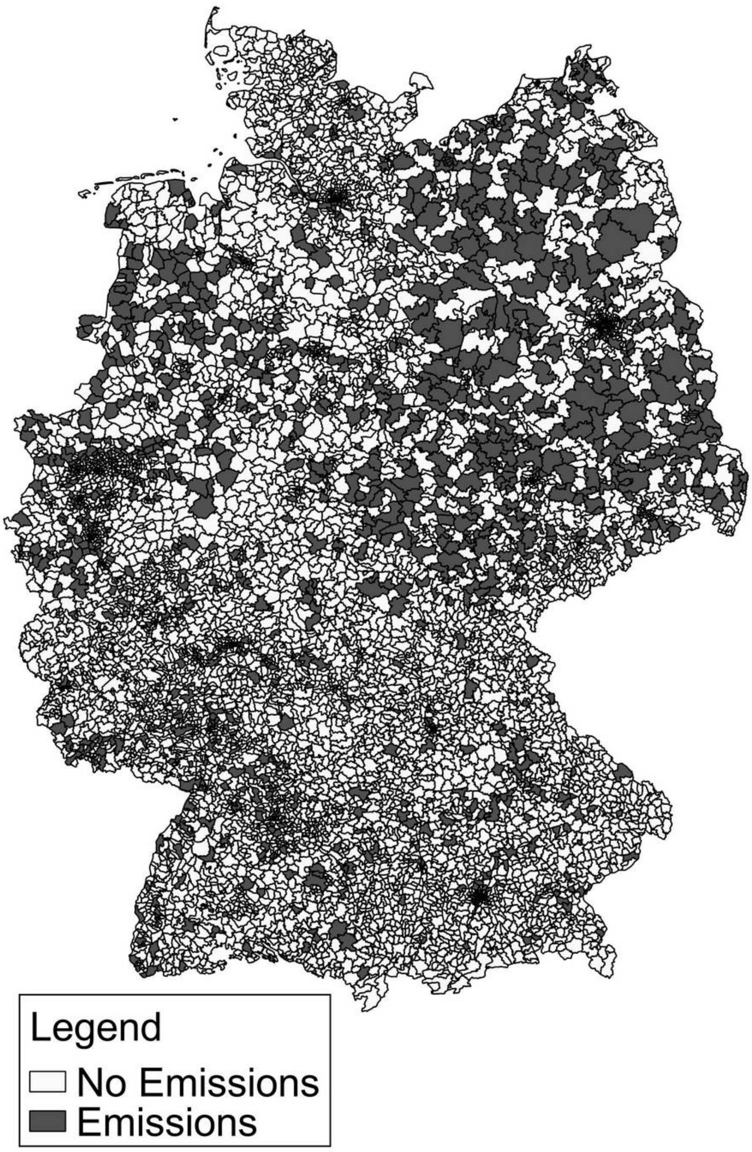


Figure 2.1: Postal code areas with emissions

2.4.3 Data on postal code areas

2.4.3.1 Corine land cover data

The Corine Land Cover project was initiated by the European Commission and is managed by the European Environmental Agency.[52] The data on land use is initially collected from satellite images and then refined through the use of aerial photographs and other ancillary sources of information. The maps are aggregated such that the smallest unit of any type is at least 25 hectares. The location precision of the data is 100 m. As part of the Corine Land Cover project, the land use in Germany was mapped in 2006. Varying categories of land use, like e.g. urban area, infrastructure and natural areas, are defined resulting in a total of 44 categories, 37 of which exist in Germany. We aggregate these into a total of 7 categories: Urban area, Urban green space, Natural area, Agriculture, Water body, Industrial area and, finally, Landfills and construction sites. Based on the land use data, we calculate the respective share of individual postal code areas allocated to each type of land use. An example can be seen in Figure 2.2, where the different categories of land use are demonstrated for the postal code covering the center (bottom right) and the industrial harbor (left) of Mannheim, Baden-Wuerttemberg. The dots in the example represent the locations associated with emission reports in the 2007 E-PRTR. Clearly, most of them are located within industrial areas.

[52]The data can be downloaded from the European Environment Agency website: http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2006-raster-3

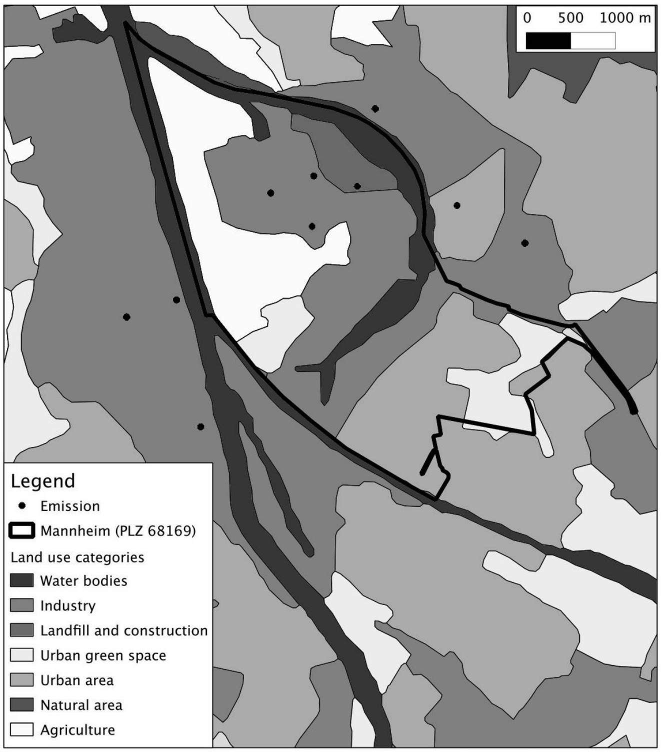


Figure 2.2: Land use in Mannheim, Germany

2.4.3.2 Municipality Data

At the municipality level, we have access to the 2008 wave of the INKAR[53] database provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development. These data describe the demographic, economic and social composition of municipalities. Among other things, they contain information about the unemployment rate, prevalent type of housing, age composition and population size as well as tax revenues at the municipal level ("Gemeinde" or "Gemeindeverband"). A list of all used variables from our data set of observed characteristics can be found in Table 2.1 and the corresponding variable descriptions are compiled in Table A.8 in Appendix A.2.1.

[53]INdikatoren und KARten zur Raum- und Stadtentwicklung in Deutschland und in Europa - Indicators and maps on spatial and urban development in Germany and Europe.

We used the Corine Land Cover information on urban area coverage in the postal code areas to merge postal code areas with municipalities. In Germany, municipalities and postal codes do not overlap perfectly. In some cases, several postal code areas will be contained in one municipality. In other cases, several municipalities will lie within a single postal code area. In the latter case, we merged postal codes with municipalities based on the share of the total urban area within a postal code area, such that each postal code was assigned to the municipality with the largest portion of shared urban area. If there was no urban area in the postal code area, the municipality with the largest share of land was used. Using this procedure, a few postal code areas were lost as we were not able to match them with municipalities.[54] Our available sample for the estimations using these observable characteristics for matching purposes was therefore reduced to 8,194 postal code areas.

2.4.3.3 Summary Statistics

A detailed summary of descriptive statistics for the full sample is presented in Table 2.1. Variable definitions can be found in Appendix A.2.1, Table A.8.

[54] Over the last years, there have been several municipal reforms merging and dividing municipalities. Since our INKAR data refers to the state ultimo 2008 we had to match municipalities from this time period to present municipal structures and then to the postal code areas. As a result, 18 postal code areas were lost in the first step of this process.

Table 2.1: Summary table of mean characteristics (full sample)

Entire Germany				
Variable	Mean	SD	Min	Max
Unemployment level	5.1	3.2	0.8	19.8
- long term	28.1	12.5	0.0	94.1
- long term, change	-30.1	38.7	-100.0	400.0
Employed in the primary sector	2.5	3.8	0.0	54.7
- secondary sector	37.7	16.8	0.0	94.2
- tertiary sector	59.7	16.9	5.5	100.0
Commuters into municipality	64.1	13.6	12.2	95.7
Commuters out of municipality	69.1	22.8	6.9	96.7
Total tax revenues	636.5	359.4	64.2	14093.8
Population density	599.0	908.4	6.8	4274.5
Value added tax revenues	32.8	26.3	-50.5	535.2
Commercial tax revenues	332.3	393.9	-241.9	11982.7
Income tax revenues	329.6	112.6	79.6	779.5
Distance to freeway	14.5	12.4	0.0	139.2
Distance to airport	58.6	32.1	1.3	269.0
Distance to fast trains	22.9	16.4	0.0	170.7
Distance to large urban center	27.3	19.5	0.0	194.7
Distance to medium urban center	9.5	9.0	0.0	137.3
Access to European neighbors	247.6	29.9	179.5	431.6
Newly constructed buildings	2.3	1.9	-3.5	42.9
Share of single/two family housing	84.9	13.4	46.3	99.7
- multiple family housing	15.1	13.4	0.3	53.7
Small apartments	6.5	4.2	0.7	40.7
Large apartments	50.4	16.4	16.0	84.2
Size of postal code area (km^2)	43.5	52.5	0.002	890.0
Pct. agriculture	52.1	26.8	0.0	100.0
Pct. urban area	15.5	21.9	0.0	100.0
Pct. water bodies	1.4	4.3	0.0	100.0
Pct. natural areas	26.5	22.0	0.0	100.0
Pct. industrial areas	2.7	7.3	0.0	99.6
Pct. landfills etc.	0.4	1.5	0.0	38.8
House Price Index pre (2007Q2-2009Q1)	95.3	4.0	81.2	115.1
House Price Index post (2009Q2-2011Q1)	96.9	5.5	76.7	128.7
Δ House Price Index (post-pre)	1.6	3.0	-11.6	16.6
Number of facilities	0.2	0.6	0.0	14.0
Weighted emission score	8.9	165.8	0.0	11656.5
Number of postal codes	8212			

Note: House Price Index values are averages over the respective periods.

2.5 Results

2.5.1 Full sample

After the release of the E-PRTR, the housing market in Germany was dominated by a positive trend resulting in an average increase of roughly 3-4% for the subsequent two-year-period (see Appendix A.2.4). Comparing the housing price averages over the 8 quarters before treatment and over the following 8 quarters confirms the Germany-wide positive trend in housing prices in the later time period (see Table 2.1). In the main specification, we define those postal code areas as treated that had at least one report published in the E-PRTR register for the year 2007. Raw mean comparisons, calculated as average differences before and after treatment, indicate a trend-malus of the treatment group in comparison to the control group for Eastern Germany, while there is no difference between treatment and control group in Western Germany (see Δ House Price Index in Table 2.2). The different developments in Eastern and Western Germany underline the importance of controlling for regional housing markets.

Table 2.2: Mean comparison across treatment groups and regions (full sample)

	Entire Germany		Western Germany		Eastern Germany	
Variable	Mean (Treated)	Mean (Control)	Mean (Treated)	Mean (Control)	Mean (Treated)	Mean (Control)
House Price Index pre	95.56	95.28	96.23	95.28	94.23	95.28
(2007Q2-2009Q1)	(0.12)	(0.05)	(0.14)	(0.05)	(0.21)	(0.14)
House Price Index post	96.76	96.94	97.95	96.99	94.41	96.65
(2009Q2-2011Q1)	(0.16)	(0.07)	(0.18)	(0.07)	(0.26)	(0.22)
Δ House Price Index	1.20	1.66	1.72	1.71	0.17	1.37
(post-pre)	(0.08)	(0.04)	(0.09)	(0.04)	(0.14)	(0.11)
Number of Facilities	1.43	0.00	1.46	0.00	1.36	0.00
	(0.03)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
Weighted Emission Score	65.44	0.00	88.75	0.00	19.64	0.00
	(13.32)	(0.00)	(19.97)	(0.00)	(3.39)	(0.00)
Number of postal codes	1118	7094	741	6058	377	1036

Note: Housing index values are averages over the respective periods.
Standard deviations in parentheses.

In a first step, we compute Average Treatment Effects on the Treated (ATET) based on the mean difference in the changes in housing prices pre and post treatment (Δ House Price Index) between treatment and control group, taking into account state fixed effects to control for legislative and systematic differences in the German federal states.[55] In this preliminary setup, we find a negative effect of treatment for Eastern Germany (column (iii) in Table 2.3), while the observed ATET for Western Germany (ii) is significantly positive. The overall effect appears to be negligible in the full sample (i).

In a next step, we move to our baseline regression model with postal code fixed effects and time-by-state fixed effects in order to capture state-specific time trends. Standard errors are clustered at the postal code level. For the full sample, housing prices in the treated postal codes rose just as strongly as those in the control group (Column (1) in Table 2.3). We proceed to look at the Eastern part and the Western part of Germany separately (columns (2) and (3) in Table 2.3) and again find that the results differ strongly between these two regions. The effect is strongly significant across the board, but with opposite signs for Eastern and Western Germany. In Eastern Germany, a negative effect is found and in Western Germany a positive effect. However, these findings are rather naive as they do not control for important characteristics of postal codes that are confounded with treatment and that cannot be captured by spatial and temporal fixed effects.

[55]Note that due to the inclusion of state fixed effects the results cannot be directly inferred from Table 2.2.

Table 2.3: Naive panel estimates, full sample

Mean comparisons	Entire Germany	Western Germany	Eastern Germany
	(i)	(ii)	(iii)
ATET	0.0005	0.217**	-0.425*
	(0.083)	(0.090)	(0.169)
State-specific FE	Yes	Yes	Yes

Note. Dependent variable is House Price Index; robust standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Regression models	Entire Germany	Western Germany	Eastern Germany
	(1)	(2)	(3)
Post*Treatment	0.053	0.236**	-0.399**
	(0.081)	(0.091)	(0.166)
Postal code FE	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes
R^2	0.394	0.387	0.424
Observations	8212	6799	1413
Treated observations	1118	741	377
Control observations	7094	6058	1036

Note. Dependent variable is House Price Index normalized to 100 in 2004Q2.
*/**/*** Significant at the 5%/1%/0.1% level. Clustered standard errors in parentheses.

The underlying assumption in the differences in differences approach is that the treatment and the control group are similar in terms of observable and unobservable characteristics except for the fact that the treatment group was exposed to treatment. Moreover, if the treatment group and control group are similar in terms of observable characteristics it seems more plausible that they should also be similar in terms of unobservable characteristics. If, however, the control group differs significantly from the treatment group, any effects found using the differences in differences estimator may be due to the underlying heterogeneity between treatment and control group, specifically, when these differences concern properties with direct relevance for housing prices. In particular, the trend in housing prices prior to treatment should be identical in control and treatment group. Based on the data we have at hand, we can test for differences in pre-treatment trends and a rich set of additional observables.

Table 2.4: Mean characteristics of treatment and control group (full sample)

Western Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	5.1	3.9	55.1	15.1	0.00
- long term	29.2	28.0	8.9	2.4	0.02
- long term, change	-24.5	-26.1	4.0	1.0	0.30
Employed in the primary sector	1.5	2.2	-27.2	-6.3	0.00
- secondary sector	38.6	39.1	-2.9	-0.7	0.46
- tertiary sector	59.9	58.7	7.3	1.9	0.06
Commuters into municipality	61.8	66.2	-37.3	-9.6	0.00
Commuters out of municipality	59.1	72.5	-63.6	-16.3	0.00
Total tax revenues	763.6	672.1	24.8	6.7	0.00
Population density	821.7	520.3	36.7	9.7	0.00
Value added tax revenues	45.9	30.9	53.6	14.0	0.00
Commercial tax revenues	491.0	334.0	34.8	10.0	0.00
Income tax revenues	351.6	365.2	-15.4	-3.9	0.00
Distance to freeway	11.1	14.4	-29.2	-7.1	0.00
Distance to airport	48.5	57.8	-34.5	-8.5	0.00
Distance to fast trains	19.0	23.3	-27.8	-7.1	0.00
Distance to large urban center	22.7	27.5	-25.5	-6.7	0.00
Distance to medium urban center	5.2	10.1	-59.1	-14.2	0.00
Access to European neighbors	238.7	244.4	-21.4	-5.5	0.00
Newly constructed buildings	2.2	2.5	-18.6	-4.3	0.00
Share of single/two family housing	81.7	87.3	-44.4	-11.9	0.00
- multiple family housing	18.3	12.7	44.4	11.9	0.00
Small apartments	7.0	6.2	20.2	5.1	0.00
Large apartments	47.5	54.6	-46.9	-12.4	0.00
Size of postal code area (km^2)	49.0	35.0	35.2	10.2	0.00
Pct. agriculture	49.5	53.4	-15.0	-3.9	0.00
Pct. urban area	17.1	14.0	16.9	4.0	0.00
Pct. water bodies	1.9	1.3	16.3	4.0	0.00
Pct. natural areas	21.4	27.8	-30.9	-7.6	0.00
Pct. industrial areas	7.3	2.0	56.7	19.7	0.00
Pct. landfills etc.	0.8	0.3	35.5	10.9	0.00
Number of postal codes	741	6058			

Note. Bias is defined as the difference in means between the treated and the non-treated subsample divided by the square root of their average sample variances. Means are unweighted across samples.

Table 2.5: Mean characteristics of treatment and control group (full sample)

Eastern Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	10.6	9.9	25.4	4.4	0.00
- long term	28.9	27.3	11.9	2.0	0.05
- long term, change	-49.6	-50.8	4.6	0.8	0.45
Employed in the primary sector	5.9	4.1	29.3	5.0	0.00
- secondary sector	33.5	30.4	20.6	3.3	0.00
- tertiary sector	60.6	65.5	-29.1	-4.7	0.00
Commuters into municipality	62.0	54.4	45.5	7.0	0.00
Commuters out of municipality	66.3	57.4	35.7	5.5	0.00
Total tax revenues	421.1	413.7	2.4	0.4	0.69
Population density	338.8	996.6	-60.8	-8.8	0.00
Value added tax revenues	32.6	34.3	-9.7	-1.7	0.10
Commercial tax revenues	249.8	237.6	3.9	0.7	0.50
Income tax revenues	150.9	169.8	-38.8	-6.0	0.00
Distance to freeway	17.2	16.4	6.8	1.1	0.26
Distance to airport	75.6	64.2	25.8	4.2	0.00
Distance to fast trains	27.2	21.7	30.0	4.9	0.00
Distance to large urban center	35.8	26.7	40.0	6.5	0.00
Distance to medium urban center	10.2	8.8	15.0	2.5	0.01
Access to European neighbors	275.6	263.0	37.6	5.8	0.00
Newly constructed buildings	1.4	1.7	-13.2	-2.0	0.00
Share of single/two family housing	80.6	74.6	40.9	6.5	0.00
- multiple family housing	19.4	25.4	-40.8	-6.5	0.00
Small apartments	6.5	8.3	-47.0	-7.2	0.00
Large apartments	36.2	32.3	33.7	5.5	0.00
Size of postal code area (km^2)	140.0	54.0	84.9	16.5	0.00
Pct. agriculture	60.8	42.7	66.3	10.5	0.00
Pct. urban area	9.3	25.4	-68.0	-9.8	0.00
Pct. water bodies	2.1	1.8	7.5	1.2	0.22
Pct. natural areas	22.7	23.5	-3.7	-0.6	0.56
Pct. industrial areas	3.2	3.5	-4.3	-0.7	0.49
Pct. landfills etc.	1.0	0.4	28.0	5.4	0.00
Number of postal codes	377	1036			

Note. Bias is defined as the difference in means between the treated and the non-treated subsample divided by the square root of their average sample variances. Means are unweighted across samples.

It turns out treatment group and control group differ with respect to a large number of the observable characteristics (see Tables 2.4 and 2.5). The standardized percentage bias is computed as suggested by Rosenbaum and Rubin (1985). Generally speaking, the postal code areas in the treatment group in Western Germany have fewer commuters out of the municipality, higher proximity to large and medium sized urban centers, and a higher population density also evidenced by a larger share of apartment buildings than single family houses compared to the untreated postal code areas. The treated areas seem to be less residential in nature: They tend to have higher VAT and higher commercial tax revenues than the average postal code area without emissions and they have a higher percentage of industrial area and a lower percentage of natural areas than the untreated postal code areas. In Eastern Germany in contrast, the treated postal code areas tend to be of a more rural nature. A larger share of employment is in the primary sector and a lower share in the tertiary sector. The treated postal code areas in Eastern Germany also have lower population density, more agricultural area and less urban area than the postal code areas without emissions. They are further away from large urban centers and from main line train stations. In consequence, while treatment in Western Germany is associated with the prevalence of industry and proximity to urban centers, the opposite seems to be the case in Eastern Germany. These differences in observable characteristics of the treatment and control group in both parts of Germany could explain the findings in Table 2.3, where treatment in Western Germany is associated with higher price increases in the housing market, and lower price increases in Eastern Germany. It is conceivable that the housing market trend differs between rural and urban areas, which we have not controlled for when we use the full data set. Analyzing pre-treatment trends confirms this picture as we have to reject the common trend assumption, finding significant differences in opposite directions for Eastern and Western Germany (see Chapter 2.5.2.2).

In both Eastern and Western Germany, treated postal codes tend to have a higher unemployment level, lower income tax revenue, and the treated postal code areas tend to be larger and to have a larger share of landfills than the untreated postal code areas. These differences mirror the findings in Bui and Mayer (2003) when looking at the characteristics of affected counties in Massachusetts. For instance, in their sample, the counties with non-zero emissions had a lower median household income and lower health and welfare spending than their unaffected counterparts. Davis (2011) finds evidence of taste-based sorting in and out of polluted areas in his study of power plant openings in the US, and also concludes that power plants are likely to be sited in low-density areas. As the siting of pollutant sources in general is unlikely to be random, controlling for observable characteristics of postal code areas is important. In particular, a recent paper by Taylor et al. (2016) analyses stigma effects of undesirable land use following the clean up of hazardous waste sites. They show that once surrounding land use, which is often also undesirable, has been taken into account for in a hedonic model, there is no evidence of stigma keeping prices low after a cleanup. Their result emphasizes that the evolution of prices depends strongly on land use characteristics of the surrounding area. For this reason, we think that the inclusion of data on land use is crucial and should play an important role in the following process of creating adequate control groups.

2.5.2 Matching

2.5.2.1 Methodology

The idea underlying the matching approach is to find control units which are comparable to the treatment group in terms of relevant observable characteristics. This approach has recently become popular in the study of environmental impacts in housing markets (see e.g. Abbott and Klaiber, 2013; Sanders, 2014; Muehlenbachs et al., 2015). One option is to do exact matching on characteristics, however, given the number of characteristics in our data set, and the fact that several of them are continuous measures, aggregating the information by propensity scores seems prudent. The propensity score can be estimated and is a measure of the individual postal code area's likelihood of being treated, as far as this can be predicted given observable variables. Generally speaking, a probit or a logit is estimated with the treatment indicator as the dependent variable.

A number of assumptions are important when it comes to using matching estimators. The most important of these is that unobservable characteristics do not play a role in determining treatment assignment or price evolution so that the propensity score is based on all relevant characteristics. Secondly, the common support assumption, i.e. that the distributions of propensity scores overlap for the treatment and control group, is necessary to ensure that there is a comparable match for each treated observation included in the analysis. Finally, there is the stable unit treatment assumption, namely that treatment does not indirectly affect untreated observations.[56] Implementing propensity score matching also requires a number of decisions. In addition to choosing which control variables to include, the number and selection of matches must also be decided upon. Nearest neighbor matching is commonly used in the environmental economic literature, e.g. Muehlenbachs et al. (2015). The number of neighbors to match with, as well as whether to match with or without replacement, are both issues of bias versus efficiency. The more neighbors included, the more efficient, yet the further away the matches may be from the treated unit they should correspond to in terms of the propensity score. This may in turn induce bias due to lower quality of the match. Radius matching is a way to address these issues wherein the treated observations are matched to all controls within a radius distance of their propensity score. In this way, efficiency is increased while bad matches are dropped (as are some of the treated units without any suitable controls within the specified radius). Also the specification of the model for the propensity score is important and there are different ways to implement such a model. Mahalanobis matching can improve the balance of covariates in the control and treatment group as matching solely on propensity scores may not be sufficient due to sampling variation and non-exact matching (see Rosenbaum and Rubin (1985) for further information). Mahalanobis matching is based on the multivariate distance between individuals in different groups weighted by the sample covariance matrix. For two observations i and j, the respective Mahalanobis distance (MD) is given by $MD(X_i, X_j) = \sqrt{(X_i - X_j)^T S^{-1}(X_i - X_j)}$, where X_i and X_j are the corresponding covariate vectors and S is the sample covariance matrix. It would be possible to assign

[56] In our case, some 12 percent of the postal code areas are affected and general equilibrium effects are conceivable if households respond strongly. If treatment has the effect of increasing house prices in surrounding non-treated areas, this would make an estimated effect larger rather than smaller and thus make it more likely that we would find a significant treatment effect.

subjectively chosen weights to the matching variables or consider only a chosen subset for the Mahalanobis procedure but any such restriction could potentially give rise to a bias arising from personal preference. Therefore, reporting the results for the generic matrix seems the most objective method. We carry out nearest neighbor matching with a single neighbor, radius matching and Mahalanobis matching for our main treatment specification. Our propensity score matching procedures are all carried out using the procedure *psmatch2* for Stata (Leuven and Sianesi, 2003).

A logit model is estimated for each region based on the postal code characteristics.[57] Several of the covariates are highly significant reflecting the different characteristics discussed above. We impose common support for the matched sample and trim the data sections that exhibit thin support.[58] This procedure reduces the sample by 14 postal code areas in Western Germany for both nearest neighbor and Mahalanobis matching. In Eastern Germany, enforcing common support results in the loss of 7 postal code areas. For radius matching we consider the distribution of p-score distances and set the radius to half the 90th percentile. This radius specification eliminates a substantial number of treated units (129 in Western Germany and 58 in Eastern Germany), for which the distance to the closest match is too large. Our specification of the radius is an adaption of the approach used in Huber et al. (2013), where half of the maximum distance is used as radius setting.[59] Imposing common support in all these methods has the direct consequence of changing the population under study. In particular for the radius matching case, this could potentially affect the results in the presence of heterogeneous treatment effects.

[57] To avoid multicollinearity we left the share of labor force employed in the primary sector, the share of single family housing, and the share of natural land use out of the logit models used for matching.

[58] In addition to dropping treated units with propensity scores above the highest score for the potential control units, we also exclude the 2 % of the treated units with the lowest p-score density.

[59] Huber et al. (2013) additionally use 1.5 and three times the maximum distance in an assessment of the performance of matching estimators. We choose the lower end specification to avoid including too many poor matches.

2.5.2.2 Control group comparison and the common trend assumption

A comparison of the treatment group with the matched control group shows large improvements in terms of matching characteristics with sample means on almost all characteristics insignificantly different from each other. A set of histograms comparing the propensity scores distribution for the full and the matched samples can be found in the appendix for each of our treatment definitions together with the estimates of the logit models (Appendix A.2.6 and Appendix A.2.7).

The spatial extent of both control and treatment group defined by nearest neighbor matching carried out separately for each region are shown in Figure A.16 in Appendix A.2.8. It is clear that both the treatment and the control postal code areas are scattered across each of the regions, i.e. although spatial proximity is not directly a condition for matching, the outcome is not a control group spatially distinct from the treatment group.

Table 2.6 provides a raw mean comparison after nearest neighbor matching for both parts of Germany has been carried out and serves as a preliminary test before the regression analysis. The subsequent tables (Table 2.7 and Table 2.8) give an overview over treated and control group characteristics after matching and demonstrate that the procedure was successful in reducing percentage biases (see Rosenbaum and Rubin, 1985) across the board.

Table 2.6: Mean comparison across treatment groups and regions (matched sample)

	Western Germany		Eastern Germany	
Variable	Mean (Treated)	Mean (Control)	Mean (Treated)	Mean (Control)
House Price Index pre	96.22	95.87	94.20	93.99
(2007Q2-2009Q1)	(0.14)	(0.15)	(0.22)	(0.26)
House Price Index post	97.94	97.73	94.44	94.38
(2009Q2-2011Q1)	(0.19)	(0.21)	(0.27)	(0.36)
Δ House Price Index	1.73	1.86	0.24	0.40
(post-pre)	(0.09)	(0.11)	(0.14)	(0.19)
Number of facilities	1.45	0.00	1.35	0.00
	(0.04)	(0.00)	(0.04)	(0.00)
Weighted emission score	82.45	0.00	19.94	0.00
	(19.87)	(0.00)	(3.47)	(0.00)
Number of postal codes	727	585	368	227

Note: Housing index values are averages over the respective periods.
Standard deviations in parenthesis.

Table 2.7: Mean characteristics of treatment and control group (matched sample)

Western Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	5.1	5.0	6.9	1.3	0.21
- long term	29.1	28.6	3.3	0.6	0.55
- long term, change	-24.7	-26.7	4.9	0.9	0.38
Employed in the primary sector	1.5	1.5	0.3	0.1	0.96
- secondary sector	38.6	39.0	-2.7	-0.5	0.63
- tertiary sector	59.9	59.4	2.6	0.5	0.64
Commuters into municipality	62.0	62.0	-0.7	-0.1	0.90
Commuters out of municipality	59.5	59.5	-0.1	0.0	0.99
Total tax revenues	762.0	758.1	0.7	0.1	0.89
Population density	811.4	773.4	4.4	0.8	0.43
Value added tax revenues	45.6	44.5	3.1	0.6	0.57
Commercial tax revenues	487.7	471.2	3.0	0.5	0.59
Income tax revenues	352.1	353.2	-1.4	-0.3	0.80
Distance to freeway	11.1	11.9	-8.5	-1.5	0.13
Distance to airport	48.6	50.4	-6.8	-1.2	0.22
Distance to fast trains	19.0	19.1	-0.6	-0.1	0.92
Distance to large urban center	22.8	22.9	-0.8	-0.1	0.89
Distance to medium urban center	5.3	5.5	-2.6	-0.5	0.64
Access to European neighbors	238.8	240.2	-5.3	-1.0	0.34
Newly constructed buildings	2.2	2.2	0.6	0.1	0.91
Share of single/two family housing	81.8	82.0	-1.4	-0.3	0.81
- multiple family housing	18.2	18.0	1.4	0.3	0.81
Small apartments	7.0	7.1	-3.1	-0.6	0.57
Large apartments	47.7	48.2	-3.0	-0.5	0.59
Size of postal code area (km^2)	48.0	47.0	2.3	0.4	0.68
Pct. agriculture	49.9	49.6	1.3	0.2	0.81
Pct. urban area	17.1	18.0	-4.6	-0.8	0.40
Pct. water bodies	1.9	1.8	2.2	0.4	0.68
Pct. natural areas	21.5	22.6	-5.2	-1.0	0.34
Pct. industrial areas	6.9	5.1	16.4	3.0	0.00
Pct. landfills etc.	0.8	0.5	18.0	3.3	0.00
Number of postal codes	727	585			

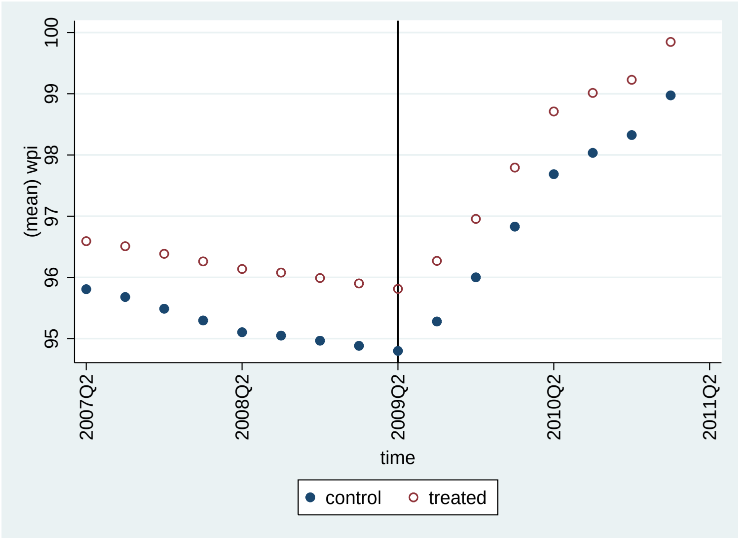
Note. Bias is defined as the difference in means between the treated and the non-treated subsample divided by the square root of their average sample variances. Means are unweighted across samples.

Table 2.8: Mean characteristics of treatment and control group (matched sample)

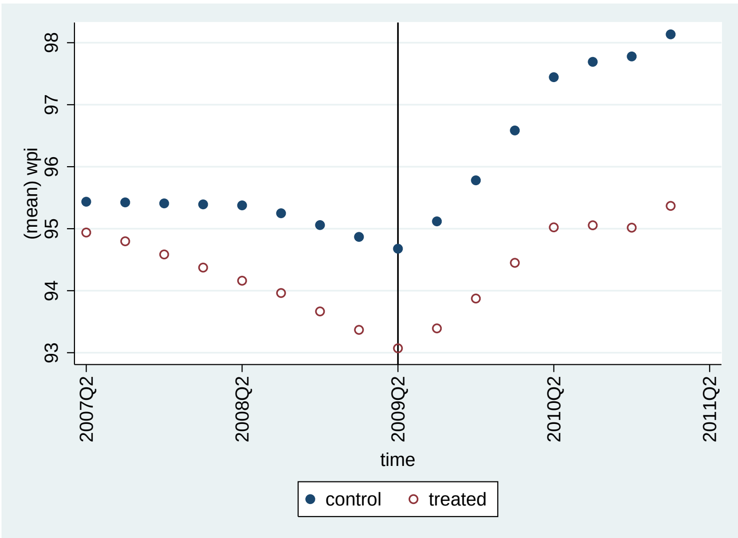
Eastern Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	10.6	10.5	2.8	0.3	0.74
- long term	29.1	28.4	4.6	0.6	0.58
- long term, change	-49.3	-50.6	5.1	0.6	0.54
Employed in the primary sector	5.9	6.5	-8.6	-1.0	0.30
- secondary sector	33.6	34.2	-3.7	-0.4	0.66
- tertiary sector	60.4	59.3	6.9	0.8	0.41
Commuters into municipality	62.2	63.0	-6.2	-0.7	0.46
Commuters out of municipality	66.5	68.9	-12.0	-1.4	0.16
Total tax revenues	422.8	403.2	6.3	0.7	0.46
Population density	343.8	330.1	2.2	0.3	0.80
Value added tax revenues	32.7	31.9	4.2	0.5	0.63
Commercial tax revenues	251.9	239.1	3.5	0.4	0.67
Income tax revenues	151.2	149.4	4.3	0.5	0.60
Distance to freeway	17.1	17.3	-1.4	-0.2	0.87
Distance to airport	75.4	79.2	-8.8	-1.1	0.30
Distance to fast trains	27.0	28.4	-7.7	-0.9	0.36
Distance to large urban center	35.4	35.0	1.6	0.2	0.85
Distance to medium urban center	10.4	11.3	-10.3	-1.2	0.22
Access to European neighbors	275.9	277.3	-5.1	-0.6	0.55
Newly constructed buildings	1.4	1.4	4.1	0.5	0.63
Share of single/two family housing	80.6	80.9	-2.3	-0.3	0.79
- multiple family housing	19.5	19.2	2.3	0.3	0.79
Small apartments	6.5	6.4	5.6	0.7	0.50
Large apartments	36.2	36.8	-5.3	-0.6	0.53
Size of postal code area (km^2)	130.0	100.0	28.1	3.3	0.00
Pct. agriculture	60.7	61.1	-2.0	-0.2	0.82
Pct. urban area	9.5	10.5	-6.7	-0.8	0.42
Pct. water bodies	2.1	1.9	5.0	0.6	0.55
Pct. natural areas	22.6	21.9	3.8	0.5	0.65
Pct. industrial areas	3.3	3.0	2.9	0.3	0.73
Pct. landfills etc.	1.0	0.8	8.5	1.0	0.32
Number of postal codes	368	227			

Note. Bias is defined as the difference in means between the treated and the non-treated subsample divided by the square root of their average sample variances. Means are unweighted across samples.

Common trends in the treatment and control group prior to treatment is an important assumption in our research design. Figure 2.3 and Figure 2.4 display the raw mean comparisons across all postal codes in the control and treatment groups for the unmatched and matched samples respectively. Since the House Price Index is normalized to 100 in 2004Q2 for each separate postal code area, it can be seen that relative to this reference point prices had dropped on average by 4-7% before treatment. The subsequent recovery of the housing market resulted in a 3-4% increase in average housing prices relative to 2004Q2. The trend graphs for the unmatched sample show a similar overall development but hint towards an underlying heterogeneity between treatment and control group. The observable differences in 2009Q2 index levels imply that this prevailing heterogeneity drove the index levels comparatively further down for the treatment group in Eastern Germany and further down for the control group in Western Germany during the 2004Q2-2009Q2 time period (see Figure 2.3). The figures are strongly supportive evidence for the assumption that our procedure of nearest neighbor matching is successful in ensuring a common trend for the two groups in both parts of Germany (see Figure 2.4). This reinforces our argument in favor of a matching approach designed to minimize the observable differences between the two groups. Overall, the analysis at hand demonstrates that our approach not only succeeds in providing groups with a common trend but also in reducing aggregate index level gaps at the time of treatment. A more formal test can be found in Table A.11 in Appendix A.5.

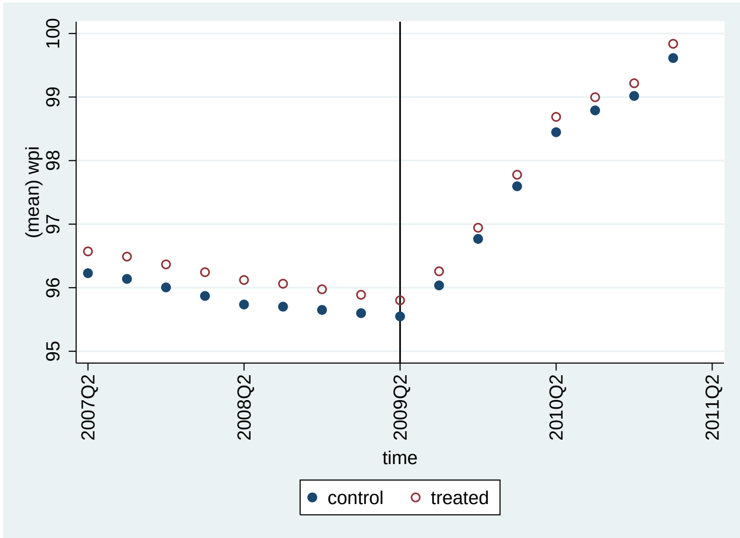


West Germany

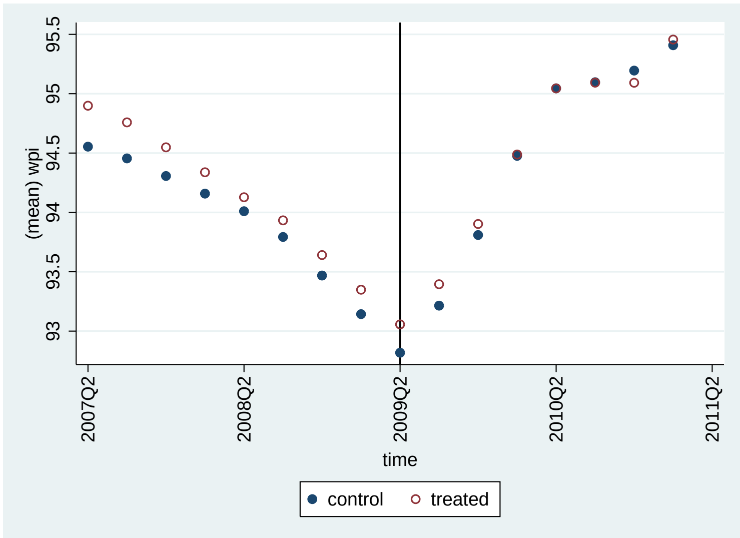


East Germany

Figure 2.3: Price trends (House Price Index), unmatched sample



West Germany



East Germany

Figure 2.4: Price trends (House Price Index), matched sample

2.5.2.3 Matched regression results

We carried out the difference-in-differences estimation and computation of Average Treatment Effects on the Treated (ATET) using our matched samples but otherwise with the same specifications as in Table 2.3.[60] The results of the estimations and calculations with different matching approaches are given in Tables 2.9 and 2.10, where we also report the previous results for convenience of the reader (see (i) and (1) respectively). The main coefficient of interest (Post*Treatment) for each of the matching approaches (see (2)-(4)) is markedly reduced towards zero in comparison with the coefficients from the unmatched sample estimations for both Eastern and Western Germany. This finding suggests that there is some bias in the original estimations due to the inherent differences between the treatment and control postal code areas. The estimated coefficients across all specifications with matching are small (between -0.11 and +0.12) suggesting an economically insignificant effect of around 0.1 percent on average house prices in 2004 levels. Consequently, these results suggest that the publication of the E-PRTR data had no significant impact on the evolution of house prices in the affected areas once other observable differences are accounted for. As we would expect, the standard errors of the radius matching approach are slightly smaller reflecting the higher number of observations included in the estimation. Significant findings for the ATET are also eliminated through the process of matching as the treatment effects in the matched samples for both regions (see column (ii)-(iv)) are found to be insignificant. The insignificance of the resulting coefficients is a clear indication that at this level of aggregation the release of E-PRTR data had no effect on the housing price trends in the affected zip codes.

[60] Following Dehejia and Wahba (2002) we use the weights generated in the matching procedure as frequency weights and estimate weighted regressions. The same weights are used in the calculation of the ATETs.

Table 2.9: Panel estimates, matched samples, Western Germany

Mean comparisons	Western Germany			
	Full sample	NN	Radius	Mahalanobis
	(i)	(ii)	(iii)	(iv)
ATET	0.217**	-0.069	0.036	-0.0017
	(0.090)	(0.136)	(0.114)	(0.131)
State-specific FE	Yes	Yes	Yes	Yes

Note. Dependent variable is House Price Index; robust standard errors in parentheses. */**/*** Significant at the 5%/1%/0.1% level.

Regression models	Western Germany			
	Full sample	NN	Radius	Mahalanobis
	(1)	(2)	(3)	(4)
Post*Treatment	0.236**	-0.074	0.041	0.0018
	(0.0910)	(0.138)	(0.113)	(0.131)
Postal code FE	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes
R^2	0.387	0.452	0.414	0.431
Observations	6799	1312	5617	1342
Treated observations	741	727	612	727
Control observations	6058	585	5005	615

Note. Dependent variable is House Price Index; clustered standard errors in parentheses. */**/*** Significant at the 5%/1%/0.1% level.

Table 2.10: Panel estimates, matched samples, Eastern Germany

Mean comparisons	Eastern Germany			
	Full sample	NN	Radius	Mahalanobis
	(i)	(ii)	(iii)	(iv)
ATET	-0.425*	-0.063	0.125	-0.164
	(0.169)	(0.232)	(0.212)	(0.225)
State-specific FE	Yes	Yes	Yes	Yes

Note. Dependent variable is House Price Index; robust standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Regression models	Eastern Germany			
	Full sample	NN	Radius	Mahalanobis
	(1)	(2)	(3)	(4)
Post*Treatment	-0.399***	-0.0839	0.121	-0.113
	(0.166)	(0.233)	(0.213)	(0.216)
Postal code FE	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes
R^2	0.424	0.271	0.274	0.267
Observations	1413	595	1140	615
Treated observations	377	368	317	368
Control observations	1036	227	823	247

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

2.6 Robustness Checks

Several robustness checks were carried out to assess the impact of the definition of treatment. These robustness checks are intended to address concerns about the level of aggregation in our data and treatment definition. First, we introduce a finer treatment definition based on the actual amounts of substances emitted. Second, we define treatment by the number of facilities emitting pollutants in a postal code area. Third, we introduce buffers to allow for an expanded treatment effect on postal code areas within 500 m of a facility. Finally, as our House Price Index concerns residential property, we estimate a model where we limit the treatment definition to only those postal code areas with urban area or urban green space within 500 m of an emitter facility. In each of the robustness checks, nearest neighbor matching is applied. To summarize, the robustness checks provide the same picture as the main results discussed above: the publication of emissions information seems to have had little impact on average prices in affected postal code areas. The robustness checks are described in more detail below.[61]

2.6.1 Quartiles of emissions

The binary definition of treatment status underlying the preceding analyses may be too crude as we do not account for the amount of substances emitted. To address the concern that the quantity emitted may be important (see e.g. Sanders, 2014) we aggregate the emissions of different substances to a weighted measure of total emissions within a postal code area, where the weights assigned to different substances are intended to account for the potential severity of the effects of these individual emissions. We use the inverse reporting thresholds from the E-PRTR as a proxy for these weights. In general, these thresholds are lower for more potent substances such as benzene or dioxin than for less potent substances such as nitrogen oxides. Furthermore, the thresholds are publicly available via the different websites and thus easily available to households. The lack of more precise toxicity measures contained within the E-PRTR framework makes our Weighted Emission Score a reasonable measure of the perceived severity of pollutant emissions.[62] This exercise also addresses potential concerns that large emitters may have been more obvious to the public and should thus be treated differently in the analysis.

[61] It is well-known that matching techniques can be sensitive to the specification of the logit/probit model. We tested alternative specifications without qualitatively changing the results.

[62] Nevertheless, the reporting thresholds are an imperfect proxy for toxicity. They are not directly intended to capture toxicity but rather to ensure that a large fraction of emissions is covered by the register while at the same time minimizing unnecessary burdens for small emitters. Still, when looking across the table of thresholds and individual substances, there is a clear pattern that lower thresholds are associated with substances generally perceived as being dangerous. The full list of pollutants and their thresholds can be accessed under http://prtr.ec.europa.eu/docs/Summary_pollutant.pdf.

For this treatment definition we consider a model that separates the group of treated postal codes into 4 quartiles according to their Total Weighted Emissions, calculated as the sum over all emissions within the postal code area weighted by their corresponding reporting thresholds. For a detailed description of the computation of Weighted Emission Scores, we refer the reader to Appendix A.2.2. The lowest quartile represents the least affected 25% of postal codes, while the fourth quartile represents the most heavily polluted areas as identified by the 2009 E-PRTR dataset. The regression model takes the form:

$$Y_{ist} = \alpha_0 + \alpha_1 Post_t + \sum_{j=1}^{4} [\alpha_{2,j} TQ_{ij} + \alpha_{3,j} Post_t TQ_{ij}] + \alpha_{4,i} + \alpha_{5,st} + e_{ist} \quad (2.2)$$

The coefficients of interest are now the $\alpha_{3,j}$ as they correspond to the interaction of the shift dummy variable ($Post_t$) and the treatment quarterly dummies (TQ_{ij}) with respect to each of the $j = 1, 2, 3, 4$ quartiles.[63] The results of main interest are shown in Table 2.11. For Western Germany, the full sample without matching again yields a positive treatment effect. However, the effect is largest for the higher quartiles of emissions and insignificant for low emissions. Once matching is employed, we find no significant impact of treatment for any of the quartiles.

For Eastern Germany, the effect of emissions information is negative and significant for the second quartile before matching. With the matched sample however, no significant effect of the information release is found for any of the quantiles (TQ1-TQ4). Summarizing, the results from the main specifications are confirmed by this robustness check and no isolated effect can be found for postal codes with higher relative severity of reported emissions.[64]

[63] Similar to the main specification, the isolated treatment dummies are dropped due to the inclusion of postal code area fixed effects in all robustness checks.

[64] We also carried out analyses distinguishing between emissions to air and water respectively. With only 6 emissions to soil the data is too thin to analyze this medium separately. Again, no significant effect could be found in either Western of Eastern Germany after matching was carried out. A table of these results is available from the authors upon request.

Table 2.11: Quartiles of emissions

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*TQ1	0.003	-0.360	-0.438	-0.0890
	(0.189)	(0.216)	(0.248)	(0.290)
Post*TQ2	0.038	-0.296	-0.537*	-0.189
	(0.201)	(0.226)	(0.246)	(0.288)
Post*TQ3	0.442**	0.0924	-0.299	-0.0714
	(0.157)	(0.191)	(0.305)	(0.363)
Post*TQ4	0.350*	0.129	-0.138	0.166
	(0.140)	(0.175)	(0.405)	(0.432)
Postal code FE	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes
R^2	0.388	0.453	0.424	0.272
Observations	6799	1312	1413	595
Treated observations	741	727	377	368

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level. Estimations based on nearest neighbor matching.

2.6.2 Number of facilities

In an alternative specification, we define treatment based on the number of reporting facilities in the postal code area. Of the treated areas, 73.8% contain one facility, 16.9% two, 5.2% three and 2.8% four facilities that report emissions under E-PRTR. Based on this distribution, we form three categories (1 facility, 2 facilities, more than 2 facilities):

$$Y_{ist} = \alpha_0 + \alpha_1 Post_t + \sum_{k=1}^{3} [\alpha_{2,k} TC_{ik} + \alpha_{3,k} Post_t TC_{ik}] + \alpha_{4,i} + \alpha_{5,st} + e_{ist} \quad (2.3)$$

As in the previous robustness check, the coefficients of interest are now the different $\alpha_{3,k}$ as they correspond to the interaction of the shift dummy variable ($Post_t$) and the treatment category dummies (TC_{ik}) with respect to each of the $k = 1, 2, 3$ facility number categories. Based on this specification, there are effects for a small subset of the matched sample in Eastern Germany as shown in Table 2.12 as the interaction coefficient for postal code areas containing 2

Table 2.12: Number of facilities

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*1Facility	0.123	-0.204	-0.193	-0.130
	(0.106)	(0.148)	(0.180)	(0.243)
Post*2Facilities	0.515**	0.257	-1.036***	-0.722*
	(0.194)	(0.229)	(0.309)	(0.342)
Post*3+Facilities	0.621**	0.380	-0.856	-0.692
	(0.216)	(0.233)	(0.624)	(0.663)
Postal code FE	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes
R^2	0.388	0.453	0.425	0.275
Observations	6799	1312	1413	595
Treated observations	741	727	377	368

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level. Estimations based on nearest neighbor matching.

facilities becomes significant at the 5% level.[65] There is no obvious explanation why there should have been a significantly negative effect in these areas in particular and the small number of remaining observations for these categories (75 postal codes with 2 facilities in Eastern Germany and 13 postal codes with 3 facilities) as compared with the larger number of observations in Western Germany (114 and 45 respectively) may be partly to blame. However, this result taken together with the results from the previous robustness check may hint towards an isolated effect for medium sized polluters grouped in small batches of 2-3 facilities in this part of Germany, which had been overlooked or underestimated by consumers before and were revealed as emission sources in the 2009 information release. Overall, this robustness test reinforces our finding that after controlling for postal code characteristics via matching, there is no evidence for a robust effect of the E-PRTR publication on housing prices.

[65]This result survives the robustness check of grouping 2-3 facility postal codes together in an alternative specification but remains at a fairly low level of significance throughout these tests.

2.6.3 Buffers

E-PRTR requires the geographical coordinates to be reported with a maximum of +/- 500 m distance from the actual location of the facility and some emitters will be located on the border of the postal code area. We therefore construct an alternative treatment measure that defines a postal code area as treated if some part of its land is within a 500 m buffer distance from an emitter. Of course, the number of affected postal code areas in our study increases with the buffer distance around the point sources. With a 500 m buffer around point sources, the number of affected postal code areas rises to 1,585. We would not expect there to be systematic error in the reported location of facilities such that postal code areas in the narrow treatment definition are wrongly identified as treated. That would require facilities to be generally located on the border of postal code areas and wrongly assigned. By broadening our treatment definition we allow for cross border effects but also get a noisier sample. We expect broadening of the treatment definition to weaken the results rather than change the conclusions. We match treatment postal code areas to controls based on the new treatment definition. Looking at the results in Table 2.13, the new treatment definition does not change the estimates substantially for either the ATET computation or the regression model. Overall, previous results are confirmed showing that they did not suffer from a bias due to emitters located close to the border of the postal code areas.

2.6.4 Urban areas only

In a final robustness check, the sample is reduced to those areas that contain urban land use, i.e. areas labeled as "Urban feature or urban green space" according to the Corine Land Cover project. Here, postal code areas are defined as treated if there is an emission reported within 500 meters of the urban area. As a result, the number of treated areas drops by about 50 % as compared with the original treatment definition using the 500 m buffer.

Table 2.13: Treatment based on buffers

Mean comparisons	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
ATET	0.368***	-0.010	-0.332*	-0.002
	(0.078)	(0.117)	(0.160)	(0.224)
State-specific FE	Yes	Yes	Yes	Yes

Note. Dependent variable is House Price Index; robust standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Regression Models	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*Treatment	0.408***	-0.0109	-0.286	-0.000
	(0.0801)	(0.117)	(0.154)	(0.228)
Postal code FE	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes
R^2	0.388	0.460	0.424	0.313
Observations	6799	1917	1413	710
Treated observations	1127	1105	458	447
Control observations	5672	812	955	263

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level. Estimations based on nearest neighbor matching.

Compared to the definition without a buffer the reduction is by about 40 %. Since we are restricting attention to postal code areas with non-industrial urban areas in close proximity to emissions, this treatment definition should be the one most likely to show an effect of treatment in comparison to all other specifications. In total there are 826 affected postal code areas with the urban treatment definition. Their spatial distribution is seen in Figure A.17 in Appendix A.2.9.

Estimations are carried out for the full sample divided into Eastern Germany and Western Germany. Additionally, nearest neighbor matching is carried out using propensity scores based on the extensive dataset collected for the characterization of postal code areas. Two matching definitions are used: Match A and Match B. In contrast to A, the latter excludes all postal code areas from the control group, which had emissions in 2009 but not in the direct vicinity of urban areas. As in the baseline estimation, matching yields a control group in Western and Eastern Germany which is largely similar to the treatment group in terms of observable characteristics (see Appendix A.2.10 for a comparison of characteristics pre and post matching with respect to this robustness check based on Match A). The regression results are shown in Table 2.14 along with the ATETs. For both types of matched samples, no significant effects can be found in either Western Germany or Eastern Germany.[66]

Table 2.14: Urban areas only

Mean comparisons	Western Germany			Eastern Germany		
	Full sample	Match A	Match B	Full sample	Match A	Match B
ATET	0.287***	-0.113	-0.094	-0.397**	-0.290	-0.372
	(0.097)	(0.154)	(0.163)	(0.185)	(0.270)	(0.310)

Note. Dependent variable is House Price Index; robust standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Regression models	Western Germany			Eastern Germany		
[1em]	Full sample	Match A	Match B	Full sample	Match A	Match B
Post*Treatment	0.319**	-0.118	-0.0797	-0.396*	-0.285	-0.350
	(0.099)	(0.156)	(0.164)	(0.185)	(0.273)	(0.307)
Postal code FE	Yes	Yes	Yes	Yes	Yes	Yes
State-specific time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.387	0.491	0.490	0.424	0.328	0.360
Observations	6799	1070	991	1413	400	357
Treated observations	603	591	591	223	219	219

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
Match A: Nearest neighbor matching of treated and untreated postal code areas within region.
Match B: As A but excluding areas with emissions outside urban areas.
*/**/*** Significant at the 5%/1%/0.1% level.

[66] All results are summarized in Appendix A.2.11 in Table A.14 to allow for a quick comparison of estimated values across all methods and robustness checks.

2.7 Concluding discussion

The quasi-experimental literature aims to get as close to a lab experiment as possible, however, the events under study do take place in the real world and require that care be taken in ensuring that the control and treatment units are comparable. In the present study, we address the question whether the publication of the first wave of the E-PRTR in Germany, containing information on pollutant emissions, affected the German housing market. Our data suggest that the location of polluting facilities is indeed non-random. Using a sizable data set characterizing the areas under study and analyzing pre-treatment trends, postal code areas with and without emissions are found to be quite different in the full sample. Moreover, the characteristics of postal code areas with emissions differ vastly between Eastern and Western Germany, which hints at the importance of considering the market in which capitalization takes place as a way to control for unobservable differences in addition to observable characteristics. We use matching based on postal code characteristics to form adequate control groups and find no evidence that the publication of emissions information capitalized into housing prices in Germany. While our results show that appropriate matching is crucial to the validity of our difference-in-differences estimates, matching is not an exact science. However, our results are robust to variations in the model used to calculate propensity scores and survive a considerable number of robustness checks.

A possible threat to recovering an effect on housing prices is aggregation bias. We are working with housing data at the postal code level as access to nation-wide micro data for the German housing market is generally very limited. While our analysis shows that the publication of E-PRTR data in 2009 had no effect on mean housing prices at an aggregate level, a more disaggregated data set would be needed to capture effects at the very local scale. Gamper-Rabindran and Timmins (2013) emphasize that locally undesirable land use is more likely to be present for homes at the lower quantiles of the price distribution. As such it may be that the impact on the mean is not significant, but an effect on lower percentiles of the distribution cannot be ruled out based on our analysis.

Even if our findings should hold at the disaggregate level, this does not necessarily imply that German households do not care about pollution or that the release of E-PRTR information has been ignored by the public. There can be several reasons why no adjustment of risk perception takes place upon the publication of emissions information. One possible explanation is that households already had a good idea about the amount of local emissions prior to the publication, and that pollution from emitters in the area was therefore already capitalized in the prevailing housing prices. In this case, the data available on the E-PRTR website might not have contained enough new information for households living in areas with high pollutant emission levels to adjust their behavior. Alternatively, it may be that households did not understand the information provided in the E-PRTR since they were possibly not acquainted with the toxicity of the individual pollutants. In particular, it may be that households expect no adverse effects from pollution as long as emission levels are not in excess of legal limits. In that case, more information may be needed on the adverse effects from exposure to the pollutants emitted. Finally, it may be that the mere existence of the online register is not sufficient to provide adequate access to the information contained therein, and that more or better outreach is necessary to enhance household awareness of emissions in their neighborhood. Early studies of the TRI also failed to find an effect at the community level (Bui and Mayer, 2003). More recent studies do find effects of TRI publications, but there may also be a heightened awareness with respect to these issues now than in the early days of the TRI. Anecdotal evidence suggests that the published information in the TRI is spread to a much larger degree than in the case of the E-PRTR. In the U.S., there are e.g. top 10-lists of worst polluters and green company rankings (see e.g. Lyon and Shimshack, 2015). Such simplified information is no doubt easier to spread and process (even if it is less accurate) than information provision that requires individuals to visit a website and look up their own address. Research by Schlenker and Scorse (2012) suggests that companies react to their placement on such scorecards perhaps in anticipation of community pressure.

Given the rather brief existence of the E-PRTR, it may also be worthwhile to study longer time-series in the future to address potential long-term effects. We therefore strongly encourage further research based on richer time series and ideally micro level data in Europe. The robustness checks and regressions in this paper may provide researchers with hints as to where to look for such local effects if they do exist with respect to E-PRTR data releases.

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Chapter 3

Empirical Research in Economics with German Spatial Environmental Data - A Practical Guide for Data Preparation and Research Design

3.1 Introduction

Novel environmental datasets containing spatial information see the light of day due to advances in Geographical Information Systems (GIS) technology and allow for the analysis and empirical exploitation of regional effects and phenomena. With respect to Germany, the need to visualize environmental data for the public and the inception of a long-term project called GRETA ("Gridding Emission Tool for ArcGIS") have encouraged the UBA to expedite the compilation of detailed emission raster data, which can be utilized by agency members, researchers and policy-makers for numerous purposes.

This chapter contains a descriptive analysis of the most prominent datasets along with a practical guide providing details on how I utilized raster and point-source data from the UBA for my own empirical research projects. The chapter is designed to aid other researchers in dealing with these datasets, preparing them for empirical research projects and getting the most out of the available information. It compares the characteristics of these datasets, evaluates their usefulness for different research questions and provides methodological insight on how to harness their potential for the questions at hand. It thereby also highlights some of the advantages and inherent limitations that the usage of these datasets entails. Within this chapter, I focus on raster data products provided by the UBA and the industry emission reports contained in the E-PRTR register compiled for the EEA[67].

The former consist of (i) spatial grid data provided in the form of Optimal Interpolation (OI) rasters, which can be used for evaluating local immission concentrations of airborne pollutants such as NO_2, SO_2 and $PM10$ in lieu of point source measurements, as well as (ii) recently compiled rasters with higher resolution based on the GRETA tool, which distributes emission quantities onto local sources. This tool employs sophisticated methods to distribute aggregated emission data both spatially and onto various source categories defined by the Nomenclature for Reporting (NFR) including industrial sectors and transportation. OI rasters contain grids cells with an areal extent of $4-57km^2$, while emission rasters from the GRETA tool are compiled at $1km^2$ precision. The E-PRTR register contains (iii) obligatory reports of pollutant releases from industrial facilities exceeding predefined thresholds and covers a broader set of chemical agents[68].

In summary, OI rasters provide a convenient and reliable alternative to point-source measurements from individual stations if a project requires access to environmental data in regions without measuring stations and exploits variation in pollution averages over a longer time horizon. The rasters address potential measuring errors due to missing observations and use methodological approaches accounting for emission dispersal that are superior to simple inverse-distance weighted interpolation. They combine top-down methods of emission field creation and bottom-up corrections, which capture some short-term variation and override underlying emission fields in the proximity of measurement stations.

Point-source data on the other hand is more appropriate if the research

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[67] Other useful data sources like the CORINE dataset used in Chapter 2 or satellite data are beyond the scope of this chapter and only touched upon briefly.

[68] While chemical agents released from a point source are defined as emissions, they may travel and lead to aerial concentrations in other areas, where they constitute the so-called local immisions. Thus, Chapter 1 utilizes immission concentrations for its empirical analysis, whereas Chapter 2 analyzes the public response to emission reports.

question focuses on environmental quality at the very local level or is limited to urban areas containing multiple stations. Since OI rasters and GRETA products obtain some of their variation from top-down procedures reallocating aggregated emissions, they are imperfect dependent variables in econometric research relying on short-term variation or localized shock responses in pollution concentrations. Nevertheless, they always provide useful control variables and excellent descriptive maps if aggregated at a reasonable level. Given a high enough level of aggregation and an observation window of several years, this limitation of OI raster values vanishes and researchers benefit from the improved interpolation and consistency of reported immission concentrations.

A lot of relevant information regarding the more technical aspects of data preparation has been outsourced from the earlier chapters and compiled in this chapter. This technical information can serve as a practical guide on how to utilize the data for subsequent projects and related empirical questions. The chapter also seeks to provide details on the typical workflow leading up to an econometrical analysis along with applied examples. These examples, illustrations and tests build upon the research presented in Chapter 1 as well as the exploration of spatial data necessary for recent projects.

3.2 Datasets

3.2.1 Overview

The following Tables 3.1 and 3.2 provide an overview of the main datasets presented in this chapter. As explained in Chapter 3.1, there are trade-offs for researchers when using the individual datasets. According to Auffhammer et al. (2013), available environmental, climate and weather datasets suffer from missing data issues and panel attrition within the universe of point source measuring stations even in highly developed countries. If researchers want to include regions and time periods without actual measurements into their analysis, they are forced to interpolate the available information and to account for panel attrition.

The gridded raster products attempt to perform these steps at a high level of scientific rigor and to alleviate this burden on researchers. However, the products often rely on the identical set of stations and the providing agencies perform additional steps to validate their products or mitigate missing observation bias. On the other hand, they also add model components and even reanalysis elements as they see fit. While some of them (e.g. chemical transport models, topology and altitude correction) add a level of precision to the products that clearly outperforms simple inverse-distance weighted interpolation approaches, other model components (e.g. outlier corrections, distribution according to land use characteristics, top-down allocation of emissions) introduce patterns that impede the usage of the datasets for causal econometric analysis.

In general, station-level measurements are the best source for observations that are supposed to capture actual short-term variation in response to shocks or policy measures. Consequently, they can yield reasonable outcome variables for an empirical analysis if the spatial and temporal limitations are of no concern. Gridded raster products alleviate these concerns and provide solid control variables but lose their power as observables for econometric regressions the more reanalysis elements and top-down allocation procedures are incorporated. I try to outline these aspects in the following subchapters in order to help researchers find a fitting data product for their research design. Figure 3.1 contains a simplified tree diagram of the different datasets presented in this chapter and visualizes their relationships.

- Conventional $7 \times 8km^2$ OI rasters
- Sectoral NFR information from GRETA emission rasters
- Refined $2 \times 2km^2$ OI rasters
- Point source industry emissions from E-PRTR
- Point source data from measuring stations

Table 3.1: Available UBA Grids/Rasters

Product	**Resolution**	**Available Sample**	**Pollutants**	**Variables**	**Notes**
OI Rasters	$7 \cdot 8 \approx 57km^2$	1995, 2000-2018	NO_2, SO_2, $PM10$, CO, O_3 (Immissions)	Yearly Concentration Average ($\mu g/m^3$) Days exceeding threshold (defined in $\mu g/m^3$)	- Used for Chapter 1 due to its extended time horizon. - Local readjustments through point source measurements from background stations (OI). - Underlying emission fields derived from top-down reallocation of ZSE emissions. - Incorporates a chemical transport model (RCG) and meteorology.
GRETA/NFR Rasters	$1 \cdot 1 \approx 1km^2$	2000, 2005, 2010, 2015	NO_X, SO_2, $PM10$, $PM2.5$, CO, O_3 (Emissions)	Yearly emitted pollution quantities per grid cell ($kT/(a \cdot km^2)$) split by NFR Code	- Available since 2016. - Uses methods from OI Raster compilation but enhances top-down allocation of ZSE emissions. - Spatial and sectoral disaggregation in high resolution utilizing E-PRTR, TREMOD, etc. - Reports emission quantities split by NFR sector instead of immissions concentrations.
Refined OI Rasters	$2 \cdot 2 \approx 4km^2$	2004-2016	NO_2, SO_2, $PM10$, CO, O_3, $PM2.5$ (Immissions)	Yearly Concentration Average ($\mu g/m^3$) Days exceeding threshold (defined in $\mu g/m^3$)	- Available since 2016. - Based on spatially disaggregated emissions via the GRETA tool and the main methods of OI Raster compilation. - Older years are computed sequentially. - Higher resolution relies on fine grid emission distributions from GRETA .

Table 3.2: Other UBA Data Products

Product	Resolution	Available Sample	Pollutants	Variables	Notes
UBA Point Source Stations	Unprojected Long/Lat Coordinates	1956-2018	NO_2, SO_2, $PM10$, CO, O_3 (Immissions)	Yearly Concentration Average ($\mu g/m^3$) Days exceeding threshold in $\mu g/m^3$	- Point source measurements from background, traffic or industrial stations. - Raw data. - Sample attrition. - Varying frequency of station reports. - Missing observations in rural areas.
E-PRTR Industrial Point Sources	Unprojected Long/Lat Coordinates	2001 & 2004 (via EPER), 2007-2017 (via E-PRTR)	NO_X, SO_x, $PM10$ and 67 other substances reported by German facilities (Emissions)	Yearly emitted pollution quantities (for example in kg/a) linked to NACE1.1/2.0 codes	- Obligatory reports from industrial facilities. - Annual reports published on UBA and EEA websites with a lag of up to 2 years. - Impact on housing market analyzed in Chapter 2. - Reporting sectors, facility density and reporting thresholds limit spatial data availability. - Point source emissions for a broad variety of pollutants and chemical substances. - Major source of reference for the spatial allocation of emissions in the GRETA tool. - Raw data suffers from misreporting and requires clean-up procedures.

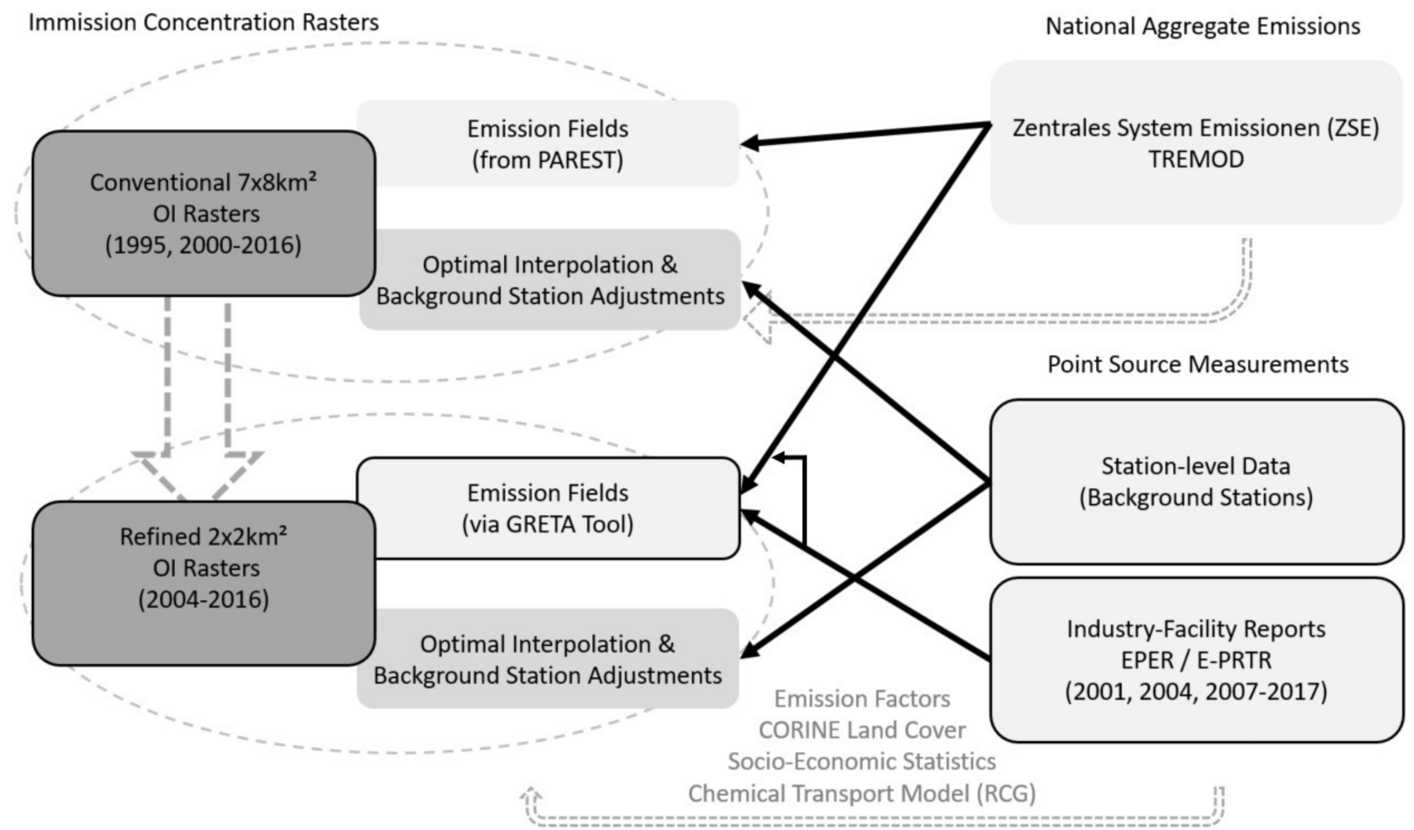

Figure 3.1: Simplified Tree of UBA Spatial Datasets

3.2.2 Raster Data from the Umweltbundesamt

The earliest gridded dataset provided by the UBA consists of polygonized rasters with a resolution of $57km^2$ resulting in 10,332 rectangular grid cells. Each raster contains information on either the yearly average concentration of a certain pollutant in $\mu g/m^3$ or the number of days with concentrations above EU thresholds. The available pollutants NO_2, SO_2 and $PM10$ can be obtained on a yearly basis from 2000 onward. An additional raster has been computed retroactively for the year 1995 and relies on less precise emission rasters at the European level that required additional temporal and spatial interpolation steps as described in Stern (2015). For a limited number of years, O_3 concentrations may also be available. All datasets are available from the UBA upon request[69]. The gridded concentration values are the result of a sequence of advanced scientific methods designed to approximate local immission concentrations. They are named after the Optimal Interpolation (OI) method presented by Flemming and Stern (2004), which applies field computations based on background station measurements to local emission regimes in order to readjust and distribute these emissions onto a grid spanning the entirety of Germany.

Thiruchittampalam et al. (2013) and Joerss et al. (2013) document the creation and the evaluation of these rasters linked to the internal PAREST project of the UBA. The generation of these OI rasters combines top-down methods of emission field creation with bottom-up corrections based on measurements from background stations, which capture short-term variation in pollution emissions. In a first step, emissions from the central emission database of the UBA ("Zentrales System Emissionen", ZSE) are distributed onto the local level via detailed information on industry employment shares and regional characteristics. The ZSE represents a national inventory of emissions that is used for internal and external reporting. It utilizes advanced accounting methods along with detailed micro data to obtain national aggregates at the sectoral level, which are reallocated to grid cells via complex top-down source

[69]The UBA department "Fachgebiet II 4.2 Beurteilung der Luftqualität" provides services such as the provision of raster datasets (E-mail: immission@uba.de).

apportionment formulas described in Thiruchittampalam et al. (2013). Distributional parameters take activity rates, energy footprint and emission factors into account and emission quantities are allocated by matching the sectoral classifications used in national accounting to the Selected Nomenclature for Air Pollution (SNAP) in order to obtain sectoral-specific parameters. These classification systems and the accounting standards have been synchronized with classifications and recommendations of the Intergovernmental Panel on Climate Change (IPCC). For a precise allocation of traffic-based emissions, the UBA relies on its Transport Emission Model (TREMOD), which accounts for vehicle stock and the prevalence of European emission standards (EURO1-6) in the vehicle fleet. The framework is explained in Knoerr et al. (2010) and Knoerr et al. (2014) and also provides parameters for the allocation of emissions towards line sources, shipping, railways and aviation. Shapefiles from the CORINE land use database combined with administrative data at the county-level enhance the regional distribution of aggregated emissions.

Taking these parameters and topology into accounts, emission fields are dispersed according to meteorological parameters and the REM-CALGRID (RCG) model developed in Yamartino et al. (1992), which simulates the transport of chemical substances in various media[70]. This yields hourly predictions at high spatial precision, which are readjusted locally through hourly station measurements according to the OI framework described in the methodological papers by Flemming and Stern (2004) and Stern (2009). The data manual Umweltbundesamt (2018) and Flemming and Stern (2004) explain that only stations classified as "background" stations should be taken into account for the field computations, while stations classified as "traffic" or "industrial" represent "hot spots" that report extreme values and outliers compared to the pollution averages in surrounding areas. The emission levels captured by these stations influence concentrations measured by background stations but cannot be used for the field correction interpolation since they would distort grid averages if given too much weight .

For an analysis of the air quality experienced by the local population,

[70]Wickert (2001) discusses properties of chemical transport models which have been used in the context of OI raster creation especially during earlier stages.

the selection of background and especially suburban stations for calibration seems reasonable as the conditions captured by traffic and industrial stations only affect a subset of the population. The locations of all active measuring stations for the given pollutants during the extended observation period (1995-2008) of Chapter 1 are shown in Chapter 3.2.3. There have been 488 active background stations for NO_2 over this time frame and 933 stations in total. For $PM10$, there have been 361 active background stations and 699 stations in total. For SO_2, there have been 455 background stations and 701 stations in total. The remaining stations are split between traffic and industrial measuring stations but typically represent smaller panels.

Table 3.3 reports summary statistics from the past decade (2009-2018) for comparative purposes, while Chapter 3.4.1 analyzes the relationship between raster products and point source measurements. It can be shown that the correlation between background stations and OI rasters is high, which supports the claim that station measurements override top-down emission fields in the vicinity of measuring stations and therefore preserve local variation needed for the identification of causal economic effects on local air quality.

3.2.3 Point Source Data from the Umweltbundesamt

The UBA maintains an extensive network of measuring stations for the various pollutants[71]. This network has been expanded over time but leaves major gaps in rural areas and less populated counties. The UBA station-level data shares the typical weaknesses of point source measurement panels identified by Auffhammer et al. (2013) and listed below.

[71]Metadata on the stations has been obtained from a section of the UBA website (https://www.env-it.de/stationen/public/downloadRequest.do) that is currently unavailable. Such meta information and comprehensive station-level datasets with daily measurements are available upon request and I rely on the dataset covering all available station-level data between 2000 and 2014 that have been obtained by Holub (2015).

- Missing information for regions without point source measuring stations
- Panel attrition through the closing and opening of stations introduces measurement bias
- Interpolation of missing data due to infrequent station reports introduces measurement bias

Stations may be located in so-called "hot spots" (Flemming and Stern, 2004) if their purpose is to specifically track extreme pollution exposure in locations that are interesting from an urban planning or political perspective. This includes traffic measurement stations, stations on mountains or stations close to industrial facilities. Combining their data with data from background stations may give these extreme measurements too much weight if the weighting scheme does not control for the fact that they are not representative of surrounding areas. The choice of station types introduces an additional degree of freedom and has an impact on the obtained aggregates as Table 3.3 and Chapter 3.4.1 imply. The selection of stations should therefore be tailored to the research question at hand. Point source data may be preferable to the usage of gridded data products if the analysis is restricted to urban areas and well-defined local shocks. One appropriate application of station-level data is the evaluation of traffic-related pollution in response to the introduction of Low-Emission Zones (LEZs) as in Wolff (2014) and Klauber et al. (2020).

The maps in Figure 3.2 show the locations of point source measurement stations in Germany with at least one annual pollutant report over the period of observation in Chapter 1 [72]. It can be seen that coverage is similar for all pollutants (NO_2, $PM10$ and SO_2). The panel on the left shows stations of all types (including "background", "industrial" and "traffic"), while the panel on the right depicts only the background stations used for the OI emission field adjustment. All counties (according to 2008 definitions) with at least one station reporting in the time period from 1995 to 2008 are coloured in dark green. This demonstrates that the occurrence of missing observations is

[72] These figures use the OpenStreetMap layer provided within QGIS courtesy of openstreetmap.org (Contributors) (2019). There are 413 counties as of 2008.

a phenomenon concentrated in rural areas. It can be seen that the network of background stations offers almost the same coverage as the full panel. Stations also tend to report values for multiple pollutants, so the underlying data quality for pollutants should be comparable.

The maps in Figure 3.3 show the locations of point source measurement stations in Germany with at least one annual pollutant report between 2009 and 2018. Counties in dark green contain at least one of these stations. Due to the shorter time period, these maps are populated with less stations and coverage for SO_2 is more spotty. The county borders pertain to the 2014 territorial definitions, so there are 402 counties with significantly larger areas in Eastern Germany due to county restructuring, which makes coverage in Eastern Germany appear more extensive. The maps and summary statistics in Table 3.3 demonstrate that the density of the station network, which provides inputs for the emission field correction, is excellent for urban areas and sufficiently dense for NO_2 and $PM10$. The prevalence of counties without a single station emphasizes the relevance of solid interpolation methods if researchers prefer to work with station-level data.

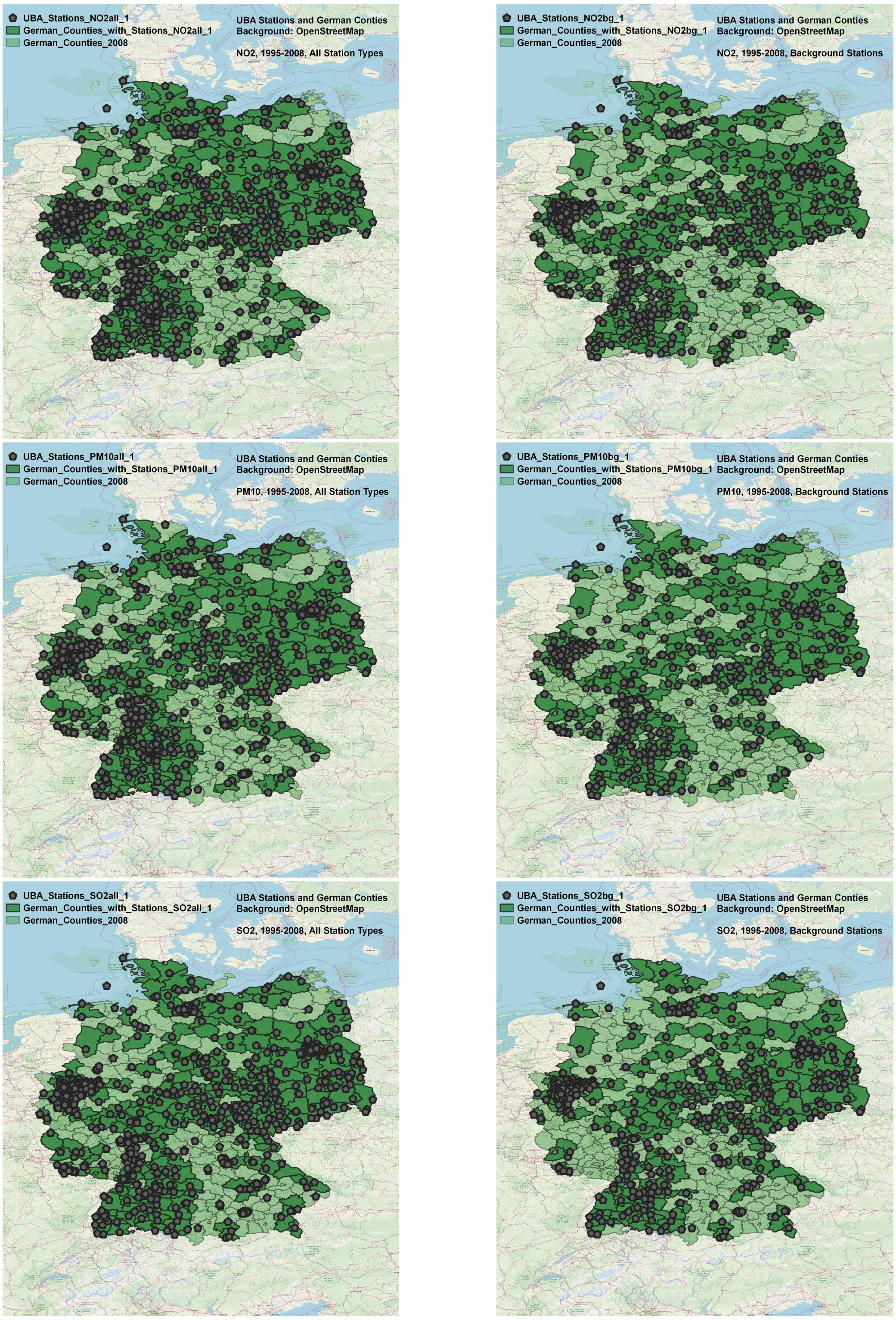

Figure 3.2: UBA Point Source Stations by Pollutant (All vs. Background stations active in 1995 - 2008)

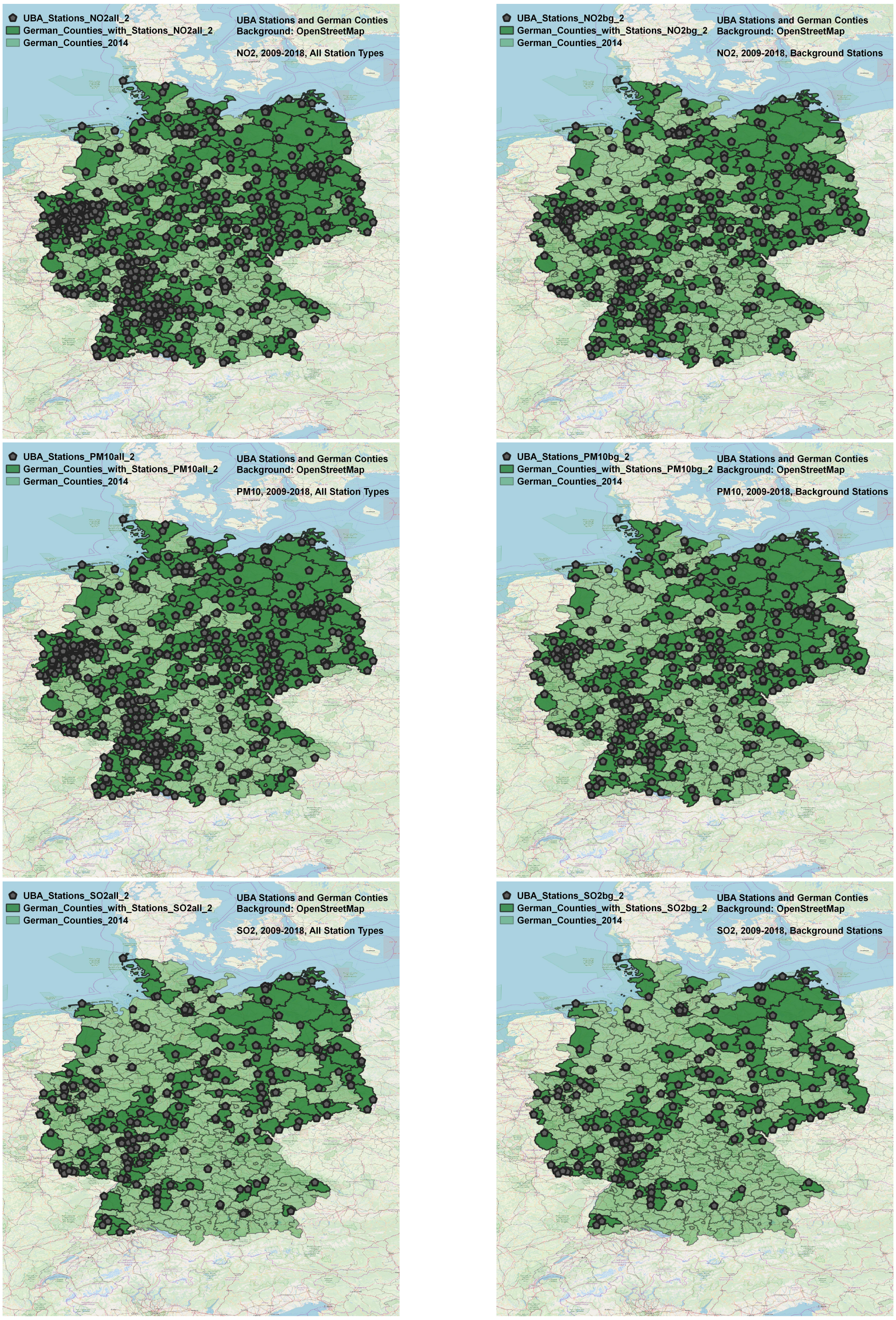

Figure 3.3: UBA Point Source Stations by Pollutant (All vs. Background stations active in 2009 - 2018)

Table 3.3: Station Coverage (1995-2008 and 2009-2018)

Time Period	1995-2008					
Pollutant	NO2		PM10		SO2	
Station Types	Background	All Stations	Background	All Stations	Background	All Stations
Number of Stations	488	933	361	699	455	701
Counties with Coverage	246 / 413	295 / 413	233 / 413	281 / 413	227 / 413	279 / 413

Time Period	2009-2018						1995-2018
Pollutant	NO2		PM10		SO2		PM2.5
Station Types	Background	All Stations	Background	All Stations	Background	All Stations	All Stations
Number of Stations	317	758	294	599	163	215	236
Counties with Coverage	214 / 402	274 / 402	208 / 402	258 / 402	124 / 402	148 / 402	152 / 402

Note: County territorial definitions correspond to those used in the maps (413 counties as of 2008 and 402 counties as of 2014). Station counts and county averages are based on all stations with at least one relevant annual report over the course of the time period.

3.2.4 Raster Data based on GRETA

3.2.4.1 GRETA in a nutshell

The UBA commissioned the development of the "Gridding Emission Tool for ArcGIS" (GRETA) with the aim of improving the quality and utility of emission raster generation. Simply put, it is a collection of tools used internally for the generation of various important UBA products supposed to meet contemporary quality standards. Schneider et al. (2016) provide an overview of the improved workflows and methodologies facilitating the compilation of GRETA emission fields and adjunct products[73].

One key aspect is the availability of emission quantities split by NFR codes in raster products enhanced by GRETA information. Another improvement is the allocation of emission quantities onto a more precise $1 \times 1km^2$ grid, which contains these quantities in kilotons (kT) per NFR source sector. Table 3.4 provides a non-exhaustive selection of high-level NFR codes outlining the

Table 3.4: Selection of NFR Codes covered by GRETA

NFR Code	Source Description
1	Energy
1A	Fuel Combustion Activities
1A1	Energy Industries
1A2	Manufacturing Ind. and Construction
1A3	Transport
1B	Fugitive Emissions
2	Industrial Processes and Product Use
2A	Mineral Products
2B	Chemical Industry
2C	Metal production
2D	Solvents
2H	Other (Pulp & paper, Food)
2I	Wood Processing
2K	Consumption of POPs and HMs

NFR Code	Source Description
3	Agriculture
3B	Manure Management
3D	Agricultural Soils
3F	Field burning of Agricultural Waste
3I	Other (Agriculture)
5	Waste
5A	Solid Waste disposal on land
5B	Biological Treatment of waste
5C	Waste Incineration
5D	Waste-water handling
5E	Other (Waste)
6	Other Sources

sectoral segmentation of GRETA products[74].

An important aspect for the spatial distribution of emissions are traffic arteries within both GRETA and the allocation procedures of conventional raster products. TREMOD emissions are combined with national ZSE emissions for road traffic and redistributed at the local level (for example onto line sources such as highways) according to parameters for road condition, road usage and emission output contained in TREMOD. The model is described in Knoerr et al. (2010) and Knoerr et al. (2014) and also provides parameters for the allocation of aviation, railway and shipping emissions.

One of the main advantages of the GRETA tool is that it incorporates in-

[73] A short summary of the external project can be obtained via the official website (https://www.umweltbundesamt.de/publikationen/arcgis-basierte-loesung-zur-detaillierten). Raster files covering all compiled reference years can be obtained (E-mail: immission@uba.de) from the UBA department “Fachgebiet II 4.2 Beurteilung der Luftqualität”.

[74] GRETA datasets specify emissions at more disaggregated NFR levels. Official websites provide complete code lists (http://naei.beis.gov.uk/glossary?view=nfr) and correspondence tables (https://www.ceip.at/fileadmin/inhalte/emep/pdf/2019/ConversionTableReporting Codes_06122019_01.xlsx). The UBA hosts detailed descriptive statistics by NFR sector for Germany (https://iir-de.wikidot.com/start) because the nomenclature is the current standard format for reporting national emissions according to the Convention on Long-Range Transboundary Air Pollution (CLRTAP) and regulations established by the United Nations Economic Commission for Europe (UNECE).

formation from the E-PRTR database. First of all, reported facility emissions are treated as point measurements that are factored in during the emission field creation to pinpoint locally dominant emitters. In a second step and in order to ensure consistency with NFR totals and ZSE national accounts, differentials between aggregate emissions and total E-PRTR quantities at the sectoral level are reallocated onto local NFR sectors and fields via top-down methods informed by sectoral quantities. The distribution of these emissions onto local sources and NFR sectors is achieved by linking NFR, E-PRTR and SNAP sector codes in order to assign appropriate emission factors.

E-PRTR data therefore enhances the precision of the allocation procedure but individual facility-level reports are absorbed by surrounding emission fields if their individual contribution is small compared to the reallocated differentials. These discrepancies between E-PRTR reports and overall emission output will persist by design due to the E-PRTR reporting thresholds and negligible sanctions for false reporting[75]. Since the raster products based on GRETA emission fields rely on similar distribution and OI background station calibration models, they share many advantages of the OI rasters presented in Chapter 3.2.2.

3.2.4.2 GRETA Emission Raster

The GRETA emission quantities are allocated onto a more precise grid than previous iterations ($1 \times 1km^2$ with 560,466 grid cells) and attributed to individual source categories. Each category corresponds to a single NFR code and occupies one attribute field per grid cell in the underlying dataset. Some key aspects of the GRETA emission framework are only computed for reference years including the years 2000, 2005, 2010 and 2015. All reference years are already available upon request. I have aggregated annual emission quantities from the 2015 GRETA wave across all NFR sectors (measured in kT/km^2) and have plotted the resulting totals in the form of heat maps. Figure 3.4 plots quantiles of total NO_X emissions per grid cell in a map of Northern Germany. Figure 3.5 plots quantiles of total $PM10$ emissions per

[75]Refer to Chapter 3.2.6 for more information on E-PRTR reports.

grid cell in a larger-scale map centered on the city of Mannheim, while Figure 3.6 plots quantiles of total SO_2 emissions per grid cell in the vicinity of Berlin.

The maps show that highways and traffic arteries represent major agglomerations of emissions. This is a warning sign regarding the interpretation of computed quantities as short-term variation exploitable for causal identification within econometric regression designs. Especially highly localized shocks that drive traffic-related emissions in the short term will not be captured by the underlying emission fields. Schneider et al. (2016) confirm that the distribution of emissions in the GRETA tool is heavily influenced by TREMOD parameters and that a significant share of aggregate ZSE emissions is allocated according to these parameters. Emission quantities near roads are therefore highly dependent on top-down reallocation mechanisms and experience corrections only in the vicinity of background stations since traffic stations are outliers excluded from OI interpolation procedures.

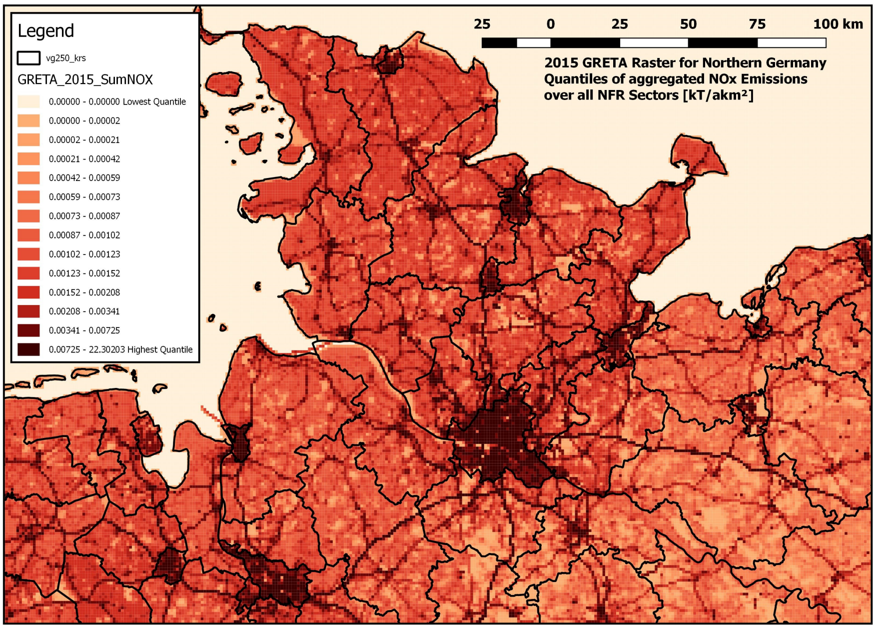

Figure 3.4: Heat map: NO_X Totals in GRETA (Northern Germany, 2015)

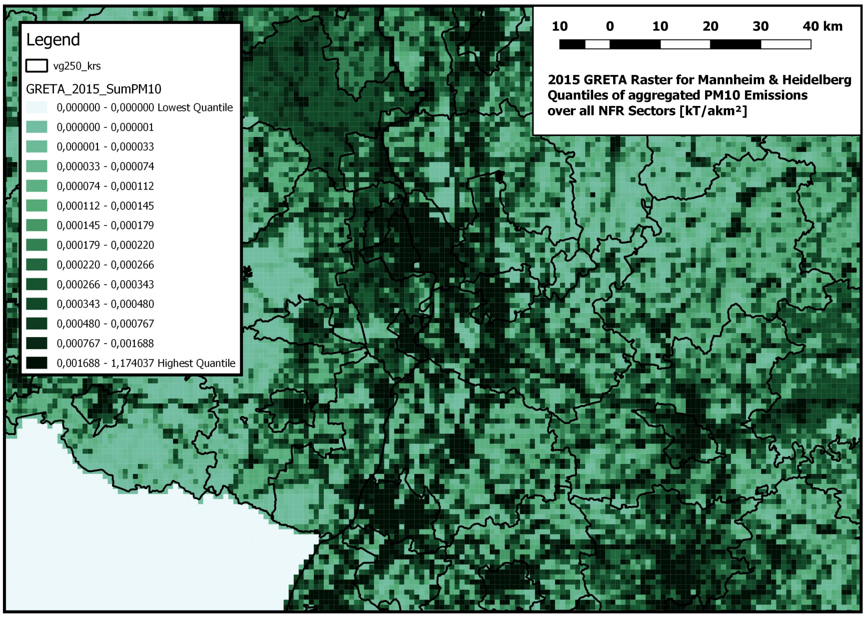

Figure 3.5: Heat map: $PM10$ Totals in GRETA (Rhine-Neckar Region, 2015)

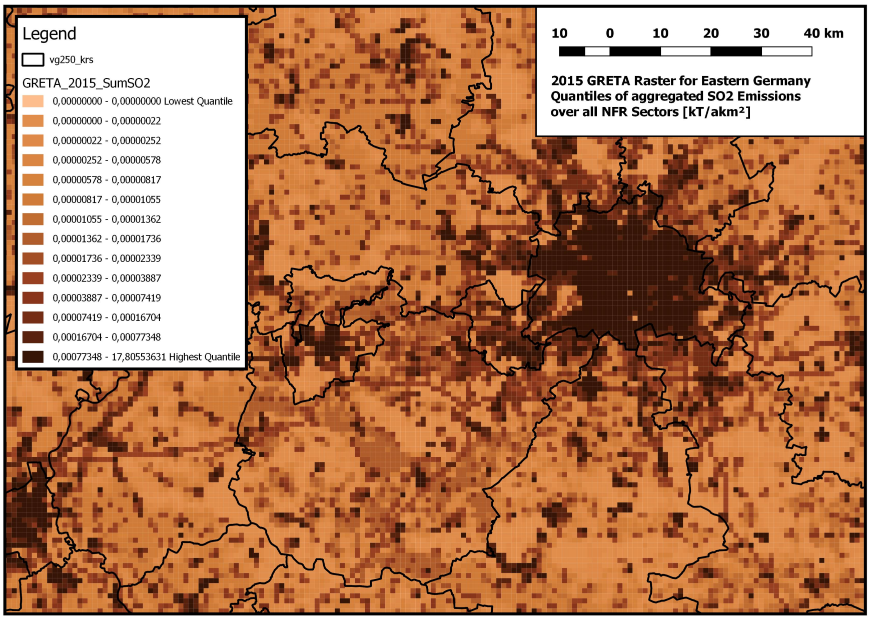

Figure 3.6: Heat map: SO_2 Totals in GRETA (Eastern Germany, 2015)

Emission fields and raster products based on GRETA take E-PRTR and background station reports into account but do not possess the same potential as diligently reported E-PRTR quantities at the facility level for causal identification strategies based on actual short term variation. If researchers are interested in precise facility-level shock responses, they should therefore use the facility-level quantities reported via the E-PRTR database. This entails dealing with problems such as panel attrition, missing observations due to reporting thresholds and false reporting as discussed in Chapter 3.2.6, though. The number of facilities reporting emission quantities for a pollutant under study may also be too low in individual counties to satisfy standard criteria of statistical inference.

The rasters suffer to a much lesser degree from misreporting and thresholds, as they apportion a significant share of emissions according to sophisticated top-down accounting methods. For research projects with a broader scope and higher aggregation levels, this top-down apportionment can actually provide a meaningful approximation of emission quantities and researchers can extract emission estimates for selected NFR codes from GRETA products in order to obtain extremely detailed control and explanatory variables.

3.2.4.3 Refined OI Rasters

Following the completion of the GRETA project in 2016, the UBA has implemented OI raster computation procedures that map annual immission concentrations at a much higher resolution than former versions due to the higher precision of GRETA emission fields of $1 \times 1km^2$. These refined rasters contain grid cells with a spatial extent of $2 \times 2km^2$. They rely on underlying emission fields from the GRETA tool based on E-PRTR point source information, the RCG chemical transport model and the OI readjustment procedures described in Chapter 3.2.2. Stern (2015) uses cross-validation tools to evaluate the differences between the two raster products and finds that national aggregates deviate by less than 25%, while the local distribution of emissions onto spatial units and sources may deviate to a significantly higher degree. My own analysis of immission concentrations in Chapter 3.4.1 demonstrates that the vintage OI rasters ($7 \times 8km^2$) differ most strongly from the refined rasters ($2 \times 2km^2$) in regions without background stations. This proves that the new emission fields lead to different immission patterns besides providing a higher level of precision.

The refined rasters are computed retroactively for past years and are currently available for the years 2004-2016, which precludes their usage for the analysis in Chapter 1. Researchers evaluating a more recent time period have the opportunity to use the refined OI rasters for the entirety of their research design and can reap the benefits of an enhanced emission field generation supported by E-PRTR data. One caveat is that high quality E-PRTR data is only available since 2007 and that the computation of emission fields in previous years relies on the less detailed EPER reports for 2001 and 2004 as described in Chapter 3.2.6.

Moreover, all limitations of OI rasters discussed in Chapter 3.2.2 with respect to identification strategies relying on short term variation pertain to these rasters as well. Short term variation persists in raster areas in which adjustments from background stations or diligently reported E-PRTR emissions are able to override the underlying emission fields. Last but not least, these rasters provide the first instance of gridded $PM2.5$ concentrations in Germany, albeit only for years since 2009. Consequently, the $2 \times 2km^2$ OI rasters certainly have the potential to become a valuable source of immission estimates in combination with an appropriately defined research question.

3.2.5 Particulate Matter - 2.5µm

Comprehensive data on $PM2.5$ concentrations is not available in gridded UBA datasets before 2009 and is only reported by a small sample of point source measuring stations before 2009. Figure 3.7 depicts the locations of those stations reporting $PM2.5$ values after 1995 and shows that many counties do not contain a single station. The map is based on the 402 counties in existence in 2014. This means that many Eastern German counties have completed mergers in the meantime, which give them a higher chance of containing at least one station with $PM2.5$ measurements (identified by dark green colouring).

The $2 \times 2km^2$ rasters contain values for $PM2.5$ across the entirety of Germany since 2009. These values are also based on the sophisticated top-down methods of emission field creation and local field corrections discussed in Chapter 3.2.4.3. A comparison of $PM2.5$ and $PM10$ measurements for the time period of mutual availability performed in Table 3.10 of Chapter 3.4.1 demonstrates a high degree of correlation. This confirms that the emergence of particles from the two diameter classifications is likely coupled and that $PM10$ concentrations can be used as a sufficiently reliable proxy for $PM2.5$ concentrations in their absence. This finding is not surprising as the two particle groups contain derivatives of the same chemical substances such that health effects are often impossible to disentangle due to the high level of correlation (e.g. Janssen et al., 2013).

Satellite images combined with modeling techniques from geoscience and statistics provide the basis for recent fine-resolution datasets containing $PM2.5$ measures, which have been developed by van Donkelaar et al. (2019) and provide an attractive but computationally more demanding alternative for researchers interested in evaluating particles with lower diameter[76].

[76]These datasets incorporate predictions based on geographically weighted regressions (GWR) and can be obtained from the website of the Atmospheric Composition Analysis Group (http://fizz.phys.dal.ca/~atmos/martin/?page_id=140#V4.EU.02) or the Socioeconomic Data and Applications Center (SEDAC) website (https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod). Fowlie et al. (2019) explore satellite-based $PM2.5$ measurements for the USA and compare their implications to those from EPA station-level measurements.

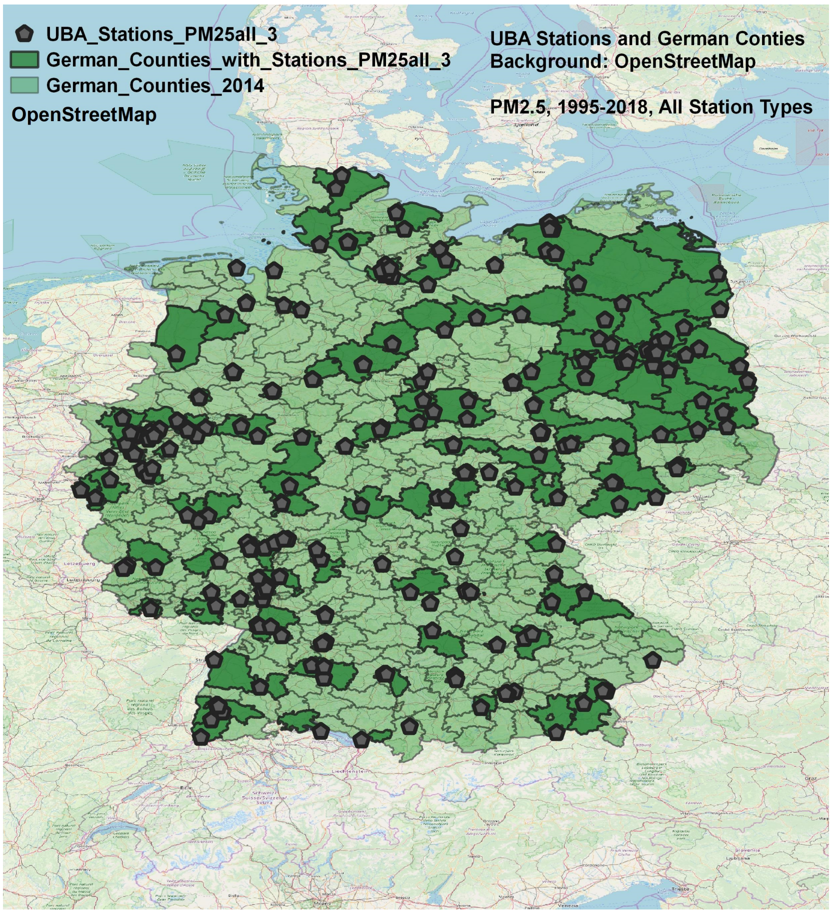

Figure 3.7: UBA Point Source Stations with PM2.5 measurements (All stations active in 1995 - 2018)

3.2.6 Facility-level Reports via E-PRTR

3.2.6.1 E-PRTR: General Information

Pollutant emissions on the facility-level can be obtained from the European Pollutant Release and Transfer Register (E-PRTR) established in 2009 following EU legislation (i.e. Regulation (EC) No 166/2006 implementing the UNECE PRTR Protocol signed in 2003). The E-PRTR is a web-based register maintained by the European Environment Agency (EEA) that is accessible to the public and obliges industrial facilities within EU member states to report emitted pollutant quantities. It is based on similar disclosure principles as the US Toxics Release Inventory (TRI) and follows the general idea of fostering "regulation by information" through the dissemination of data on negative externalities to the public. The implementation of such regulation has been motivated by the Aarhus Convention[77] signed in 1998.

German facilities have to report their emissions to the UBA under certain criteria. Most importantly, the respective industrial acitivities have to be included in a list defined within the regulation and pollutant emissions have to exceed predefined quantity thresholds[78]. National agencies then compile this information, forward it to the EEA and make it available to the public. The reported emissions are afterwards available as raw data for researchers and as post-processed aggregates or mapped data on the website hosted by the EEA and on localized websites of the national reporting agencies[79].

The complete database containing point source information for scientific use is hosted by the EEA and lists pollutant emissions from non-anonymized point sources on the facility-level in absolute quantities for all EU member states[80]. It contains releases into air, water and soil measured in kg as well as transfers to external waste treatment sites. The E-PRTR reports differentiate between 96 pollutant categories including aggregate classes and 91 individual pollutants, out of which 66 pollutant reports actually occurred in Germany in 2008. This reporting year marks the second E-PRTR wave and contains 4,834 German point source releases to air and water across 1,762 individual facilities. The first E-PRTR wave for the year 2007 contains 4,727 point source releases and 952 waste transfers across 70 pollutant categories and

[77] The full title is "UNECE Convention on Access to Information, Public Participation in Decision-making and Access to Justice in Environmental Matters".

[78] All 65 relevant economic activities are listed in the Annex (p. 8ff) to the regulations published in European Union (2006b). The register at the European level includes information for over 33000 facilities in 33 countries (EU28, Iceland, Liechtenstein, Norway, Switzerland and Serbia) as of April, 2019. The specific thresholds have been chosen to ensure that about 90% of industrial emissions are captured by E-PRTR reports (see http://prtr.ec.europa.eu/#/faq).

[79] The main website is managed by the EEA (https://prtr.eea.europa.eu/#/home). German data is also made available to the public on a localized website maintained by the UBA (https://www.thru.de/daten/suche/). Citizens can use these websites to obtain information on the reported emissions from non-anonymized industrial facilities filtered by self-selected criteria such as zip-code.

[80] The database is accessible via the EEA website (https://www.eea.europa.eu/data-and-maps/data/member-states-reporting-art-7-under-the-european-pollutant-release-and-transfer-register-e-prtr-regulation-22).

1,976 individual facilities and was published in 2009. Chapter 2 analyzes whether this publication event had an impact on housing prices since actual or perceived air quality can be seen as a determinant of real estate values.

The predecessor of this register is the European Pollutant Emission Register (EPER), which can be seen as an extended test-run with nearly the scope of the E-PRTR. It differentiated between 50 key pollutants from large and medium-sized industrial facilities in at least 17 EU member states. EPER reports have been integrated into the available E-PRTR database and provide the data base for the years 2001 and 2004. German EPER data for the year 2001 comprises 3,665 individual point source releases across 1,635 facilities and 44 individual substances[81].

Table 3.5: Volume of German EPER and E-PRTR Data

Selected Reporting Years	Pollutant Categories	Point Source Releases (Air, Water & Soil)	Reporting Facilities (FacilityIDs)
Year 2001 (EPER)	44 / 50	3,665	1,635
Year 2007 (E-PRTR First Wave)	70 / 96	4,727	1,976
Year 2008	66 / 96	4,834	1,762
Totals over the Years 2001 - 2013	70 / 90	40,098	4,547
Year 2017 (E-PRTR Latest Report)	67 / 96	$\geq$4,358	$\leq$1,784

Note: Table contains own calculations for the years 2001-2013 and summary statistics provided by the UBA for 2017.

Since the end of 2007, facility-level reports have to be submitted annually and the resulting E-PRTR revisions are published over the course of the following 1-2 years with varying lags. Table 3.5 and Figure 3.8 summarize descriptive statistics and publication timing for the waves under study.

Figure 3.8: Timeline of EPER and E-PRTR Publications

[81] Information on EPER is stored in the EEA archives (https://www.eea.europa.eu/data-and-maps/data/eper-the-european-pollutant-emission-register-4).

3.2.6.2 E-PRTR: Data Exploration and Empirical Research

All facilities engaging in at least one of the specified economic activities are obliged to report their yearly emissions of specified substances as long as these exceed thresholds defined in kg for each pollutant and release medium. The database contains longitude and latitude coordinates (WGS84) of each facility and GIS tools can be used to locate the point source measurements and to aggregate these across spatial units such as counties or zip-codes ("Postleitzahlen", PLZ). This spatial data can be exploited for the computation of emission developments at both the industry-level and the regional level but suffers from several issues such as misreporting[82] and sample attrition due to the reporting thresholds.

Garcia-Perez et al. (2008) demonstrate that the point source coordinates in EPER records differ significantly from the actual facility locations. Since the switch to E-PRTR, coordinates have to be provided with an imprecision of less than 500m (e.g. Garcia de Gurtubay and Telletxea, 2010) and are likely more reliable than the zip-code and the physical address of the facility as these entries are often misreported. While it is tempting to use zip-code information, the data exploration described in Chapter 2.4.2.2 reveals that these frequently belong to the headquarter of a firm rather than the location of the point-source emitter. The research design in Chapter 2 therefore uses geocoded information to allocate emission quantities onto the zip-code level.

Another promising application of the E-PRTR database is the construction of emission time-series. The dataset suffers from sample attrition at the lower end, though, as firms close to the reporting threshold may drop out of the

[82] According to European Union (2006a), penalties for non-compliance are within the discretion of the individual member states. Rathmer et al. (2009) explain that the reporting agency can force facilities to disclose their internal records on the reported emissions if there is reasonable doubt regarding the credibility of reports. If facilities violate their reporting obligations, they can potentially be fined for an administrative offense. The latter requires a reasonable suspicion, though, and it is a priori difficult for agencies to ascertain, whether a lack of reported values is due to negligence or due to an undercutting of emission thresholds. Because of the existence of a convenient online reporting tool (https://www.bube.bund.de/), the UBA assumes a high rate of compliance among German firms but has few levers to audit reports as long as these fall within a credible range. Even if intentional misreporting is rare, erroneous and accidental misreporting remains an issue in the database that can never be ruled out.

sample and report infrequently over the observation period. This becomes a serious issue in the context of time-series as individual firms may drop from a positive quantity to zero even though their annual emissions have barely changed. Because the E-PRTR does not capture emissions from firms below the reporting threshold and because important polluters are able to claim exemption status in order to blind exact emission quantities[83], total emission quantities are an incomplete and imprecise representation of real emission patterns. The reporting thresholds also non-randomly eliminate small polluters from the panel, which can introduce severe selection bias. In fact, this divergence leads the UBA to allocate a significant fraction of industrial emissions via top-down methods in the GRETA tool as discussed in 3.2.4.

On the other hand, the E-PRTR database contains information on the NACE1.1 or NACE2.0 codes of the main industrial activities of a given facility, which makes assigning emissions to industry sectors feasible[84]. It is possible but challenging to construct a balanced panel of facilities reporting over an observation period by utilizing the "FacilityID" field and textual information on company names, locations and ownership structure. This is complicated by the fact that the ownership structure of corporations and company identities may change over time, making it impossible to correctly track the emission output of a single firm over time. In contrast to processing firm identities, the aggregation of emissions at the sectoral level is therefore a comparatively straight-forward endeavour. One major caveat is that firms maintain operations and activities in several NACE codes and that emissions are not proportionally assigned to the individual activities. Using only the NACE code of the main activity is a practical but strong assumption that distorts the correct assignment of emission quantities.

I therefore use the geocoded location parameters for the spatial allocation of emissions and develop simple algorithms for attributing emissions to

[83]For example if their production is relevant for military purposes.

[84]Appendix A.3.1 contains details on the procedures performed for the analysis in Chapter 3.4.2. Individual facilities are identified by a unique "FacilityID" and their annual reports are identified by a unique "FacilityReportID", which can pertain to multiple pollutant release quantities.

industrial sectors. Figure 3.9 depicts all EPER and E-PRTR point sources with NO_X, $PM10$ or SO_X emission reports at the facility-level in either 2001 (EPER) or 2008 (E-PRTR). The regional distribution of point sources in Figure 3.9 illustrates that researchers need to overcome severe challenges when trying to exploit regional variation in E-PRTR quantities. Chapter 3.4.2 demonstrates that restricting E-PRTR records to subsamples or individual pollutants soon limits the statistical power of econometric identification approaches. Nevertheless, the database provides a treasure trove of information that has not yet been properly exploited by environmental economists.

Consequently, I use E-PRTR point source data to validate the spatial analysis in Chapter 1. To this end, I combine records from the years 2001 and 2008 in order to approximate the given period of observation and to facilitate a supplementary analysis at the industry-level. Chapter 3.4.2 presents the results of this supplementary analysis, while Appendix A.3.2 provides a review of important aspects when combining EPER and E-PRTR data.

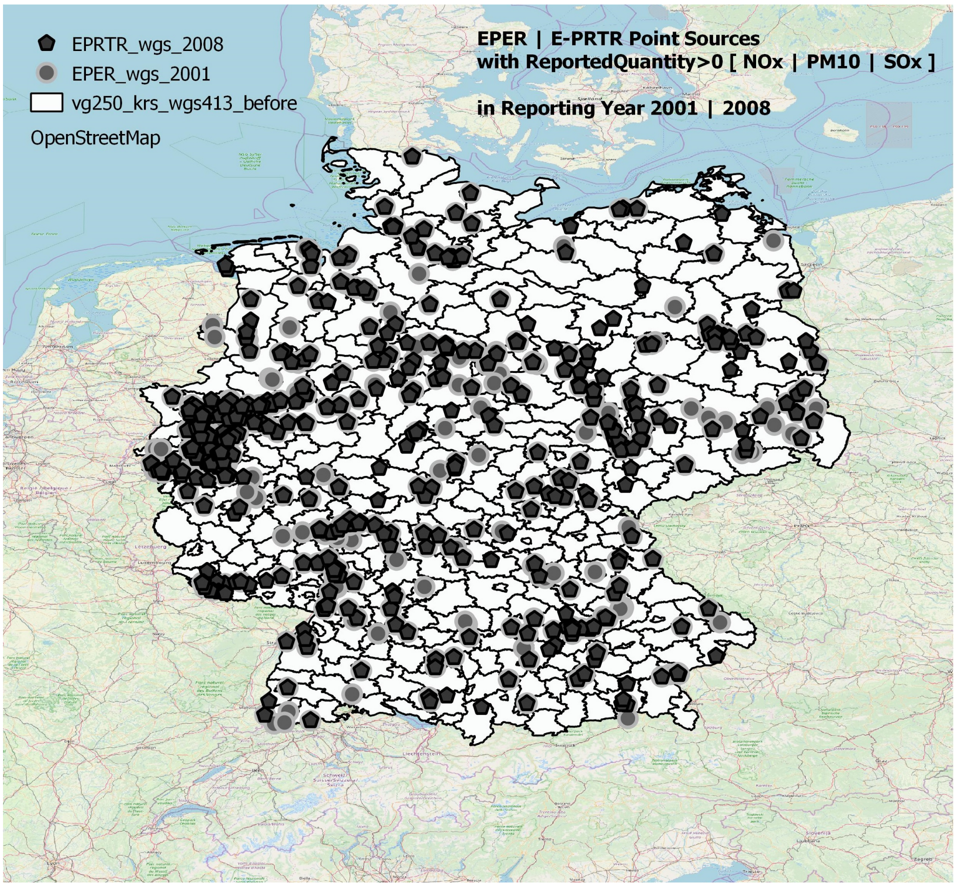

Figure 3.9: Map of EPER (2001) and E-PRTR (2008) Point Sources

3.2.7 Auxiliary Datasets

When working with environmental data, it has to be taken into account that pollutant concentrations are dispersed by the wind and that the sedimentation of pollutants depends on weather phenomena such as precipitation and temperature. When using data at daily or higher frequency, it is therefore essential to control for weather characteristics in regressions. Weather phenomena can even have an impact on yearly averages if these are persistent over the entire year or exhibit extreme seasonal spikes. I control for such spikes in Chapter 1 by smoothing environmental variables over several years, which reduces the need for weather controls. At a higher frequency or across larger areas, the inclusion of weather controls becomes imperative.

For Germany, gridded weather data at $1 \times 1km^2$ resolution is available from the Climate Data Center (CDC) of the German Weather Service ("Deutscher Wetterdienst", DWD) at annual or higher frequency. Alternatively, researchers can use hourly or daily measurements from point source station but have to deal with an unbalanced panel, panel attrition and regional gaps by employing reasonable aggregation methods[85]. For research limited to urban areas, meaningful averages can be constructed from individual weather stations as in Holub (2015) and Klauber et al. (2020), whereas the gridded products fill spatial gaps outside of urban areas using the inverse-distance weighted interpolation methods described in Maier and Müller-Westermeier (2010) and Müller-Westermeier (1995).

[85]Gridded DWD datasets with annual averages for temperature, precipitation, sunshine duration and other variables can be downloaded from the CDC open data archive (https://opendata.dwd.de/climate_environment/CDC/grids_germany/annual/). This data is stored in an ESRI-ASCII-Grid-Format and represents non-vectorized rasters defined by x-y-point-coordinates pertaining to one vertex of the respective raster cells (e.g. bottom-left) and by the spatial extent of the cells. The values assigned to these cells can be stacked onto a single polygon layer by creating a grid from the original raster with GIS vector operations and adding the raster values from a chronological sequence of rasters to the grid features. The available documentation discusses the correct projection (DHDN / Gauss-Kruger zone 3, EPSG:31467) and the properties of the file format (https://opendata.dwd.de/climate_environment/CDC/help/Hilfe_Gauss-Krueger-Raster2GIS.pdf). Historical records from point source stations are available at daily or hourly frequency in the same archive (https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/daily/kl/).

Both Chapter 1 and Chapter 2 combine environmental data with socio-economic control variables obtained from the INKAR database hosted by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). This database provides a broad range of indicators at the level of varying territorial units [86].

The research in Chapter 2 incorporates land use datasets resulting from the CORINE (Coordination of Information on the Environment) Land Cover (CLC) project initiated by the EU and described in Keil et al. (2011). The research design uses the CLC2006 version to construct land use percentages per zip-code area in order to enhance the matching procedures as explained in Chapter 2.4.3.1. The CORINE land cover maps are powerful tools determining the main land use per area by evaluating satellite imagery at a high level of precision (5-25ha). They provide researchers with additional control variables that capture static land use characteristics[87]. I do not touch upon other satellite based datasets in this chapter, although they represent attractive alternatives if not constrained by temporal and spatial limitations. The datasets based on satellite imagery described in Chapter 3.2.5 provide precise spatial rasters for $PM2.5$ and are a valuable source of information for the evaluation of local air quality.

[86] The database can be accessed via the official website (http://inkar.de/) and is referred to as "Indicators and maps on spatial and urban development in Germany and Europe" ("INdikatoren und KARten zur Raum- und Stadtentwicklung in Deutschland und in Europa", INKAR). Appendix A.1.10 and Appendix A.2.1 provide examples of variables that are useful for empirical analysis at the county-level .

[87] Land use characteristics may change over a long period of time, however, which makes using CLC versions pertaining to different reference years (e.g. CLC1990 and CLC2000) necessary if long-term effects are to be analyzed. Recent versions of the dataset along with other data based on satellite imagery can be obtained from the website of the German Aerospace Center ("Deutsches Zentrum für Luft- und Raumfahrt", DLR, https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-8799/) or from the UBA website (https://gis.uba.de/catalog/Start.do).

3.3 Technical aspects of German Environmental Data

3.3.1 Spatial Units

3.3.1.1 Available Territorial Definitions

First of all, it has to be decided which spatial unit an empirical project will be based on. For Germany, several options are available:

- Rasters with environmental and socio-economical data in grid cells
- Administrative territorial units (municipalities = "Gemeinden", counties= "Landkreise", states = "Bundesländer")
- Zip-Codes ("Postleitzahlen", PLZ)[88]
- Customized spatial definitions based on unifying characteristics (such as labor market clusters)

The information contained in these rasters can be transferred onto other spatial entities by aggregating the information by overlapping, intersecting or joining the raster cells with spatial pbservation units at different levels of precision. Since the available rasters offer a higher precision than most administrative units, they are used for the empirical project in Chapter 1. German zip codes typically offer a higher precision than the county-level and overlap non-trivially with German municipalities especially in rural areas. Since government agencies, institutions and firms can possess own zip-codes, not all zip-codes are linked to a spatial entity. Shapefiles are often limited to

[88] There were 8412 zip-codes representing actual geographical territories in 2008 and according to correspondence tables there are 8168 left in 2019. Several websites provide recent correspondence tables and shapefiles for German zip-codes (e.g. https://www.suche-postleitzahl.org/downloads).

zip-codes with spatial extent, so restricting the analysis to such zip-codes is a reasonable approach that was also used in Chapter 2.

The optimal choice of spatial units is sometimes dictated by the availability of important data but also depends on the research question. Hsiang et al. (2017) emphasize that the choice of spatial units and thus the aggregation level may alter observed relationships. Their empirical findings imply that richer households typically live in more polluted cities but will sort into the cleaner areas within such cities. Aggregating data and interpreting the relationships at only one level of aggregation then results in an incomplete or even false interpretation of the evidence[89].

The research project in Chapter 1 aggregates data at the county level due to the availability of trade data but benefits from the multitude of socio-economic control variables available at this level and the disaggregated nature of counties in Germany with $865.8km^2$ per county and 413 counties in 2008. While counties and the zip-codes may exhibit meaningful distributional patterns within spatial entities, they both offer a high level of precision and counties or municipalities have the additional advantage that many socio-economic control variables are readily available for these official territorial units (e.g. via INKAR as described in Appendix A.1.10 and Appendix A.2.1), while socio-economic variables at the more disaggregated zip-code level may be costly to obtain. There is ample cross-sectional variation across German counties allowing for reasonable identification of economic effects and zip-codes overlap these territorial units in a non-trivial manner but can provide a useful spatial structure for research questions requiring a higher resolution.

Working with gridded data at a superior precision level (e.g. OI or GRETA rasters) allows for an aggregation of these raster values at any level of spatial segmentation, so they can be paired with data from both administrative units and zip-codes.

[89] In Hsiang et al. (2017), plotting NO_2 pollution exposure against the average income of US households per Metropolitan Statistical Area (MSA) reveals a positive relationship between wealth and pollution exposure. On the other hand, plotting pollution against household income of individual households in the United States reveals a U-shaped relationship, while plotting pollution against household income within individual MSAs reveals a negative relationship. This is a direct outcome of the sorting patterns within metropolitan areas and highlights the importance of aggregation levels for research design.

3.3.1.2 Time Frame and Territorial Reforms

The scope of the research question and the availability of data inform the choice of an adequate time period of observation. However, researchers have to decide on the reference year of the analysis and should take the territorial definitions of spatial units into account, which can change over a given time frame. For the analysis in Chapter 1, using the years 1998 to 2008 ensures comparability with Dauth et al. (2014). With 2008 being the final period of this analysis, the territorial status of German counties on December 31st, 2008, is chosen to define the spatial parameters of the cross-section. Coincidentally, the same territorial status is a chosen for the analysis in Chapter 2 as these territorial definitions were in place when the E-PRTR data release occurred in 2009. The analysis of more recent policy interventions in Germany requires the inclusion of more recent data and encourages the construction of a database pertaining to a recent territorial status[90]).

Since 1998, significant structural changes at the German county level have taken place in Lower Saxony (2001 & 2016), Saxony-Anhalt (2007), Saxony (2008), North Rhine-Westphalia (2009) and Mecklenburg-Vorpommern (2011). Especially the mergers and splits across Eastern German counties make a bidirectional and unambiguous linkage challenging. Most of the publicly available datasets use the most recent territorial definitions and historical data is automatically recalculated to fit this definition, so reported values have to be reallocated to previous county definitions with the aid of a correspondence table based on relative size or population[91]. In order to reallocate data from contemporaneous county definitions to 2008 definitions, relative weights based on the number of registered employees per county in the year 2008 have been

[90]In order to ensure consistency between datasets, the territorial status of German counties as of 2012-2014 has been used in research projects on Low-Emission Zones (LEZs) such as Klauber et al. (2020). The merger of the counties "Osterode am Harz" and "Göttingen" in 2016 resulted in a territorial status with 401 counties and represents the current status quo.

[91]The file "Referenzschlüssel Kreise von 1990 bis 2014.xlsx" has been obtained from the German Federal Office for Building and Regional Planning ("Bundesamt für Bauwesen und Raumordnung", BBR) and provides correspondence tables across all territorial reforms that allow for a reallocation of variables according to relative population, area or employment ("sozialvers.pflichtig Beschäftigte am Arbeitsort am 30.6.2008 in 1000").

used in Chapter 1 following official guidelines.

I suggest using the most recent reference year possible as German counties have generally been merged together over the course of the past three decades reducing the number of counties over time. Choosing a recent year of reference means that little official data has to be reallocated and that historical data can be reassigned to recent territorial definitions using a simple correspondence table. If it is necessary to choose an earlier reference year, the following operations assign appropriate values to counties that have been restructured (or vice versa). Given a county i only exists until the year T, this entity inherits relative or absolute variables from the more recent county definitions j overlapping i by using the official employment figures from intersection areas $(j \cap i)$ in the year T. Instead of employment figures, other county-level characteristics can be considered if they are more relevant for the respective variable. The overlapping counties j are contained in $Overlap(i) = \{k \mid k \cap i \neq \emptyset\}$ such that

$$AggregatedAbsoluteVariable_{it} = \sum_{j \epsilon Overlap(i)} \left[\frac{Employment^T_{j \cap i} \cdot AbsoluteVariable_{jt}}{Employment^T_j} \right] \tag{3.1}$$

$$AveragedRelativeVariable_{it} = \sum_{j \epsilon Overlap(i)} \left[\frac{Employment^T_{j \cap i} \cdot RelativeVariable_{jt}}{\sum_{j \epsilon Overlap(i)} Employment^T_{j \cap i}} \right] \tag{3.2}$$

3.3.1.3 Processing of Territorial Definition Files

Official shapefiles plotting the borders of territorial entities in Germany can be obtained from the German Federal Agency for Cartography and Geodetics ("Bundesamt für Kartographie und Geodäsie", BKG)[92]. Some of the databases discussed in this chapter report unprojected coordinates (e.g. point source

[92] The current definition files can be downloaded from the "Geodatenzentrum" website (https://gdz.bkg.bund.de/index.php/default/open-data.html) but files containing historical definitions have to be ordered individually and may be subject to charges. I have been able to obtain a large collection of historical definition files from the now defunct archive (http://www.geodatenzentrum.de/auftrag1/archiv/vektor/vg250_ebenen/2008/) and use WGS84 projection layers with county polygons throughout Chapter 1 (e.g. "vg250_2008-12-31.geo84.shape.ebenen.zip").

locations from E-PRTR or UBA measuring stations) but most vector layers are already provided in a projected format by UBA and BKG. The usually available Universal Transverse Mercator projection (e.g. ETRS89 / UTM32N - EPSG:3044) based on the WGS84 ("World Geodetic System 1984") standard yields an optimized and undistorted image of central Europe and can easily be combined with unprojected source files using GIS software. Geocoded datasets vary in resolution, which can make creating correct intercepts and overlaps challenging. The zip-code definition files described in Chapter 3.3.1.1 for example are provided at a different level of precision than the county definition files provided by the BKG. Borders that should align in reality therefore create tiny pockets of unwanted overlaps and intersections that need to be accounted for when performing subsequent actions by either merging polygons or specifying a margin of error within the initial GIS procedure.

24 of the 413 counties in the territorial status files for 2008 contain adjacent water bodies with structures or off-shore islands. These areas appear as separate polygons and have been merged with the respective mainland areas for the analysis in Chapter 1 before the computation of perimeters, surface areas and pollution concentration averages[93]. While the BBR correspondence files discussed in Chapter 3.3.1.2 provide sufficient statistics for transforming data between territorial statuses from different years, auxiliary datasets may not always account for restructuring processes in a timely and correct manner. In this case, manual corrections according to the formulas in Chapter 3.3.1.2 or standard GIS operations have to be performed to synchronize datasets[94].

[93]The affected counties are Flensburg, Kiel, Dithmarschen, Nordfriesland, Ostholstein, Pinneberg, Plön, Rendsburg-Eckernförde, Schleswig-Flensburg, Emden, Wilhelmshaven, Aurich, Friesland, Leer (2 water bodies), Wittmund, Bremen, Bremerhaven, Greifswald, Rostock, Stralsund, Nordvorpommern, Ostvorpommern, Rügen and Uecker-Radow. An attribute field indicates whether a feature represents the land-based portion of a county (GF=4) or a water body containing construction (GF=2). For the analysis in Chapter 1, water bodies with construction are merged with the overall county area as infrastructure contained within these areas may be related to industrial operations and measured emissions may be indicative of manufacturing production patterns.

[94]This includes the mergers of "Aachen" with the surrounding county into the region "Stadtregion Aachen" in 2009 and of "Osterode im Harz" with "Göttingen" in 2016.

3.3.2 Raster Data Aggregation

3.3.2.1 Raster Data Aggregation: Methodology

Average pollution concentration measures for a county i or other territorial entities can be computed by taking the unweighted average of all overlapping raster cells j contained in $Overlap(i) = \{j \mid j \cap i \neq \emptyset\}$. This simplified methodology can be useful when the precision of the raster or the spatial extent of the area under study create computational constraint. It is more accurate, however, to take the weighted average of the overlapping fractions of these raster cells with $j \epsilon Overlap(i)$ and to use the respective overlapping areas ($Area_{j \cap i}$) as weights.

$$PollutantConcentration_{it}^{Unweighted,Y} = \frac{\sum_{j \epsilon Overlap(i)} \left[PollutionConcentration_{jt}^{Y}\right]}{\sum_{j} 1[j \cap i \neq \emptyset]} \tag{3.3}$$

$$PollutantConcentration_{it}^{Weighted,Y} = \frac{\sum_{j \epsilon Overlap(i)} \left[PollutionConcentration_{jt}^{Y} \cdot Area_{j \cap i}\right]}{Area_{i}} \tag{3.4}$$

The first measure ($Unweighted$) is obtained by performing a "spatial join" operation on the pollution concentration raster for pollutant Y at the level of the outcome territorial unit i and by selecting "means" as desired outcome variable. The latter measure ($Weighted$) is obtained by intersecting the raster grid with the shapefile of the territorial county definitions in order to obtain segmented raster cells and by then performing a collapse of the gridded pollution concentrations onto the county level i with the areas of segmented raster cells chosen as weights for the weighted sum. The following figures depict these procedures for the city of Rostock in Mecklenburg-Vorpommern by highlighting the raster grid segments j which intersect with the county territory.

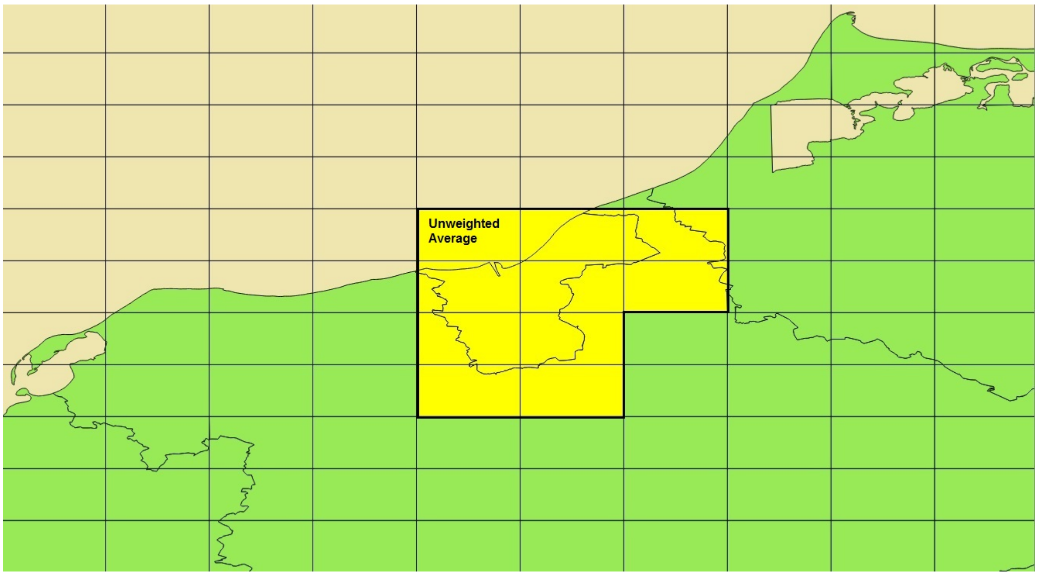

Figure 3.10: Aggregation of raster data via unweighted overlaps

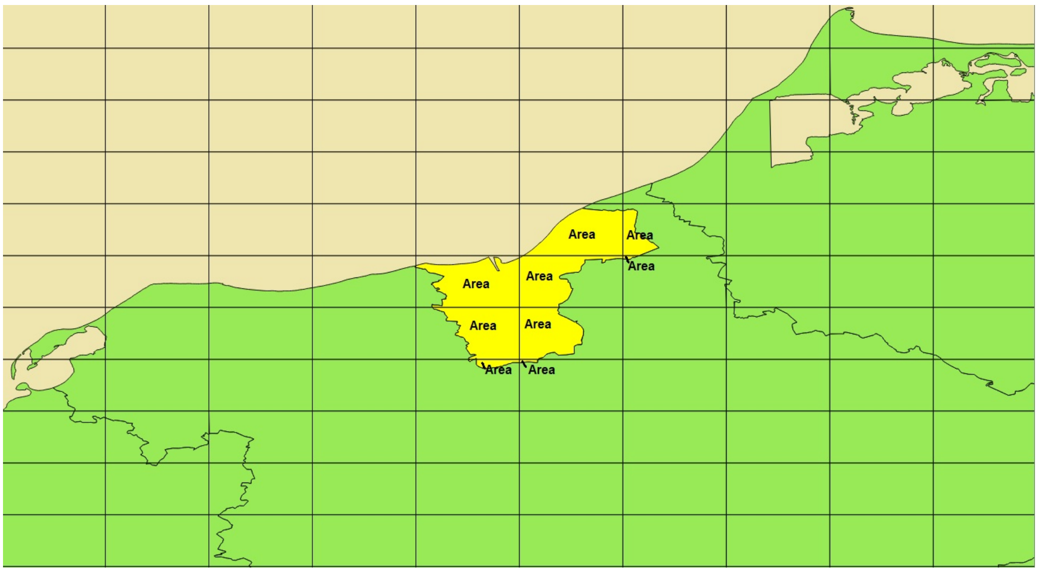

Figure 3.11: Aggregation of raster data via weighted overlaps

A visual illustration of the aggregation of a raster onto a target shapefile performed for the empirical analysis in Chapter 1 can be found in Appendix A.3.3. Such thematic maps that plot summary statistics across geographical regions through shading in proportion to normalized variable values (e.g. densities or percentiles) are called "choropleth" maps.

When finely gridded data is available (such as the $1 \times 1 km^2$ grids in GRETA or DWD rasters), the additional gain in precision achieved by using weighted overlaps vanishes as the finely gridded cells circumscribe the territorial entities with sufficient precision. It should be noted that individual grid cells then contribute to several averages. High spatial correlation makes this an even smaller issue but calls for the use of spatial autocorrelation methods. The above county intersected with a $1 \times 1 km^2$ grid of yearly DWD weather averages demonstrates the feasibility of this computationally less intensive approach, which is suitable for grids with high precision relative to the size of the target areas[95].

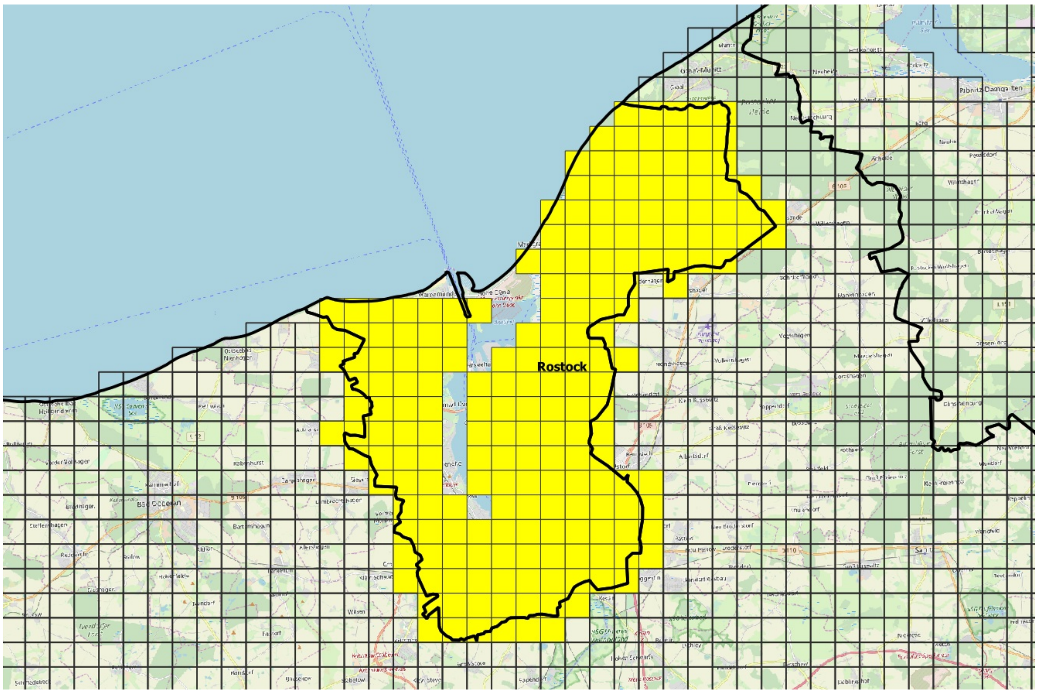

Figure 3.12: Aggregation of fine grid raster data (DWD yearly averages)

[95] Background map provided by openstreetmap.org (Contributors) (2019).

3.3.2.2 Raster Data Aggregation: Comparison

The pollution concentration differences between the year 2008 and 1998 in Chapter 1 are currently based on a non-weighted overlap of the $7 \times 8km^2$ grid onto the 2008 definition of German county borders. I have also performed a weighted overlap that takes the exact overlapping area of each grid cell into account to compute the yearly county-wide averages. While this is an improvement in precision, the difference in resulting averages is minor even for the coarse $7 \times 8km^2$ grid, which is not surprising given the construction of the grid data and the close relationship between neighbouring grid cells. The yearly averages per county computed by these two methods are highly correlated and do not yield meaningful deviations in the resulting dependent variables ($\Delta_{1998 \rightarrow 2008} PollutionConcentration^Y$):

Table 3.6: Correlation Matrix of Changes in Pollution Concentrations

		Unweighted Overlap ($7 \times 8km^2$)			Weighted Overlap ($7 \times 8km^2$)		
		NO_2	$PM10$	SO_2	NO_2	$PM10$	SO_2
Unweighted	NO_2	1	-	-	-	-	-
Overlap	$PM10$	0.3222	1	-	-	-	-
($7 \times 8km^2$)	SO_2	0.1812	0.0087	1	-	-	-
Weighted	NO_2	0.9703	0.2975	0.1657	1	-	-
Overlap	$PM10$	0.3062	0.9916	0.0118	0.2829	1	-
($7 \times 8km^2$)	SO_2	0.1907	0.0003	0.9967	0.1789	0.044	1

Note: Correlations between Changes in Pollution Concentration (1998-2008) at the county level. All coefficients based on 413 long-difference pairs at the county level.

As can be seen from Table 3.6, there exist different but positively correlated patterns in the cross-sectional development of pollutant concentrations but almost no deviation due to the spatial overlap. While it is computationally feasible to aggregate gridded data onto other territorial definitions using the exact intercepting areas as weights[96], the simplified method employed in Chapter 1 represents a useful and innocuous approximation.

[96] The comparative analysis of different raster products in Chapter 3.4.1 relies entirely on county averages from weighted overlaps.

3.4 Additional Data Analysis

3.4.1 Point Sources vs. Grid Averages

3.4.1.1 Correlations and Descriptive Statistics

In order to validate the usage of OI raster products in Chapter 1 and other projects, I compare the daily pollution measurements from UBA stations used in Holub (2015) and Klauber et al. (2020) with annualized county averages from the raster grids presented in Chapter 3.2. This comparison confirms that the OI raster used in Chapter 1 mirrors station-level data from various station types sufficiently well at the given aggregation level in all counties with actual station measurements. The different raster products fill spatial gaps with a mix of top-down emission field estimates and station measurement regimes as discussed in Chapter 3.2. The use of different underlying emission estimates becomes evident when comparing the averages from the $7 \times 8km^2$ OI raster based on conventional emission fields (Chapter 3.2.2) to the averages from the $2 \times 2km^2$ OI raster based on GRETA emission fields (Chapter 3.2.4). The correlation coefficients imply that the two datasets are almost interchangeable in most areas but exhibit differentiating patterns in areas with little station coverage, which cannot be explained by the grid cell resolutions alone but are likely due to the divergences in emission field generation.

I also aggregate station measurements at the county-level. Daily pollution concentration means are averaged over the entire year for each individual station. I then collapse yearly station averages onto the county-level by year and type of station ("background", "traffic", "industrial") and generate an additional average across "all" stations. Stations are weighted equally despite varying measurement frequency, which calls for the implementation of better controls for panel attrition and reporting frequency[97]. County-level averages rely on a time-varying number of stations, so I keep track of the number of

[97] These averages rely on a simple algorithm and are only used for comparative purposes within Chapter 3.4.1.

stations contributing to annual averages. The annual county-level averages based on station data are compared to annual county-level averages derived from the two immission raster products:

- $7 \times 8km^2$ OI raster
- $2 \times 2km^2$ OI raster based on emission fields from the GRETA tool

They are aggregated at the county-level via weighted overlaps as described in Chapter 3.3.2.1. I perform the comparison on the basis of 2014 territorial definitions (with 402 counties) since no auxiliary information is needed. Pollution concentration averages are measured in $\mu g/m^3$ and compared by means of simple unweighted Pearson's correlation coefficients. I report pairwise correlation coefficients computed across all county-year pairs for which both averages are available. The correlation coefficients between station averages and raster product averages are therefore always limited to the county-year pairs with at least one station report.

The availability of data is presented in Table 3.7. It is possible to obtain measurements from stations before 2000 from the UBA but environmental data availability deteriorates for earlier time periods. It should be noted that individual county-year pairs for a given station type contain missing values if no station report exists for this observation, whereas the raster county averages yield perfectly balanced panels.

Table 3.7: Availability of county-level pollution averages

	$7 \times 8km^2$ (balanced panel)	$2 \times 2km^2$ (balanced panel)	Station Averages (unbalanced panel)
NO_2	1995, 2000-2014	2004-2016	2000-2014
$PM10$	1995, 2000-2014	2004-2016	2000-2014
$PM2.5$	-	2009-2016	2000-2014
SO_2	1995, 2000-2014	2004-2016	2000-2014

In Table 3.8, I first compare the two immission raster products. The number of observation pairs available for each pairwise coefficient is given in parentheses. The correlation coefficients between the two rasters are usually based on $402 \cdot 11 = 4422$ county-year observation pairs because the rasters overlap during the time period from 2004-2014.

Table 3.8: Correlation Matrices of county-year averages (Rasters)

	Pairwise Correlation Coefficients (Unbalanced, 2000-2016)					
	NO_2 ($7 \times 8km^2$)	NO_2 ($2 \times 2km^2$)	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	SO_2 ($7 \times 8km^2$)	SO_2 ($2 \times 2km^2$)
NO_2 ($7 \times 8km^2$)	1 (6432)	-	-	-	-	-
NO_2 ($2 \times 2km^2$)	0.8977 (4422)	1 (5226)	-	-	-	-
$PM10$ ($7 \times 8km^2$)	0.6351 (6432)	0.5159 (4422)	1 (6432)	-	-	-
$PM10$ ($2 \times 2km^2$)	0.5709 (4422)	0.5584 (5226)	0.8771 (4422)	1 (5226)	-	-
SO_2 ($7 \times 8km^2$)	0.5583 (6432)	0.5399 (4422)	0.6652 (6432)	0.5468 (4422)	1 (6432)	-
SO_2 ($2 \times 2km^2$)	0.7327 (4422)	0.6218 (5226)	0.61 (4422)	0.6341 (5226)	0.8986 (4422)	1 (5226)

Note: Pairwise correlations between county-year pollution averages (2000-2016). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps.

	Pairwise Correlation Coefficients (Balanced, counties with continuous background station coverage only, 2004-2014)					
	NO_2 ($7 \times 8km^2$)	NO_2 ($2 \times 2km^2$)	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	SO_2 ($7 \times 8km^2$)	SO_2 ($2 \times 2km^2$)
NO_2 ($7 \times 8km^2$)	1 1848	-	-	-	-	-
NO_2 ($2 \times 2km^2$)	0.9308 (1848)	1 1848	-	-	-	-
$PM10$ ($7 \times 8km^2$)	0.6012 (1650)	0.5464 (1650)	1 (1727)	-	-	-
$PM10$ ($2 \times 2km^2$)	0.5192 (1650)	0.511 (1650)	0.9083 (1727)	1 (1727)	-	-
SO_2 ($7 \times 8km^2$)	0.597 (792)	0.4921 (792)	0.6006 (726)	0.5897 (726)	1 (858)	-
SO_2 ($2 \times 2km^2$)	0.615 (792)	0.5499 (792)	0.6625 (726)	0.6633 (726)	0.9144 (858)	1 (858)

Note: Pairwise correlations between county-year pollution averages (2004-2014). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps. Only counties with full background station coverage over the entire time period (2004-2014).

The coefficients demonstrate a highly positive relationship that is increased even further when restricting the analysis to counties with a full set of 11 annual averages from background stations in the lower panel. First of all, this reduces the number of available counties since only a subset of counties fulfills the requirement of continuous background station coverage. The fact that correlations are higher in the reduced sample implies that the rasters are more alike in counties with background station measurements, while the underlying emission fields dominate immission concentrations in counties without continuous coverage driving the raster values apart. This also implies that chaining the two products together in order to obtain an extended time series is risky as their patterns deviate systematically in such regions and Stern (2015) finds national totals to deviate by up to 25%.

Table 3.9 explores the relationship between raster averages and averages computed on the basis of the respective station types. The category "all stations" contains unweighted averages over all station types reporting pollutant concentrations within a county. In the upper panel, all county-year pairs with station values are taken into account for the resulting correlation coefficients, while the lower panel restricts the correlation coefficients to counties with continuous coverage from the respective station type over the entire observation period.

Overall, the positive coefficients in each column demonstrate that gridded products and station measurements document similar patterns. It is striking that measurements from background stations best reflect the patterns contained in both raster products with respect to both NO_2 and $PM10$ immission concentrations. This is a direct consequence of the fact that background measurements are used for the OI interpolation and readjustments in the vicinity of stations.

The lower panel proves that restricting the analysis to counties with continuous station reports severely limits the number of available observations. While background station coverage and the respective correlation coefficients remain decent, observations from traffic and industrial stations appear far more spotty. This implies that using these station types as basis for an empirical analysis over a longer time horizon is seldom feasible. OI rasters and background stations provide researchers with a more consistent panel of observations in most scenarios.

Table 3.9: Correlation Matrices of county-year averages (NO_2, $PM10$, SO_2)

	Pairwise Correlation Coefficients (Unbalanced, 2000-2016)					
	NO_2 ($7 \times 8km^2$)	NO_2 ($2 \times 2km^2$)	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	SO_2 ($7 \times 8km^2$)	SO_2 ($2 \times 2km^2$)
NO_2 / $PM10$ / SO_2	1	-	1	-	1	-
($7 \times 8km^2$)	(6432)		(6432)		(6432)	
NO_2 / $PM10$ / SO_2	0.8977	1	0.8771	1	0.8986	1
($2 \times 2km^2$)	(4422)	(5226)	(4422)	(5226)	(4422)	(5226)
NO_2 / $PM10$ / SO_2	0.6255	0.6693	0.6822	0.6791	0.8267	0.7788
(All Stations)	(3616)	(2603)	(3427)	(2557)	(2459)	(1538)
NO_2 / $PM10$ / SO_2	0.7937	0.8361	0.7412	0.7739	0.7856	0.7527
(Background Stations)	(2963)	(2101)	(2781)	(2061)	(2047)	(1264)
NO_2 / $PM10$ / SO_2	0.8553	0.8606	0.688	0.6795	0.9124	0.8313
(Industrial Stations)	(301)	(214)	(391)	(307)	(257)	(167)
NO_2 / $PM10$ / SO_2	0.4519	0.4132	0.5823	0.4987	0.6919	0.7438
(Traffic Stations)	(1435)	(1105)	(1433)	(1160)	(469)	(255)

Note: Pairwise correlations between county-year pollution averages (2004-2014). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps.

	Pairwise Correlation Coefficients (Balanced, counties with continuous coverage only, 2004-2014)					
	NO_2 ($7 \times 8km^2$)	NO_2 ($2 \times 2km^2$)	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	SO_2 ($7 \times 8km^2$)	SO_2 ($2 \times 2km^2$)
NO_2 / $PM10$ / SO_2	1	-	1	-	1	-
($7 \times 8km^2$)	(4422)		(4422)		(4422)	
NO_2 / $PM10$ / SO_2	0.8977	1	0.8771	1	0.8986	1
($2 \times 2km^2$)	(4422)	(4422)	(4422)	(4422)	(4422)	(4422)
NO_2 / $PM10$ / SO_2	0.6808	0.7368	0.7548	0.7262	0.871	0.8032
(All Stations)	(2288)	(2288)	(2178)	(2178)	(1111)	(1111)
NO_2 / $PM10$ / SO_2	0.7997	0.8409	0.8295	0.7891	0.8041	0.7604
(Background Stations)	(1848)	(1848)	(1727)	(1727)	(858)	(858)
NO_2 / $PM10$ / SO_2	0.8991	0.9095	0.6992	0.6931	0.959	0.8676
(Industrial Stations)	(132)	(132)	(176)	(176)	(110)	(110)
NO_2 / $PM10$ / SO_2	0.5988	0.5518	0.6915	0.6515	0.6938	0.783
(Traffic Stations)	(770)	(770)	(737)	(737)	(165)	(165)

Note: Pairwise correlations between county-year pollution averages (2004-2014). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps. Station averages based on counties with full coverage by the respective station type over the entire time period (2004-2014).

Table 3.10 sheds light on the availability and quality of $PM2.5$ measurements. The main finding is that both the $2 \times 2km^2$ and $7 \times 8km^2$ rasters approximate $PM2.5$ raster values well-enough through their $PM10$ values during the period of mutual availability to justify using these concentrations as proxy for $PM2.5$ concentrations. There is also a positive correlation between both rasters and $PM2.5$ values at the station-level but the station averages are severely hampered by the limited availability of consistent measurements as demonstrated by the lower panel requiring continuous coverage.

Out of $402 \cdot 6 = 2412$ potential county-year observations, only $73 \cdot 6 = 438$ pairs remain, which implies that only 73 counties exhibit a complete station history of $PM2.5$ measurements over the given time period (2009-2014). This reinforces the argument that working with German $PM2.5$ data derived from the conventional sources described in Chapter 3.2.5 is still difficult.

Table 3.10: Correlation Matrices of county-year averages (PM2.5)

	Pairwise Correlation Coefficients (Unbalanced, 2009-2014)				
	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	$PM2.5$ ($2 \times 2km^2$)	$PM2.5$ (All Stations)	$PM10$ (All Stations)
$PM10$	1	-	-	-	-
($7 \times 8km^2$)	(2412)				
$PM10$	0.8945	1	-	-	-
($2 \times 2km^2$)	(2412)	(2412)			
$PM2.5$	0.8045	0.8101	1	-	-
($2 \times 2km^2$)	(2412)	(2412)	(2412)		
$PM2.5$	0.717	0.666	0.7444	1	-
(All Stations)	(646)	(646)	(646)	(646)	
$PM10$	0.7245	0.6712	0.6068	0.7718	1
(All Stations)	(1387)	(1387)	(1387)	(612)	(1387)

Note: Pairwise correlations between county-year pollution averages (2009-2014). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps.

	Pairwise Correlation Coefficients (Balanced, counties with continuous all station coverage only, 2009-2014)				
	$PM10$ ($7 \times 8km^2$)	$PM10$ ($2 \times 2km^2$)	$PM2.5$ ($2 \times 2km^2$)	$PM2.5$ (All Stations)	$PM10$ (All Stations)
$PM10$	1	-	-	-	-
($7 \times 8km^2$)	(2412)				
$PM10$	0.8945	1	-	-	-
($2 \times 2km^2$)	(2412)	(2412)			
$PM2.5$	0.8045	0.8101	1	-	-
($2 \times 2km^2$)	(2412)	(2412)	(2412)		
$PM2.5$	0.727	0.6878	0.8056	1	-
(All Stations)	(438)	(438)	(438)	(438)	
$PM10$	0.7463	0.7136	0.6207	0.7806	1
(All Stations)	(1188)	(1188)	(1188)	(396)	(1188)

Note: Pairwise correlations between county-year pollution averages (2009-2014). Available pairs for each coefficient in parentheses. Grid averages are from weighted overlaps. Station averages based on counties with full coverage by the respective station type over the entire time period (2009-2014).

3.4.1.2 Maps of Coverage

I also plot the county-year averages stemming from both the $7 \times 8km^2$ OI raster and background stations in a series of maps covering the years 2000, 2005, 2010 and 2014. These maps are shaded according to the quantiles based on immission concentration averages reported in $\mu g/m^3$, whereas counties without a single background station measurement in the given year are blackened out. The leftmost panel contains quantiles from all weighted OI raster averages, while the rightmost panel contains quantiles resulting from the computable station averages. The panel in the center contains weighted OI raster averages with quantiles based only on the counties with station measurements for comparative purposes.

It can be seen that the maps for NO_2 and $PM10$ in Figure 3.13 and Figure 3.14 capture the station-level patterns very well, even when forced onto the same reduced county sample. The rightmost panel for SO_2, however, reinforces the argument that raster values for this pollutant share the weakest statistical foundation.

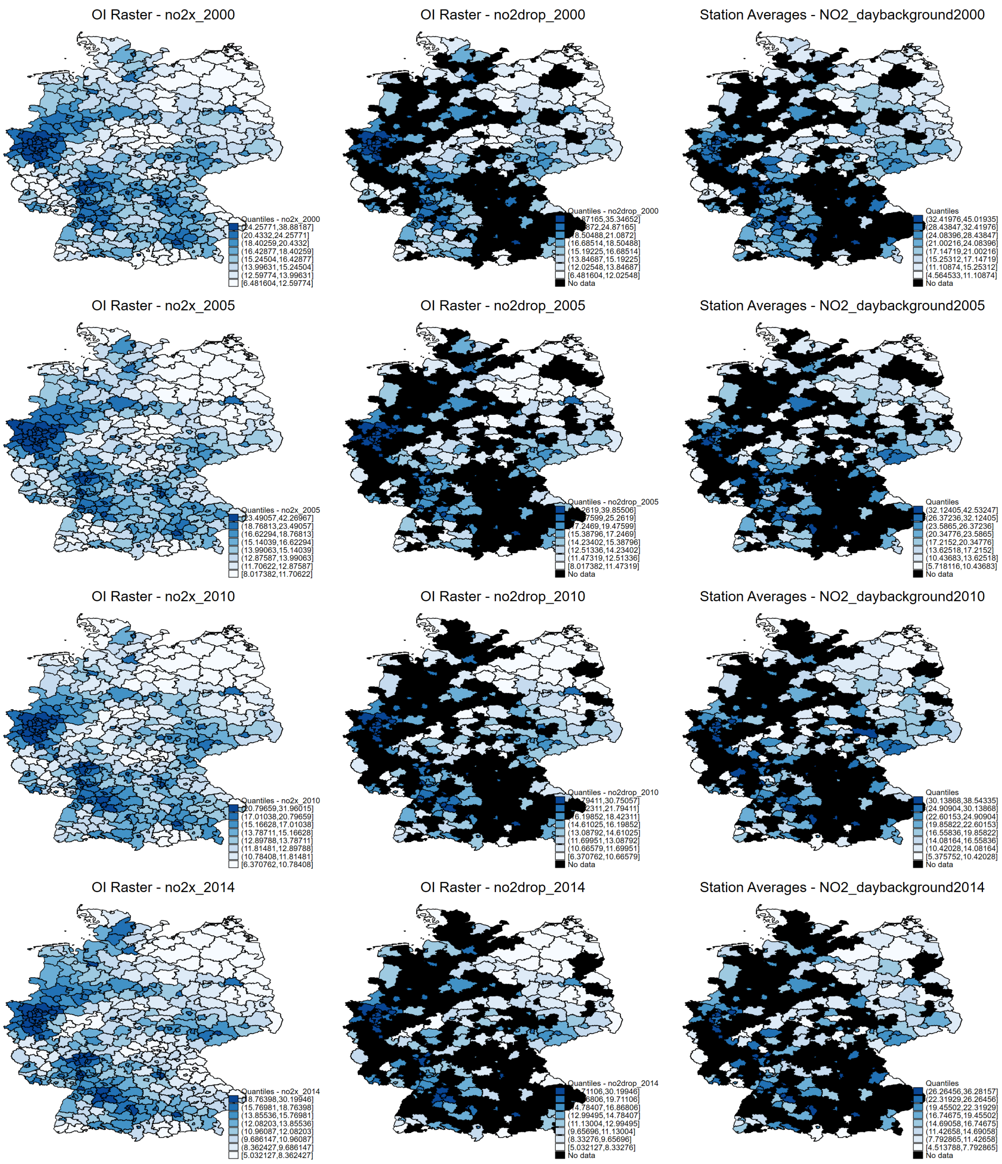

Figure 3.13: NO_2 County-Year Pollution Averages (2000, 2005, 2010, 2014)

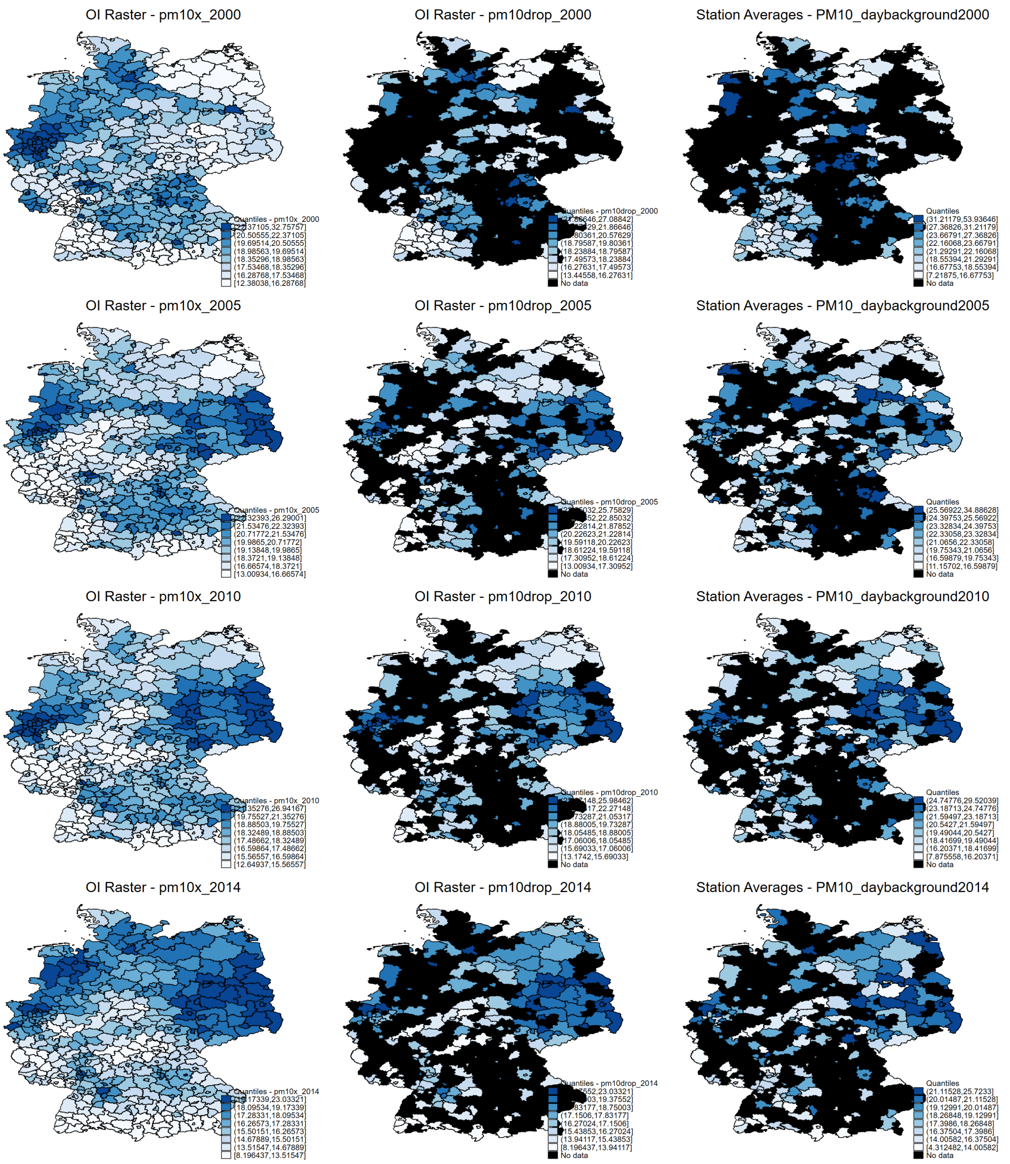

Figure 3.14: $PM10$ County-Year Pollution Averages (2000, 2005, 2010, 2014)

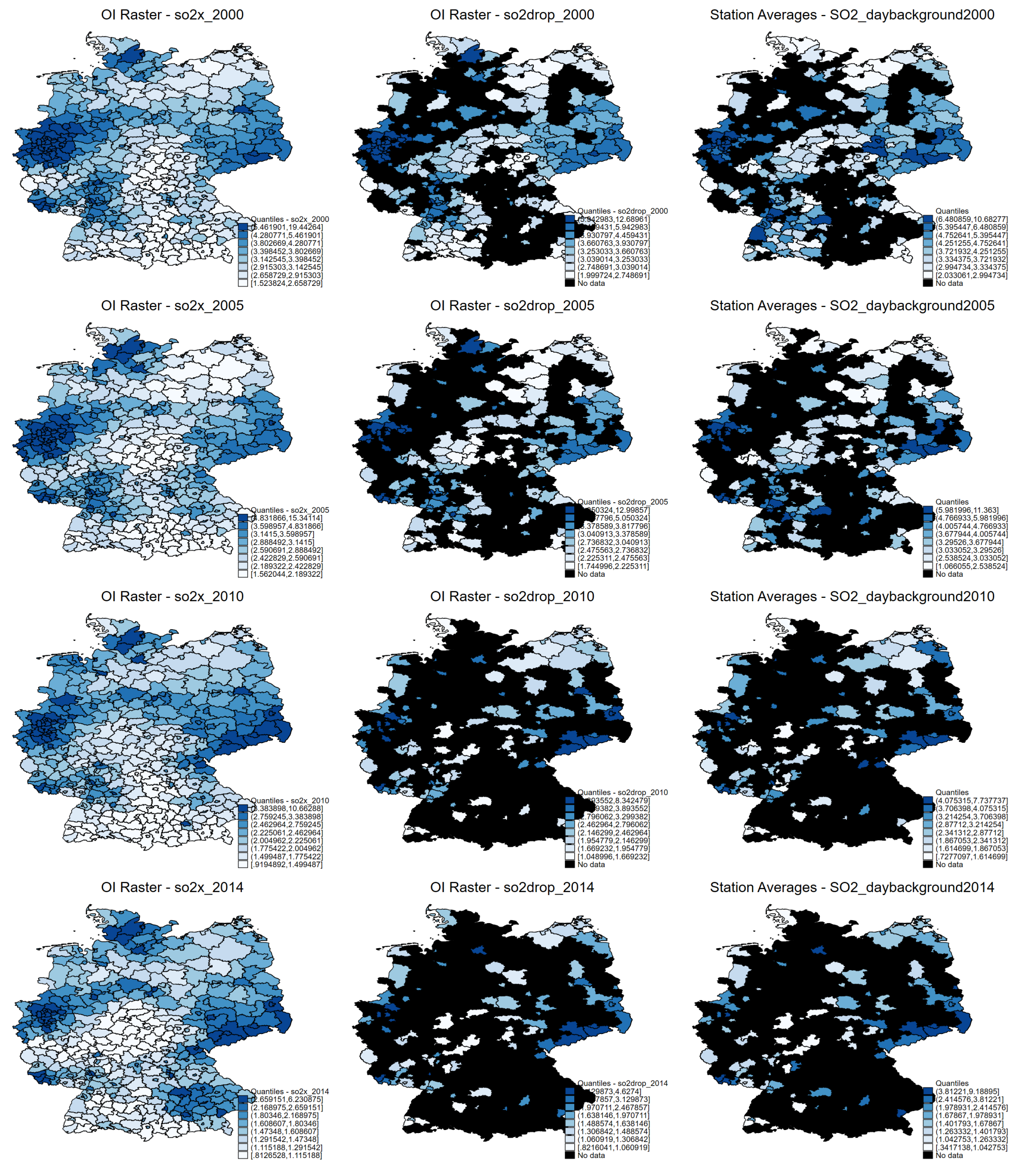

Figure 3.15: SO_2 County-Year Pollution Averages (2000, 2005, 2010, 2014)

Overall, the columns in Table 3.9 along with the patterns in Figure 3.13 and Figure 3.14 confirm that the $7 \times 8km^2$ OI immission rasters used in Chapter 1 are at least a valid approximation of background station measurements and at best a significant improvement over any interpolation attempts based on station data alone. Consequently, the rightmost panels demonstrate the enormous extent of interpolation necessary for attaining Germany-wide coverage.

The ability of OI rasters to fill these gaps with the aid of superior emission fields derived from high-quality administrative data makes them a rational choice for research projects relying on long-run cross-sectional variation. I conclude that using them within the framework of my analysis, which relates long-term developments in pollution averages to long-term developments in trade exposure, is a convenient and accurate approach for obtaining the required pollution exposure changes.

3.4.2 Industry-level Emissions and International Trade Flows

3.4.2.1 Preparation of E-PRTR Data

In an attempt to evaluate the positive aggregate effects of trade exposure on emission concentrations demonstrated in Chapter 1 at a less aggregated level, I construct a dataset based on the facility emissions contained in the E-PRTR register described in Chapter 3.2.6. Analyzing patterns at the industry-level can shed light on potential channels responsible for aggregate reductions and on which industry sectors drive aggregate effects.

I therefore combine trade flow data at the industry-level with changes in total E-PRTR facility reports between 2001 and 2008, which represent the waves closest to the original time window. Emission reports are restricted to the manufacturing sectors used in the main analysis and paired with sectoral trade flows in order to conduct a graphical analysis of the relationship between trade exposure and emission output at the micro-level. This analysis provides initial evidence regarding the industries driving pollution emission reductions in response to trade shocks.

The limited sample of facility reports precludes a detailed econometric analysis at the facility-level. Table 3.11 contains descriptives demonstrating these limitations. With at most 241 reports across the entirety of Germany, this also leaves very little room for meaningful variation at the county-level. Consequently, I aggregate annual figures at the NACE1.1 industry-level and pair these with trade flows by employing methodologies presented in DFS. For the sake of comparability, the facility reports and trade flows are limited to those manufacturing sectors corresponding to the WZ93 codes defined in Chapter 1: $WZ93 \in [150, ..., 369] \setminus [231, 232, 233]$. This is done via a number of correspondence tables linking NACE1.1, NACE2.0, SITC (rev. 3/4) and WZ93 codes[98].

[98]Refer to Appendix A.1.6 and Appendix A.3.1 for details.

Table 3.11: Summary table of E-PRTR facility reports: Manufacturing

Year 2001 (EPER)	Reports	Mean (kg)	STD (kg)	Min (kg)	Max (kg)
NO_X	241	624161.83	55806.15	101000	7670000
$PM10$	63	206998.41	48207.14	50500	2300000
SO_X	134	785940.30	121385.25	153000	11800000
Year 2008 (E-PRTR)	Reports	Mean (kg)	STD (kg)	Min (kg)	Max (kg)
NO_X	233	488008.58	45451.58	100000	6630000
$PM10$	32	266387.50	339884.54	51100	1440000
SO_X	111	839396.40	141042.83	154000	12700000

Note: Table contains descriptive statistics for the reduced manufacturing sample.

Reporting requirements have changed between EPER and E-PRTR legislation, so Appendix A.3.2 provides a review of these changes in order to validate the strategy of appending EPER to E-PRTR data within the framework of this analysis.

3.4.2.2 Graphical Analysis using E-PRTR Data

For this descriptive industry-level analysis, absolute differences in trade volumes per industry are paired with aggregate differences in reported EPER/E-PRTR emissions between 2001 and 2008. The values have been collapsed onto the 2-digit NACE1.1 level in order to obtain a sufficiently dense dataset of 22 industry observations when constructing relative changes. The resulting tuples of percentage changes $\left(\frac{\Delta_{2001\rightarrow 2008} PollutionReleases^k \cdot 100\%}{PollutionReleases^k_{2001}}, \frac{\Delta_{1998\rightarrow 2008} TradeVolume^k \cdot 100\%}{TradeVolume^k_{1998}}\right)$ for each industry k have been compiled in scatter plots to allow for a graphical analysis.

This approach isolates and reveals those industry sectors that drive changes in emission exposure. A negative relationship in Figure 3.16 or Figure 3.17 indicates that trade volume increases within affected industries are associated with emission reductions and therefore positive environmental effects. The linear fits (black lines) are simple OLS regression over tuples in the scatter plot and the estimated equations are reported containing the slope and heteroskedasticity robust standard errors. These regressions do not take control variables, the relative size of industries or the relative size of trade flows into account and suffer from high standard errors due to the small sample size. Whenever industry categories lack reports in only one of the reference years, I approximate the emission quantities in that year by multiplying the number of reporting facilities in the other year by the respective reporting thresholds. This results in conservative estimates for the absolute changes in emissions, as they are bounded by the reporting thresholds[99].

Despite the simplicity of this approach, Figure 3.16 yields a distinctly negative slope for NO_X emissions with respect to changes in import exposure, whereas the relationship in Figure 3.17 is not statistically significant. There is also a negative relationship between E-PRTR reports for $PM10$ and trade exposure in both Figures, which does not reach conventional levels of significance, however. The graphs still hint towards the existence of beneficial environmental effects along the intensive margin driven by manufacturing sectors such as "motor vehicles" and "basic metals". Given the limitations and the discrepancy in time frames, the linear fits should be interpreted with caution and only as descriptive evidence. Nevertheless, it is noticeable that negative patterns are driven by categories containing 3-digit industries with large production volumes and absolute changes in trade flows according to Dauth et al. (2014) and Dauth et al. (2021). This is especially true for the categories "manufacturing of motor vehicles", "manufacturing of machinery" and "manufacturing of basic metals". Figure 3.16 and Figure 3.17 therefore confirm that individual industries with strong trade dynamics and a high emission reduction potential can be singled out as drivers of the observed aggregate effects.

In order to evaluate the role of emission intensity, it would be necessary to construct measures weighted by real production volumes. De Loecker (2011) argues that price dynamics often distort estimates when intensities

[99] Changes in industry sectors experiencing adaptation processes below the reporting thresholds are excluded from the cross-sectional analysis by design but are bounded by the thresholds and therefore negligible. The sector "Manuf. Other Transport" has to be dropped from the cross-sectional analysis because it solely contains misreported quantities from two communal electricity providers, which have been labeled as "Manufacture of air and spacecraft and related machinery" and result in extreme outliers of $1,450,000kg$ in NO_X emissions and of $371,000kg$ in SO_X emissions in 2008.

are computed using value-denoted denominators. Export opportunities may increase prices for domestic goods, while additional import competition will lower domestic prices. Without sophisticated methods for discounting currency-denoted quantities at the industry-level, these price dynamics will bias emission intensities downwards or upwards. Compiling a dataset that is able to correctly address the emission intensity channel is therefore a difficult but insightful extension to this analysis.

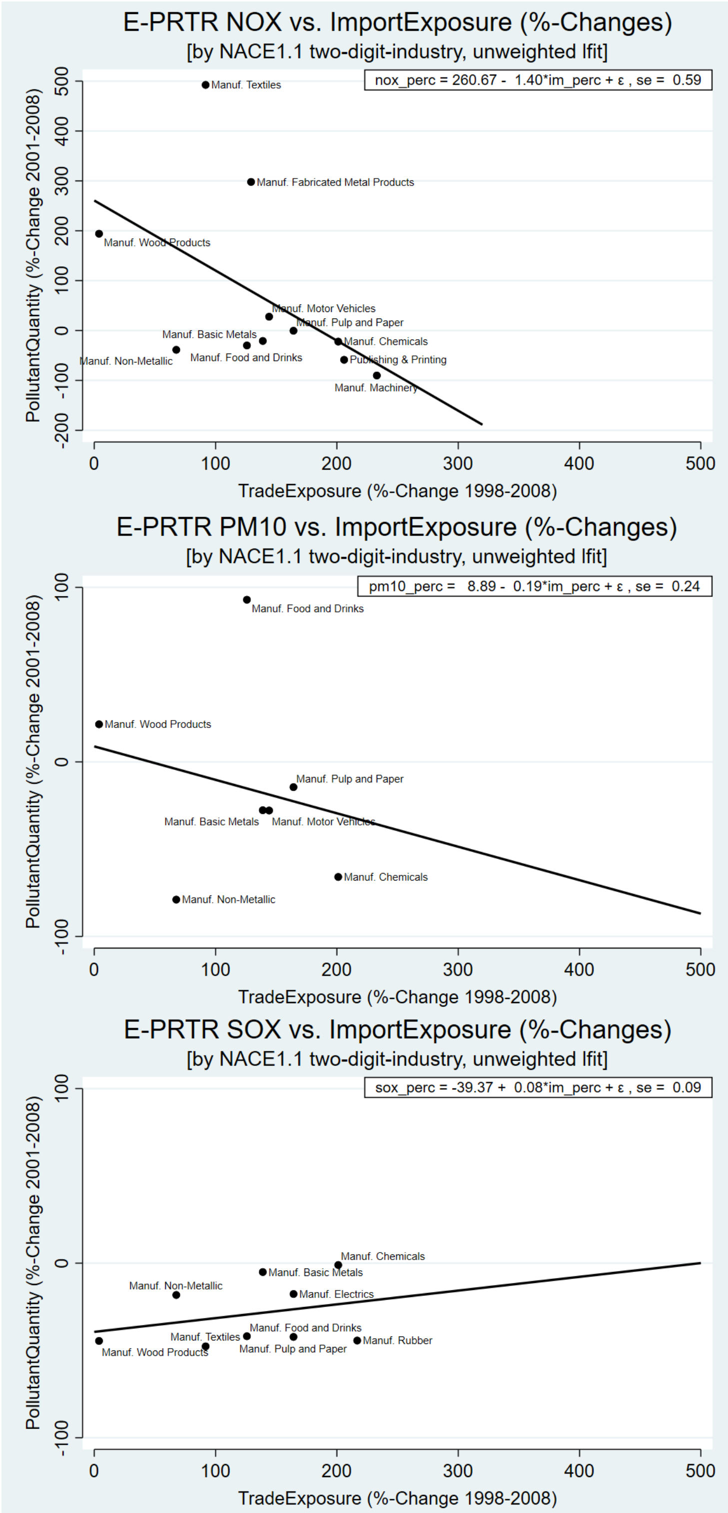

Figure 3.16: Industry-level (%-Changes): Reported E-PRTR Emissions vs. Import Volumes

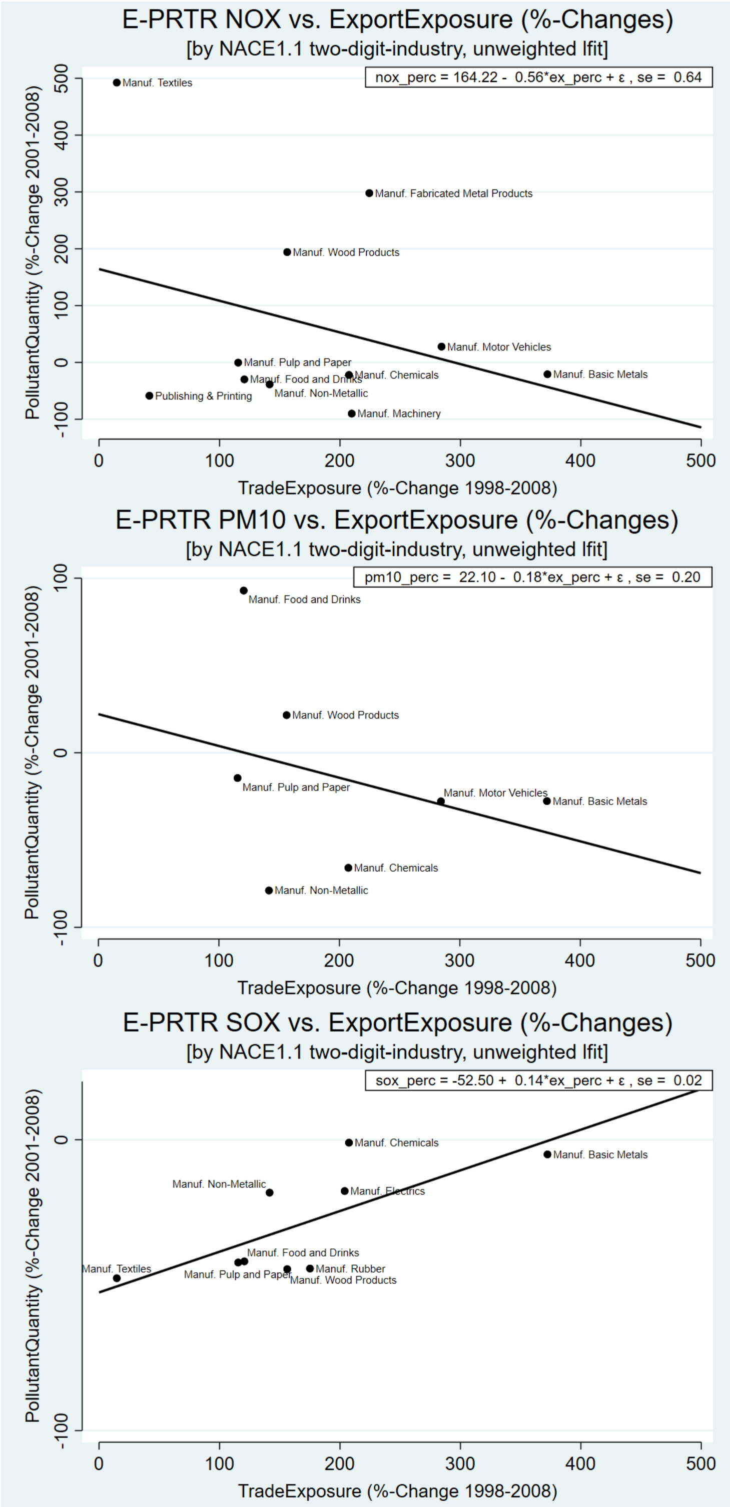

Figure 3.17: Industry-level (%-Changes): Reported E-PRTR Emissions vs. Export Volumes

3.5 Summary

This guide provides researchers with an overview of available spatial data from the Umweltbundesamt (UBA) and with practical information for choosing the right dataset for a given research question. A comparison of the main products reveals their limitations, trade-offs and advantages:

- Conventional $7 \times 8km^2$ OI rasters
- Sectoral NFR information from GRETA emission rasters
- Refined $2 \times 2km^2$ OI rasters
- Point source industry emissions from E-PRTR
- Point source data from measuring stations

I suggest using point source information if the identification strategy relies on short term variation or localized emission exposure and does not get invalidated by the prevalence of missing values in low-coverage areas, whereas projects with a long-term focus and a need for comprehensive spatial data benefit from the intricate interpolation approach behind the raster products and the perfectly balanced panels they provide.

Research projects that exploit recent data and recent policy interventions can use the refined raster products with higher precision available after 2004. They also reap the benefits of having a database built on more accurate emission fields due to the GRETA framework, which distributes industry emissions more precisely on the basis of E-PRTR data, especially after the year 2007. Research projects relying on historical data will naturally lean towards the conventional rasters as these allow for the acquisition of gridded values reaching as far back as the year 1995 in exchange for precision.

In regions without stations, raster values become more model-driven and thus share some of the beneficial and detrimental aspects of the reanalysis products used in climate science and weather forecasting. According to Auffhammer et al. (2013), such reanalysis elements do improve estimates in regions with sparse observations of poor quality but may offer a false sense of security because they will never match the accuracy of data from observation-rich regions. Both rasters provide estimates of immission concentrations, which can be used as proxy for local emission exposure within research projects that can account for underlying dispersion patterns or aggregate at a high enough level to mitigate disturbances.

Finally, E-PRTR records can provide powerful but incomplete data on industry-level or even facility-level emissions that represent pure short term variation but suffer from misreporting and a more complex data structure requiring burdensome data manipulation procedures during the preparation phase. Combined with a suitable research design, however, this database has a lot of potential that empirical researchers have not tapped into yet.

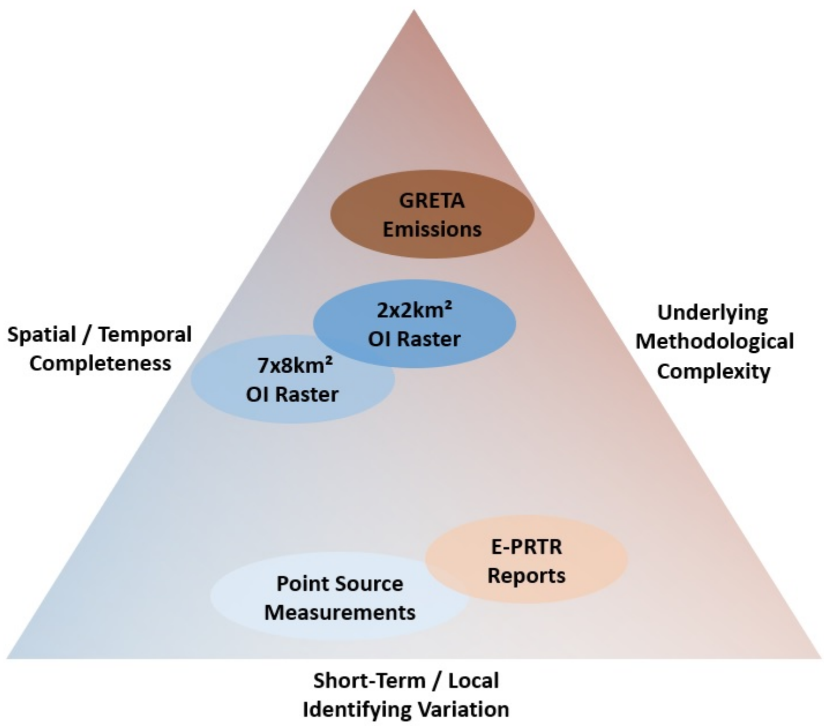

Figure 3.18: Simplified Visualization of Spatial Data Properties

The diagram in Figure 3.18 provides a simplified visualization of the datasets by tentatively rating them along the three dimensions "spatial / temporal completeness", "short-term / local identifying variation" and "underlying methodological complexity". The $7 \times 8km^2$ OI rasters occupy the space on the very left due to their high combined spatial and temporal availability - even compared to the $2 \times 2km^2$ OI rasters, which incorporate methodological innovations introduced by the GRETA tool.

This chapter also provides researchers with a head start in dealing with the technical challenges of German spatial data. Overcoming these hurdles is a worthwhile endeavour, though, as it enables ambitious empirical research projects based on German data. The excellent availability of statistical data for control and outcome variables as well as a plethora of relevant policy interventions make Germany a prime target for research in environmental economics, which can be enhanced significantly by harnessing the full potential of yet unexploited spatial data.

The above comparison of data properties validates the $7 \times 8km^2$ OI raster as most suitable option for the research project in Chapter 1 and I present descriptive evidence in Chapter 3 justifying its use over the obtainable alternatives. It is clear, however, that the alternatives may be more adequate for other projects. This chapter highlights the pros and cons of currently available alternatives measuring pollution exposure at an appropriate spatial resolution and assesses their potential for empirical research projects. Taking this information into account when deciding on the ideal combination of data products will certainly improve the empirical rigor and strengthen the identification strategies of research projects with a thirst for German environmental data.

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Appendix A

Appendices by Chapter

A.1 Appendix - Chapter One

A.1.1 Information on Pollutants

The UBA provides information on individual pollutants [100] and links the pollutants under study (NO_2, SO_2 and $PM10$) to their most important sources and their scientifically proven health effects. NO_2 (nitrogen dioxide) is a chemical compound originating from the burning of fuels in combustion engines and from reactions in the chemical industry. Both industrial production and traffic are important sources of this pollutant and chronic exposure to NO_2 causes lung diseases and pneumonia. SO_2 (sulfur dioxide) is another toxin affecting the respiratory system, which is linked to the transportation and the energy sector. Its volume has been on a steep decline since the mid 90's with the largest savings concentrated in Eastern Germany due to the rapid transformation of this region after the German Reunification. This can be illustrated by comparing the 1995 data points in Figure 1.2. While the relative importance of chemical, metal and petroleum industries in the generation of this pollutants has declined over the years, they are still a major source of SO_2 emissions. Both pollutants can also be released as isotopes and oxidate over their lifetime, which means that reported NO_X or SO_X concentrations are typically highly correlated with NO_2 and SO_2

[100] Refer to the UBA website (https://www.umweltbundesamt.de/daten/luftbelastung/luftschadstoff-emissionen-in-deutschland) for more information and the source of Figures A.1 to A.3.

concentrations. PM (particulate matter) is the result of the deterioration of other toxic substances and may contain a mix of derivatives from SO_2, NO_2 or their other isotopes. The severity of health risks is determined by the size, the geometry and the underlying base substances of these PM components. Since industrial processes are one of the prime sources of fine particle aerial pollutants, $PM10$ concentrations of those particles with a diameter smaller than $10 \mu m$ represent a useful benchmark for local pollution immissions, although more recent studies tend to focus on $PM2.5$, the even smaller and even more detrimental particles with a diameter of less than $2.5 \mu m$ (e.g. Williams and Phaneuf, 2019, and Williams et al., 2018). However, accurate measurements of this type of particulate matter are not available for the majority of German counties before the year 2009 and it can be shown that the immission concentrations are highly correlated during the time frame of mutual availability[101].

Figures A.1 to A.3 demonstrate the overall downward trends in pollutant emissions in Germany and highlight the relative importance of sources over time , while Figure A.4 presents a summary of health effects provided by the European Commission [102]. According to the European Commission, air pollution is the "largest single environmental risk and a leading cause of disease and death globally. It is a risk factor for ischemic heart disease, stroke, chronic obstructive pulmonary disease, asthma and cancer". The reductions visible in Figure A.1 to Figure A.3 are partly the result of implemented thresholds and better abatement technologies. In the case of the Clean Air Act Amendments (CAAA) in the US, Bento et al. (2014) have shown that the ensuing pollution reduction trends benefit especially low-income households

[101]See Chapter 3.2.5 and Chapter 3.4.1 for details. Table 3.10 in Chapter 3.4.1 compares the availability and correlation between $PM2.5$ and $PM10$ measurements in Germany and demonstrates the rarity of comprehensive $PM2.5$ records. Table 3.10 also proves that an approximation through $PM10$ is reasonable based on the time of mutual availability. According to the UBA website (https://www.umweltbundesamt.de/daten/luft/feinstaub-belastung), thresholds of 50mg/m$^{\mathbf{3}}$ for $PM10$ have been established by the German government in 2015, which are not to be exceeded on more than 35 days per year. EU Directive 2008/50/EG (https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex:32008L0050) has confirmed these thresholds and has introduced additional thresholds for $PM2.5$.

[102]Refer to the EC learning module (https://ec.europa.eu/environment/legal/law/5/e_learning/module_1_1.htm) for the original figure.

and highly polluted areas, which implies the existence of catch-up effects. It is therefore advisable to control for pre-sample pollution levels. According to the UBA[103], the year 2003 marks a distinct outlier with respect to high $PM10$ values, whereas threshold violations have become less frequent in recent years. Nevertheless, seasonal and annual variation in $PM10$ concentrations due to weather phenomena and other causes requires the use of smoothed averages or weather controls in empirical settings.

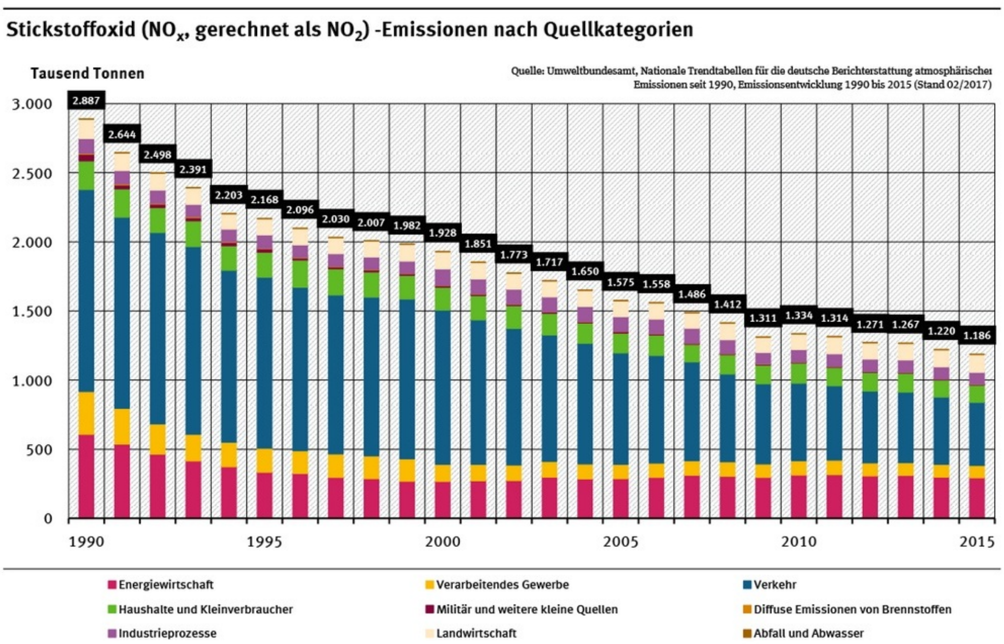


Figure A.1: Sources of Pollution Emissions (NO_2) over time

[103]Refer to the UBA website (https://www.umweltbundesamt.de/daten/luft/feinstaub-belastung) for further information.

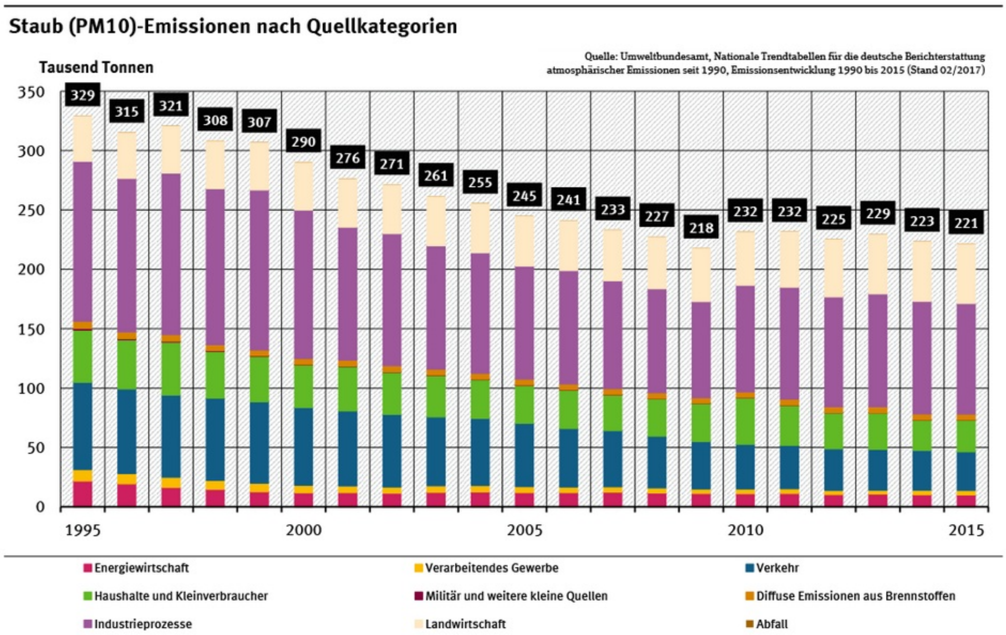


Figure A.2: Sources of Pollution Emissions ($PM10$) over time

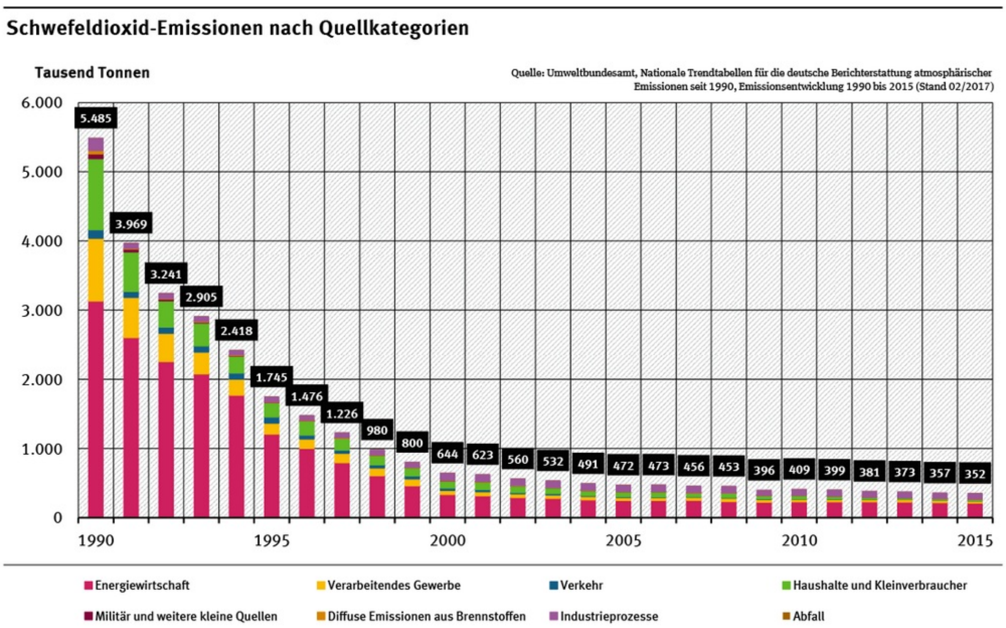


Figure A.3: Sources of Pollution Emissions (SO_2) over time

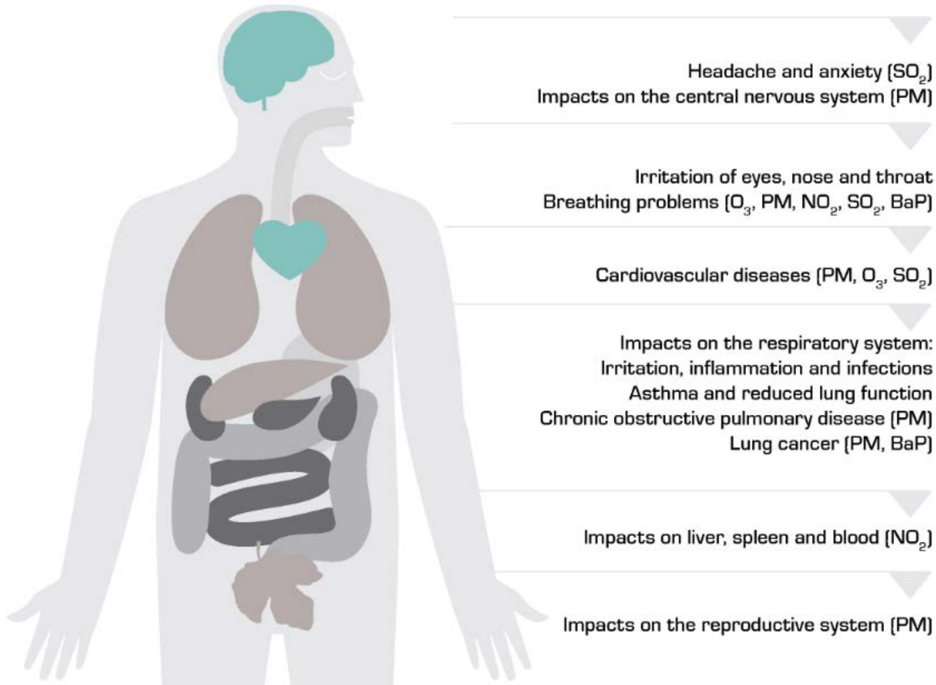


Figure A.4: Health Effects of Pollutants

A large body of literature has linked emission exposure to detrimental health effects. Landrigan et al. (2020) document that fuel combustion in industry and transportation accounts for 85% of global airborne pollution and that local aerial pollutants are the cause of severe respiratory and cardiovascular diseases. Among others, they can be linked to incidences and mortality related to chronic obstructive pulmonary disease (COPD), asthma and ischaemic heart disease. According to their review, pollution-related diseases cause global welfare losses of US$4.6 trillion (6.2% of global economic output). Empirical studies on the economic impact of pollution exposure concentrate on a similar set of pollutants and find causal links between exposure on the one hand and mortality, hospitalizations and medical costs on the other hand (e.g. Williams and Phaneuf, 2019, Deryugina et al., 2019, and Deschenes et al., 2017). Overall, NO_2, SO_2 and $PM10$ concentrations are reasonable outcome variables for the evaluation of industry-related pollution emissions because they can be empirically linked to industrial production and have been proven to bear severe health risks for the population in its vicinity.

A.1.2 Free Trade in the Environmental Kuznets Curve

The proponents of the Environmental Kuznets Curve hypothesis postulate that the growing wealth of a nation, captured by its GDP per capita, stands in an inverted U-shape relationship with observed domestic pollution levels. This hypothesis is derived from empirical observations (e.g. Grossman and Krueger, 1991, and IBRD, 1992) and its originators attribute the effect to a growing awareness in the populace suffering from externalities, increasing resources available for combating pollution and stronger regulatory institutions. This theory offers the compelling argument that economic growth will eventually lead to environmental improvements through channels inherent in the development process. The EKC hypothesis has been criticized for various reasons and empirical examples have since contradicted an inevitably inverted U-shaped relation.

When taking the role of trade into account, it can be argued that the observed relationship is exacerbated by free trade between developed and developing nations (Copeland and Taylor, 2004, and Stern, 2004). The former can abuse their bargaining power and the existing terms of trade to effectively outsource unwanted production, which is costly in terms of environmental compliance or detrimental to the environment, to developing countries looking for growth opportunities. Some developing nations may actively foster these developments by keeping environmental standards low or by not enforcing regulations, thus creating "pollution havens" that attract industries under pressure from environmental regulations. Broner et al. (2012) for example study the comparative advantages coming from regulatory differences in polluting industries. They combine data on environmental policies with data on pollution intensity at the industry and country level and demonstrate that countries with laxer environmental regulation have a comparative advantage with respect to polluting industries. Environmental regulation according to these empirical findings shapes the patterns of trade in a causal and economically relevant manner.

Strict regulations within Germany may be a driving factor behind the exit of polluting industries, which are under pressure from unregulated import competition or embrace the low production costs offered by the policy regimes of the new trading partners. Reductions in pollution concentrations that can be linked to trade liberalization towards China and Eastern Europe may then be seen as evidence that Germany is moving along the right-hand side of the EKC diagram (downward sloping arc in Figure A.5). Linking the regional trade exposure changes to environmental quality therefore has the potential to expose, which role trade openness plays in the transformation of the German industry and whether developed nations can secure a locally higher air quality through terms of trade.

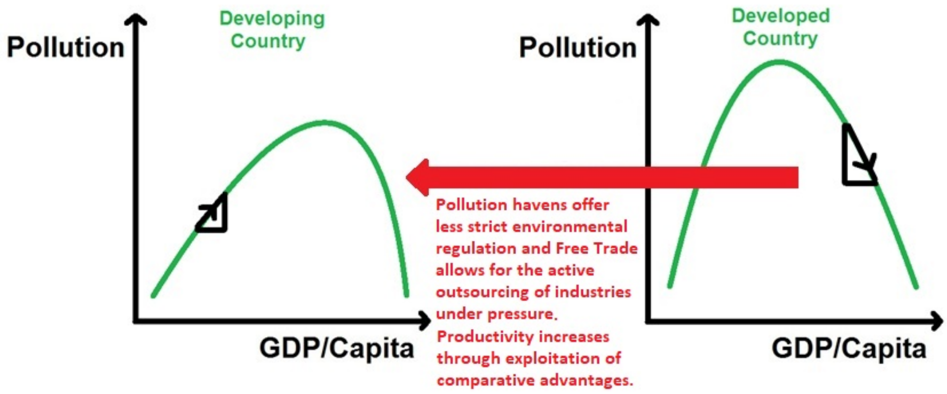


Figure A.5: The role of free trade in shaping the EKC

A.1.3 Decomposition of Impact Channels

According to Antweiler et al. (2001) and Copeland and Taylor (2004), the impact of trade on pollution concentrations can be attributed to three principal channels and can be decomposed into a pure scale effect, a composition effect and a technique component. Levinson (2009) empirically analyzes these drivers of pollution emission reductions by distributing these reductions onto the individual main channels (production volume, inter-sectoral shifts, technological improvements) and holding other factors fixed such that

$$\Delta Emissions_t = \underbrace{\theta_t' E_t dQ_t}_{Scale} + \underbrace{Q_t E_t' d\theta_t}_{Composition} + \underbrace{Q_t \theta_t' dE_t}_{Technique} \tag{A.1}$$

with θ_t being the vector of economy-wide industry output shares, E_t being the vector of industry-specific emission intensities and Q_t being aggregate output. A similar decomposition at the firm level proposed by Barrows and Ollivier (2018a) is based on a methodology introduced by Foster et al. (2008) and examines changes in emission intensity $e_{j,t}$ at the industry-level. Individual firm effects are aggregated over the individual firms denoted by f, which either belong to the set of continuing firms ($Continue_j$), the set of exiting firms ($Exit_j$) or the set of entering firms ($Enter_j$) within a given industry j. Furthermore, $\theta^j_{f,t}$ is the output share of firm f with respect to industry j's total production and $e_{f,t}$ denotes firm f's emission intensity at time t. The resulting decomposition demonstrates that both developments along the extensive margin and the intensive margin can shape emission intensities in a given industry:

$$\begin{aligned}
\Delta e_{j,t} &= \underbrace{\sum_{f \in Continue_j} [\theta^j_{f,t-1} \Delta e_{f,t}]/}_{Technology\,/\,Within\,Firm} \\
&+ \underbrace{\sum_{f \in Continue_j} [e_{f,t-1} - e_{j,t-1}] \Delta\theta^j_{f,t} + \sum_{f \in Continue_j} \Delta e_{f,t} \cdot \Delta\theta^j_{f,t}}_{Intensive\,Margin\,Reallocation} \\
&+ \underbrace{\sum_{f \in Enter_j} \theta^j_{f,t}[e_{f,t} - e_{j,t-1}] + \sum_{f \in Exit_j} \theta^j_{f,t-1}[e_{f,t-1} - e_{j,t-1}]}_{Extensive\,Margin\,Reallocation}
\end{aligned} \tag{A.2}$$

A.1.4 Discussion of Impact Channels

The observed aggregate effects of regional trade exposure on local environmental quality will usually be the result of several underlying channels. Possible channels acting as main drivers behind observed aggregate effects have been identified across a large body of literature. These channels sometimes represent countervailing effects that counteract each other. Consequently, it is not always clear in a given scenario, which channels dominate and dictate the overall outcome. Table A.1 provides an overview of the identified channels and the predicted signs of the effects. One caveat is that due to the simultaneity and countervailing nature of effects, these are generally difficult to disentangle empirically. An emission volume increase due to higher demand (e.g. in the exporting industry), for example, may either be offset by improvements in emission intensity at the firm-level or by improvements in the energy intensity of production. Another caveat is that some empirical results pertain to CO_2 emissions but can be expected to hold for local pollutants as well if these are co-pollutants at the facility-level or byproducts of the manufacturing and energy provision cycle[104].

First of all, product-mix changes within individual firms may yield a significant reaction along the intensive margin. Barrows and Ollivier (2018a) develop a multi-factor model within monopolistic competition based on Melitz and Ottaviano (2008) and the multi-product-firm framework by Mayer et al. (2014), which explains product-mix decisions of exporting firms and demon-

[104]My research evaluates the aggregate effect of trade openness on pollution concentration profiles and relies on the literature presented in this subchapter to summarize possible channels underlying the empirically observed aggregate effects. I conduct a descriptive analysis of responses at the industry-level using E-PRTR data and present the results, which partly confirm the industry dynamics highlighted by DFS, in Chapter 3.4.2. While the regional variation observed in Chapter 1 provides hints for the identification of possible drivers, additional industry-level or facility-level data is required to produce conclusive evidence on the relevance of individual channels in the German case. Furthermore, energy intensity and energy demand reductions lead to potential emission savings remote from the affected facilities or even outside of Germany. For the sake of complexity reduction, I assume that savings from energy consumption are distributed evenly across German counties and do not claim to fully capture this channel in my analysis except for facilities consuming energy generated locally (e.g. on-site). The capturing and transportation of pollutants to remote waste processing facilities is less of a concern for the validity of this analysis due to the characteristics of the pollutants under study.

strates that firms can lower emissions by focusing on their core competencies and most competitive product lines. Such heterogeneous firm models rely on the monopolistic competition setup introduced by Dixit and Stiglitz (1977) and can be augmented by the inclusion of multiple factors and technology adoption in order to study the effect of trade liberalization on CO_2 emission intensity. Empirical test conducted by Barrows and Ollivier (2018a) with Indian data reveal an aggregate drop in CO_2 emission intensity mainly driven by reallocation across firms. At the firm level, core competencies are found to be cleaner than non-core production for most Indian manufacturing sectors but export opportunities incentivize a movement away from these core competencies. They conclude that trade liberalization may reshape emission profiles due to the relative emission intensities of different product lines and that export opportunities and import competition can alleviate pollution as long as they strengthen the focus of individual firms on their core competencies and less energy intensive product lines[105].

The emerging theoretical and empirical literature suggests that trade has an important role in shaping the heterogeneity of firms. Trade liberalization incentivizes a reallocation reinforcing within-industry efficiency and forces exporters to adopt newer and cleaner technology. Cui et al. (2015) develop a heterogeneous firms model, which predicts that productive exporting firms are more likely to adopt emission-saving measures. Their US manufacturing firm-level data indicates that facility productivity is negatively correlated with emission intensity per sales volume and that exporters within a given industry have lower emissions intensities even after controlling for regulatory pressure and non-attainment status (with respect to SO_2 and other substances). Bombardini et al. (2016) examine the relationship between the import networks of Canadian firms and their productivity. They find that broader and deeper import relationships allow firms to be larger, more productive and more suc-

[105]These empirical results pertain to CO_2 emissions in India and the main drivers in the model of core competencies are the rates at which energy and labor efficiency decline for products further away from the core. The main insights and reactions along the intensive margin from the model are transferable to the German setting with local pollutants as long as the production functions with respect to energy intensity and labor intensity yield a similar pattern of cleaner core competencies compared to non-core varieties.

cessful in export markets. Koren et al. (2019) find that Hungarian machine operators benefit from importing high-end machinery, which establishes a beneficial channel of import opportunities on environmental quality through productivity gains in addition to trivial scale effects.

While Bloom et al. (2016) do not look at the environmental aspects of innovation, they are able to demonstrate the existence of significant innovation pressure due to import competition. The resulting technological upgrades at the firm-level and the reallocation of employment towards technologically advanced firms, however, can have positive effects on air quality if these firms operate at higher efficiency, implement abatement measures and erect state-of-the-art high-tech facilities. Bloom et al. (2013) demonstrate that R&D spending for innovation creates spillover effects beyond the individual firm possibly also multiplying the domestic impact of emission reduction technologies. Based on empirical results from India, however, Barrows and Ollivier (2018b) and Barrows and Ollivier (2018a) caution researchers not to ascribe firm-level emission intensity reductions entirely to technological adoption.

Forslid et al. (2018) argue that exporting firms are cleaner because production scaling supports investments into CO_2 abatement, while trade weeds out less productive and dirtier firms. Their argument is largely supported by tests relying on Swedish firm-level data. Holladay (2016) supports the hypothesis that import competition leads to the exit of pollution intensive establishments and highlights the relationship between firm productivity and emission intensity. The protection of low-productivity domestic plants through trade policies and subsidies counteracts the development but estimates show that exporting firms in the US report 9-13% less emissions than non-exporting firms after controlling for output with some heterogeneity across industries. Import competition is associated with the exit of the most polluting firms regardless of environmental regulation measures, which implies that environmental effects are not entirely explained by a relocating to "pollution havens". This section of the literature convincingly establishes an empirical link between productivity, environmentally friendly production, high energy efficiency and exporting opportunities, which lets initially productive firms enter a "virtuous circle" once hit by trade shocks. Despite the existence of a production scale effect, it may then be possible to observe a negative correlation between exporting opportunities and emission intensity.

De Loecker (2011) looks at the impact of trade liberalization on the Belgian textile industry and provides a cautionary tale against the use of sales volumes and other revenue-based productivity measures when computing the effect of trade on productivity. Correcting for unobserved price dynamics yields productivity increases through trade liberalization of 2% instead of 8% in the Belgian context. This research therefore implies that estimates of the impact of trade on productivity and environmental benefits may be biased upwards when production and emission intensity measures are generated without properly controlling for price mechanics. While the author argues that not addressing price effects and mark-ups correctly may lead to an upward bias in estimated productivity responses to trade openness, the strands of literature presented in this synopsis provide ample evidence that import competition and export opportunities can yield an overall positive effect on domestic environmental performance. It is the aim of my research to test whether this hypothesis holds true for air quality at the German county level and trade liberalization towards China and Eastern Europe between 1998 and 2008.

Table A.1: Overview of Impact Channels on Pollution Concentrations

Channel		**Trade Exposure**	**Domestic Impact Prediction**	**Empirical Evidence**	**References**
Scale	Export Opportunities	$\Delta Exports > 0$	$\Delta Pollution > 0$	Evidence for global SO2 reductions	Levinson (2009), Antweiler et al. (2001)
	Import Competition	$\Delta Imports > 0$	$\Delta Pollution < 0$		
Product Mix & Reallocation	Between Sector Reallocation	$\Delta Exports > 0$	Empirically ambiguous	Positive impacts for India, early exit of dirty competitors	Holladay (2016), Barrows and Ollivier (2018a), Cui et al. (2015)
		$\Delta Imports > 0$			
	Within Sector Reallocation	$\Delta Exports > 0$	Reallocation across firms lowers emissions, firm-level counteracts		
		$\Delta Imports > 0$			
	Cleaner Core Competencies	$\Delta Exports > 0$	Non-core varieties increase emissions	Positive impacts only through a focus on core competencies	Barrows and Ollivier (2018a)
		$\Delta Imports > 0$	$\Delta Pollution < 0$		
Productivity & Technology	Virtuous circle for productive/clean exporters	$\Delta Exports > 0$	$\Delta Pollution < 0$	Empirical link between productivity, export chances & environmental performance	Cui et al. (2015), Forslid et al. (2018)
	Modernization through imported inputs and machinery	$\Delta Imports > 0$	$\Delta Pollution < 0$	Evidence from Canada and Hungary	Bombardini et al. (2016), Koren et al. (2019)
	Modernization due to export revenues and preferences	$\Delta Exports > 0$	$\Delta Pollution < 0$	Theoretically important channel, weaker empirical evidence requiring large trade shocks	Barrows and Ollivier (2018a), Cui et al. (2015), Forslid et al. (2018)
		$\Delta Imports > 0$	$\Delta Pollution < 0$		
	Innovation Pressure	$\Delta Imports > 0$	Reductions possible	Reallocation towards High-Tech	Bloom et al. (2016)
Environmental Regulation	Pollution Haven Hypothesis	$\Delta Exports > 0$	$\Delta Pollution < 0$	Outsourcing to less regulated countries	Copeland and Taylor (2004), Stern (2004), Wagner and Timmins (2009), Dechezlepretre and Sato (2017)
		$\Delta Imports > 0$	$\Delta Pollution < 0$		
	Incentives for abatement	$\Delta Imports > 0$	$\Delta Pollution < 0$	Confounding effect unrelated to trade openness (-> IV)	Autor et al. (2013), Shapiro and Walker (2018)

A.1.5 Sample and Data Availability

The empirical analysis within this research project utilizes the sample 1998-2008, which corresponds to the main phase of trade liberalization as defined by DFS. It thereby ensures comparability and avoids confounding effects tied to the Financial Crisis after 2008. The introduction of the EURO on January, 1st, 1999, may have further reinforced the competitivity of the German exporting industry and the subsequent trade integration as argued by Xianbai (2015).

The timeline in Figure A.6 also contains information on the available trade data representing absolute values from COMTRADE and regionalized exposure changes between 1998 and 2008 as computed by DFS and discussed in Chapter 1.4.1.1. The availability of corresponding pollutant concentration rasters provided by the UBA (1995, 2000-2014) is also highlighted in the timeline and discussed in Chapter 1.4.1.2.

Additional data on the facility level is available via the European Pollutant Emission Register (EPER) for the years 2001 and 2004 and via the European Pollutant Release and Transfer Register (E-PRTR) for the years 2007-2017. EPER is the precursor of the E-PRTR, which is a register maintained at the EU level by the EEA and based on similar disclosure principles as the US Toxics Release Inventory (TRI). Industrial facilities are obliged to report emissions above predefined thresholds to national authorities and these compile the data for publication in a register containing information on over 90 pollutants at the facility level. This data can be exploited for the computation of emission developments at the industry-level. Refer to Chapter 3.2.6 and Chapter 3.4.2 for more information and descriptive evidence from this register.

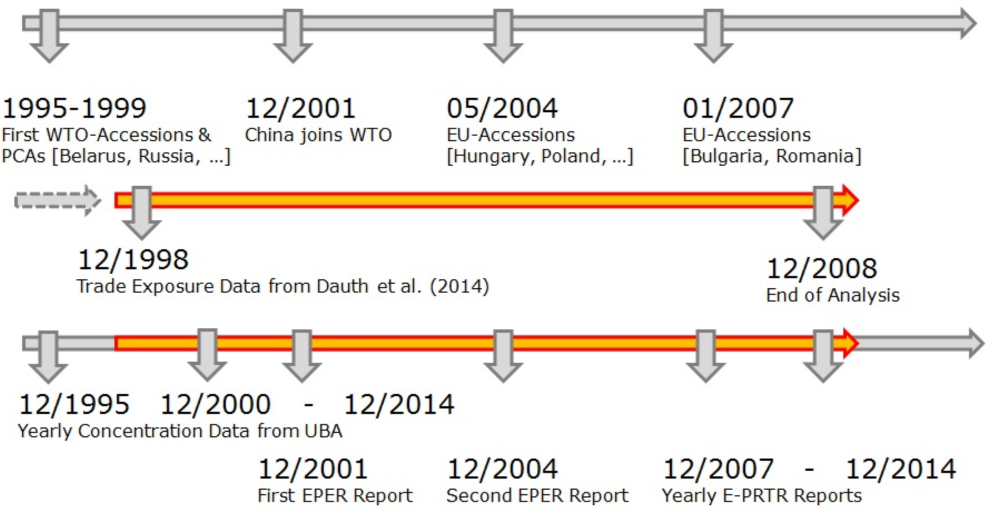


Figure A.6: Timeline of Globalization from the German perspective and Timelines of Data Availability

A.1.6 Data Generation Process for Trade Volumes

The IAB raw data is categorized according to the German WZ93 classification of industry sectors ("Klassifikation der Wirtschaftszweige, Ausgabe 1993") and all $WZ93$ categories are dropped for this analysis except for the categories with $WZ93 \in [150, ..., 369] \setminus [231, 232, 233]$. Coke oven products (231), refined petroleum products (232) and the processing of nuclear fuels (233) are dropped because these sectors are highly affected by energy legislation and shifts in oil prices. The economic size of these shocks would likely dominate the effects of any other trade shocks.

A correspondence table provided by DFS and tables from EUROSTAT allow for the conversion of three digit NACE1.1/WZ93 codes into NACE2.0 codes or SITC rev. 3 codes and vice versa[106]. The trade flow data acquired from the COMTRADE database provides yearly USD-values broken down by SITC rev. 3 (4digit) goods classifications. These can be transformed into NACE1.1/WZ93 industry classifications through the correspondence tables. All transformation and weighting schemes performed by DFS have been reiterated for my own calculations if necessary[107].

A.1.7 Correlation of Explanatory Variables

Computing correlation coefficients for the exposure changes per worker between 1998 and 2008 yields the correlation matrix in Table A.2. Exports to Eastern Europe and China are highly correlated over this time period as exporting industries are unlikely to discriminate against either trade partner. Furthermore, imports and exports to Eastern Europe are highly correlated

[106] NACE1.1 codes are equivalent to the German WZ93 (3 digit) classifications and DESTATIS provides correspondence files for these classifications (https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=wz1993). The results can be combined with EUROSTAT tables (http://ec.europa.eu/eurostat/de/web/nace-rev2/correspondence_tables).

[107] COMTRADE records have been acquired from the website (https://comtrade.un.org/data) and supplementary material has been provided by DFS. Additional information on the data generation process can be obtained from the website of the published article (https://onlinelibrary.wiley.com/doi/abs/10.1111/jeea.12092).

across counties implying equally strong trade flow increases in both ways. This is due to the exchange of intermediate goods with German facilities importing intermediary inputs and exporting these after assembly.

Furthermore, urban counties with strong international connections will likely possess active import and export firms. Chinese import and export volumes on the other hand are not as highly correlated, which implies that individual counties may either be focused on importing goods or exporting goods to China. When including too many of these as explanatory variables, multicollinearity may become an issue but the existing degree of variation across counties should allows for the identification of effects from individual trade exposures in setups with a careful selection of explanatory variables.

Table A.3 shows that dividing exposure measures by area instead of employees increases unweighted correlations especially at the lower end as it inflates the absolute size of exposure measures in small urban counties.

Table A.2: Correlation Matrix of Trade Exposure Changes per Worker

	Imports from China	Imports from Eastern Europe	Exports to China	Exports to Eastern Europe
Imports from China	1	-	-	-
Imports from Eastern Europe	0.3624	1	-	-
Exports to China	0.2102	0.7328	1	-
Exports to Eastern Europe	0.3604	0.8511	0.8653	1

Note: Correlations between Changes in Trade Exposure per Worker (1998-2008) at the county level.

Table A.3: Correlation Matrix of Trade Exposure Changes per Area

	Imports from China	Imports from Eastern Europe	Exports to China	Exports to Eastern Europe
Imports from China	1	-	-	-
Imports from Eastern Europe	0.7363	1	-	-
Exports to China	0.6026	0.8899	1	-
Exports to Eastern Europe	0.7027	0.9573	0.9157	1

Note: Correlations between Changes in Trade Exposure per Area (1998-2008) at the county level.

A.1.8 Processing of Pollutant Concentrations

Yearly concentration averages from the raster data set have been converted into averages for the respective counties by taking the unweighted means of all overlapping rectangular raster sectors for each individual year before computing the absolute changes in concentration levels. For each pollutant Y, each county i and each year t, the unweighted average over all grid cells j overlapping the county area is:

$$PollutantConcentration_{it}^{Y} = \frac{\sum_j 1[j \cap i \neq \emptyset] \cdot PollutantConcentration_{jt}^{Y}}{\sum_j 1[j \cap i \neq \emptyset]} \tag{A.3}$$

Chapter 3.3.2.2 presents correlations between the individual pollutants and between this method of aggregation and a method generating area-weighted averages. Figure A.7 provides a graphical example for the county of Rostock and Figure A.18 in Appendix A.3.3 visualizes the aggregation procedure using colour gradients.

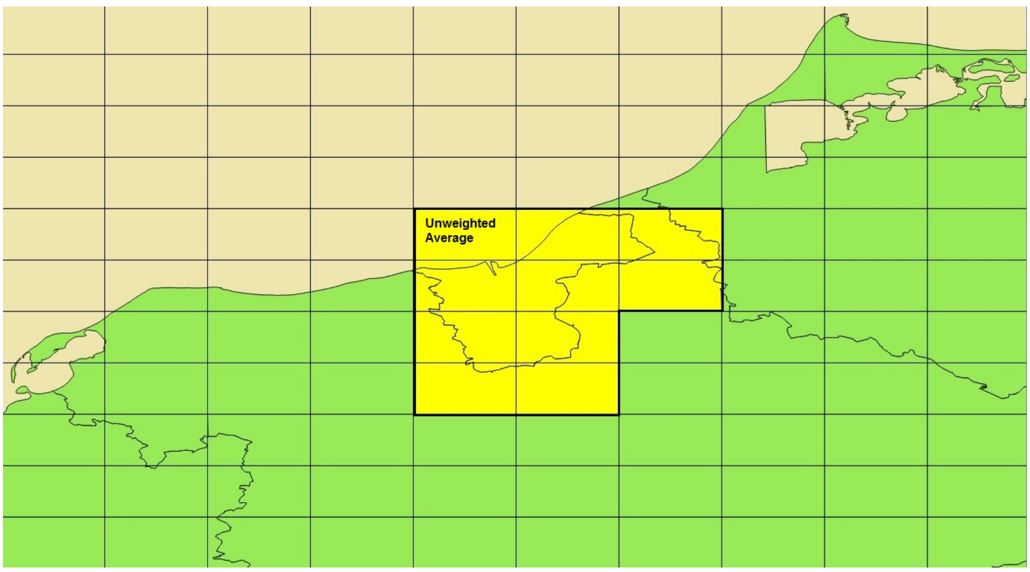


Figure A.7: Aggregation of raster data onto the county-level

The data section in Chapter 3.3.1 describes the technical details of this procedure and presents alternatives. Since individual years may see spikes in emission concentrations due to weather phenomena, I compute smoothed averages over several years in line with UBA observations and recommendations [108]. In order to obtain a smoothed estimate for the year 1998, I compute the unweighted average over the available concentrations in 1995[109], 2000 and 2001. For the year 2008, I have access to the years 2005-2011 and compute an unweighted average over 7 observations.

This strategy provides smoothed concentration estimates for the initial time period and the post-treatment period. It reduces the risk that individual years create significant outliers, which may be a concern especially with respect to Eastern German data due to a lower density of measuring stations after the reunification and the risk of weather phenomena exacerbating the confounding influence of Eastern European production facilities close to the border[110]. Figure 1.2 depicts the time series of yearly average pollution concentrations over all 413 counties along with the smoothed averages for the initial period (1998) and the end of the sample (2008). There is no noticeable drop during the initial stages of the Financial Crisis, which underscores that the time window of the analysis avoids confounding influences. Based on unweighted averages over all German counties, I observe a decrease of roughly $2.84\mu g/m^3$ in $PM10$ concentrations and of $3\mu g/m^3$ in NO_2 concentrations over the given time period.

[108] The UBA website (https://www.umweltbundesamt.de/daten/luft/feinstaub-belastung) documents the impact of weather spikes (e.g. on $PM10$ concentrations in Eastern Germany).

[109] The emission rasters for the year 1995 are the earliest grid values available and are partly based on lower resolution datasets at the European level, which require additional steps and temporal interpolation methods to arrive at a raster of comparable resolution according to Stern (2015). The SO_2 average at the beginning of the time period may therefore be a particularly biased representation of concentrations in 1998, as there has been a steep drop in SO_2 emissions over the years 1995 to 2001 (see Figure 1.2). This makes estimations based on the SO_2 average for 1998 potentially less reliable. Alternatively, averages can be computed based on asymmetrical time frames or on a shorter time span, which further reduces the information contained in the early average but preserves the main results for NO_2 and $PM10$.

[110] Another safeguard against Eastern German outliers is to restrict the sample to Western German counties as in the robustness check presented in Chapter 1.6.1.

A.1.9 OI Raster Properties and Robustness

Auffhammer et al. (2013) argue that the interpolation from a number of point sources to a continuous map may not be straight-forward and that a number of pitfalls have to be avoided when using gridded information. The methodology addresses some of these concerns by employing an advanced interpolation approach. It does, however, rely on both model-based components and actual short-term variation from local measurements. While the underlying emission fields capture long-term movements along the extensive margin by attributing aggregate emissions to local sources based on industry characteristics, short-term variation enters the grid through adjustments towards hourly "background" station measurements. Over the entire period of observation (1995-2008), there have been up to 488 background stations in up to 246 (of 413) counties actively reporting concentrations for each individual pollutant depending on the substance and year[111]. One advantage of raster data over inverse distance-weighted averages from point sources is the reduction of measurement errors in regions with scarce point source data through more sophisticated interpolation methods.

On the other hand, pollutant concentrations are inherently a measure of immissions (i.e. the locally resulting accumulation of pollutants) instead of emissions and are therefore an imperfect proxy for developments in industry-level pollution output. The pollutants under study disperse to a certain degree and the dispersion calculation takes these patterns and corrections from local measurements into account. This means that my analysis suffers from some spatial distortion as aerial pollutant concentrations are known to occur at places locally distant from their sources. Facility-level emission data, in contrast, is gated behind reporting thresholds and therefore incomplete. Emission fields are therefore created by allocating aggregate emissions from national accounts to local sources using detailed information on land use, regional characteristics and industry composition gathered in regular intervals ($\leq$ 5 years). This top-down allocation overrides some short-term variation but is able to reflect changes at the extensive margin through the usage of

[111] See Chapter 3.2.3 for the exact coverage by pollutants.

statistical data from the national account systems and the national emission inventory ("Zentrales System Emissionen", ZSE)[112].

The identification strategy of this research project does not rely on short-term variation in emission concentrations but on long-term changes. It therefore benefits from several properties of the dataset. The raster creation process addresses potential pitfalls listed in Auffhammer et al. (2013) by taking topology and meteorology into account, by closing gaps between measuring stations without exacerbating measurement errors and by refining grid values ex-post through local background station measurements[113]. Panel attrition among the measuring stations is minimized through the exclusion of those with infrequent reports and outliers are avoided through the exclusion of "hot spot" stations close to traffic or industrial facilities. The resulting raster values represent the mean level of pollution exposure experienced by the local populace and provide a valuable basis for welfare considerations.

Nevertheless, I validate the OI raster data used in this Chapter and verify its conformity with actual measurements from "background" stations by comparing it to station-based averages at the county-level in Chapter 3.4.1. I also restrict the dataset to the sample of counties that have station reports during the whole period of observation[114] and perform robustness checks on these samples. Table A.4 demonstrates that the coefficients from the preferred

[112]See Flemming and Stern (2004) and Stern (2009) for detailed information on the dispersion calculation and the OI adjustments. Thiruchittampalam et al. (2013) and Joerss et al. (2013) describe the allocation of emissions. For more information on the data processing and the properties of the available pollution concentration datasets refer to Appendix A.1.8 or Chapter 3, which is dedicated to the various datasets.

[113]In the OI framework, spatial autocovariance models yield weights for station values that take representativity and proximity into account. Ex-post OI adjustments therefore yield a smooth raster without singularities, in which background station measurements take precedence over model computations in the vicinity of stations and in which model computations take precedence in areas without station measurements (e.g. Stern, 2015). These are areas that would be afflicted by severe measurement errors when following conventional interpolation approaches. Aggregating grid values at the county level means that counties containing a background station display a higher amount of short-term variation, while values from counties without background stations are more top-down model driven. Refer to Chapter 3.2.3 and Chapter 3.4.1 for information on coverage and station density.

[114]Defined as continuous background station coverage for a given pollutant over the entire period 2000-2008, since there is a limited sample of station data at my disposal.

IV specification in Table 1.3 can be replicated very well by the much smaller samples of counties with background station coverage. This is reassuring as it implies that the identifying variation in the IV regression comes from actual measurements and not from the emission fields dominating the grid values in areas without station coverage.

Table A.4: IV Regression (2SLS) with Area-Weighted Exposures (Counties with Station coverage)

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-563.3**			-420.3***			139.9		
	(265.7)			(95.03)			(198.3)		
ΔEPA	172.9			151.1**			-144.6		
	(163.4)			(64.90)			(141.1)		
China									
ΔIPA		-691.0***			-512.9***			114.2	
		(208.7)			(111.4)			(220.0)	
ΔEPA		22.87			114.3			-368.7	
		(247.6)			(209.5)			(309.4)	
EasternE									
ΔIPA			168.3			204.4			1028.3
			(1096.6)			(656.9)			(753.9)
ΔEPA			-378.5			-296.0			-556.5
			(535.5)			(319.1)			(402.6)
Const	-2.523	-2.518	-3.337*	-4.523***	-4.402***	-5.313***	-5.232**	-5.116**	-5.600**
	(1.670)	(1.671)	(1.762)	(1.052)	(1.173)	(1.253)	(2.302)	(2.206)	(2.523)
First Stage				F-Tests of excluded instruments					
ΔIPW	169.996	1200.587	100.940	135.829	2995.325	72.675	994.959	178.674	66.027
ΔEPW	134.777	32.068	89.107	160.565	75.980	75.672	240.000	119.441	91.138
Controls				Standard Set plus Region Dummies					
Uncentered R^2	0.884	0.881	0.875	0.885	0.884	0.882	0.889	0.890	0.889
F-Statistic	2.481	4.295	2.856	72.29	42.96	45.75	7.583	8.390	7.562
Observations	180	180	180	119	119	119	107	107	107

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

A.1.10 Control Sets

A set of labor market control variables has been provided by DFS including the percentage of workers employed in the manufacturing sector for tradable goods and the percentage of workers performing routine tasks as well as the fraction of college graduates, women and foreigners within the manufacturing work force. These variables have been computed on the basis of IAB raw data at the firm-level and control for industry characteristics and industry mix within a given county. The underlying IAB Establishment History Panel ("Betriebs-Historik-Panel", BHP) covers the universe of German establishments with at least one employee subject to social security since 1975 and currently represents a panel with approximately 2.7 million annual observations constructed on the basis of mandatory social security notifications to authorities[115].

For the regressions in this chapter, I construct a baseline control set containing the initial unemployment rate, the number of Green votes in the 1998 general election ("Bundestagswahl") and the percentage of manufacturing workers. The control set is further augmented by including the regional dummies suggested by DFS and presented in Chapter 1.4.2 as well as traffic accidents per 100,000 inhabitants as a proxy for the traffic density and the nature of traffic across counties. Using changes in traffic characteristics over the time period under study bears the risk of introducing a control variable that depends endogenously on trade opportunities and environmental quality. The additional variables have been obtained from the INKAR database [116], which provides a rich set of socio-economic variables at various aggregation levels that has also been employed in Chapter 2.

The database is hosted by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) and tracks the

[115] Refer to DFS, Spengler, 2008, and the IAB website (https://fdz.iab.de/en/FDZ_Establishment_Data/Establishment_History_Panel.aspx) for more information. As the data stems from the German social security system, access is restricted and records are subject to data protection.

[116] The database can be accessed via the official website (http://inkar.de/) and is officially referred to as "Indicators and maps on spatial and urban development in Germany and Europe" ("INdikatoren und KARten zur Raum- und Stadtentwicklung in Deutschland und in Europa", INKAR).

demographic, economic and social composition of counties and municipalities. A list of important county level characteristics can be found in Table 1.1 and and definitions of INKAR variables are available in Table A.5. As the county area definitions in Germany have changed significantly over the course of the past two decades, variables pertaining to the current status of county definitions have to be reassigned to the 2008 sample of 413 counties according to reference keys provided by the Federal Office for Building and Regional Planning (BBR)[117].

Sources for the INKAR database include statistical records at the German federal and state level as well as individual data collections of federal ministries, the Eurostat Regio database, GfK ("Gesellschaft für Konsumforschung") records, official tax records and the BBSR. The variables used in this research project are capturing socio-demographic, labor market and traffic characteristics. The variables providing the best pre-sample controls are contained in the 1998 wave of county-level parameters, which are unlikely to have been influenced by the 1998-2008 changes in trade patterns. Other variables can be used regardless of their reporting year if content has not changed significantly over the observation period (e.g. distance measures).

[117] Absolute variables pertaining to new county definitions have been redistributed onto former county definitions according to the number of registered employees ("sozialvers.pflichtig Beschäftigte am Arbeitsort am 30.6.2008 in 1000"). Percentage values have been distributed according to weighted averages based on the numbers of registered employees. Chapter 3.3.1.2 contains more information on this reassignment of variables due to changing territorial definitions in Germany.

As discussed in Chapter 1.4.4.1 and Chapter 1.6.3, an indicator of initial dirtiness can be constructed to control for initial county-level heterogeneity. Including such a variable in regressions captures underlying heterogeneous trends and allows for the identification of the relative effect of trade intensity on counties with different initial conditions. I obtain such an indicator by assigning a normalized score according to the initial pollution level in counties. The normalized score has been computed for each aerial pollutant Y_{it} by weighting the smoothed averages in $t_0 = 1998$ with the maximum value over all counties i:

$$Dirty^{Y}_{i1998} = \frac{\bar{Y}_{i1998}}{\max_i(\bar{Y}_{i1998})} \tag{A.4}$$

Table A.5: INKAR and IAB Indicators

Label	INKAR Indicator	Description	Unit	Time Period
Unemployment Level	Arbeitslosigkeit	Fraction of unemployed (total) with respect to employable populace (aged 15-65)	%	1998
Employed in the primary sector	Beschäftigte Primärer Sektor	Fraction of SVs in the primary sector	%	2000
- secondary sector	Beschäftigte Sekundärer Sektor	Fraction of SVs in the secondary sector	%	2000
- tertiary sector	Beschäftigte Tertiärer Sektor	Fraction of SVs[118] in the tertiary sector	%	2000
Traffic Accidents	Straßenverkehrsunfälle je 100k	Recorded traffic accidents per 100,000 inhabitants	per 100,000	1998
Percentage of Green Votes	Stimmenanteile Gruene 1998	Percentage of votes for the party "Bündnis 90 / Die Grünen" in the general election 1998	%	1998
Label	**IAB Indicator[119]**	**Description**	**Unit**	**Time Period**
Employment Share in manufacturing of Tradable Goods	-	Percentage of workers in manufacturing of consumption, production, or capital goods relative to total employment.	%	1998
Percentage of college-educated employees	-	Percentage of workers with a university degree relative to total employment.	%	1998
Percentage of foreign-born employees	-	Percentage of foreign-born employees in the work-force.	%	1998
Percentage of women	-	Percentage of women in the work-force.	%	1998
Percentage of employment in routine jobs	-	Percentage of workers in basic unskilled occupations relative to total employment according to the definitions of Blossfeld (1987).	%	1998

118 Abbreviation for "Sozialversicherungspflichtig Angestellte" (Registered employees subject to social insurance contributions).

119 All of these variables have been computed by Dauth et al., 2014 on the basis of IAB raw data.

A.1.11 Shapefiles and Geographical Information Systems

The shapefiles rendering German counties and their borders have been obtained from the website of the German Federal Agency for Cartography and Geodetics ("Bundesamt für Kartographie und Geodäsie", BKG)[120]. With respect to point sources, I usually obtain files containing unprojected coordinates but some of the UBA and BKG raster or vector layers are already provided as projected versions for common Universal Transverse Mercator (UTM) specifications based on the WGS84 ("World Geodetic System 1984") standard. I generate maps using either the standard WGS84 (EPSG:4326) projection or the ETRS89 / UTM zone 32N [N-E] (EPSG:3044) projection, as the latter offers an optimized and undistorted image of central Europe.

The shapefiles used in Chapter 1 reflect the status quo of German county definitions on December 31st, 2008. They contain 413 separate counties ("Landkreise" and "Kreisfreie Städte") and 24 of these counties possess adjacent water bodies with structures or off-shore islands. These shapes have been merged with the respective mainland areas and have been included in the computation of perimeters and surface areas. Refer to Chapter 3.3.1.3 for additional information on the technical preparation steps.

[120]The most recent definition shapefiles can be downloaded from the open data section of the "Geodatenzentrum" website (https://gdz.bkg.bund.de/index.php/default/open-data.html) but historical shapefiles have been obtained from the now defunct archive before January 2020 (http://www.geodatenzentrum.de/auftrag1/archiv/vektor/vg250_ebenen/2008/) and are now subject to charges.

A.1.12 Area-Weighted IV Regressions without Controls

Table A.6: IV Regression (2SLS) with Area-Weighted Exposures (No Controls)

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-436.7**			-696.1***			186.6		
	(220.6)			(258.8)			(133.6)		
ΔEPA	86.31			135.9			-89.93**		
	(114.9)			(135.0)			(45.76)		
China									
ΔIPA		-601.7**			-787.5***			352.2	
		(301.0)			(253.9)			(225.9)	
ΔEPA		-89.98			-403.6			-332.0**	
		(287.1)			(677.1)			(137.0)	
EasternE									
ΔIPA			-495.2			-2150.3			-206.0
			(669.2)			(1389.8)			(428.9)
ΔEPA			-49.85			597.9			163.2
			(260.9)			(534.1)			(217.0)
Const	-2.788***	-2.792***	-2.799***	-2.507***	-2.514***	-2.507***	-3.283***	-3.281***	-3.276***
	(0.159)	(0.152)	(0.180)	(0.256)	(0.260)	(0.246)	(0.417)	(0.414)	(0.417)
First Stage	F-Tests of excluded instruments								
ΔIPW	703.961	157.238	239.180	703.961	157.238	239.180	703.961	157.238	239.180
ΔEPW	695.298	113.621	156.089	695.298	113.621	156.089	695.298	113.621	156.089
Controls	None								
Uncentered R^2	0.807	0.807	0.808	0.777	0.775	0.776	0.798	0.798	0.797
F-Statistic	9.876	11.28	6.177	3.536	5.201	4.492	1.828	2.748	0.371
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the difference in smoothed concentration levels between 1998 and 2008.
*/**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses.
First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

A.1.13 Dirtiness Indicator: Area-Weighted IV Regressions

Table A.7: Dirtiness Indicator: IV Regression (2SLS) with Area-Weighted Exposures

Regression	ΔNO2	ΔNO2	ΔNO2	ΔPM10	ΔPM10	ΔPM10	ΔSO2	ΔSO2	ΔSO2
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled									
ΔIPA	-27.24		1020.7	989.6***		-104.7	-715.9***		-1490.1
	(303.0)		(1040.9)	(147.0)		(911.5)	(262.2)		(1064.5)
ΔIPA*Dirty	221.3		-1644.0	-1526***		-85.38	2438.7***		5553.5
	(435.0)		(1979.0)	(187.3)		(1440.7)	(646.8)		(3385.9)
ΔEPA		-165.8	-858.4		852.3***	890.3		-468.6***	555.4
		(214.5)	(812.4)		(137.5)	(689.4)		(181.0)	(609.6)
ΔEPA*Dirty		392.9	1484.7		-1251***	-1155.8		1433.1***	-2195.2
		(306.5)	(1483.6)		(195.7)	(1064.8)		(399.7)	(2010.0)
Dirty	-7.038***	-7.351***	-7.108***	-10.39***	-10.50***	-10.45***	-10.44***	-9.783***	-10.57***
	(1.629)	(2.186)	(1.841)	(0.638)	(0.626)	(0.605)	(2.113)	(2.189)	(2.053)
Const	0.642	0.787	0.659	2.797***	2.838***	2.819***	0.559	0.406	0.615
	(1.024)	(1.236)	(1.083)	(0.410)	(0.385)	(0.388)	(0.681)	(0.708)	(0.678)
First Stage	F-Tests of excluded instruments								
ΔIPA	1767.323		2437.400	730.638		1358.802	837.093		715.186
ΔIPA*Dirty	1042.689		2569.335	858.569		1906.869	267.833		1353.871
ΔEPA		1015.517	590.141		175.342	244.703		378.509	441.265
ΔEPA*Dirty		593.064	486.627		287.333	592.230		379.162	359.021
Controls	Regional Dummies only (dirtiness indicator used instead of controls to capture county heterogeneity)								
Uncentered R^2	0.859	0.860	0.859	0.918	0.919	0.919	0.961	0.962	0.956
F-Statistic	24.39	4.496	113.2	141.0	2034.1	873.1	28.54	24.17	38.62
Observations	413	413	413	413	413	413	413	413	413

Note: Dependent variable is the smoothed averaged difference in concentration levels between 1998 and 2008. */**/*** Significant at the 10%/5%/1% level. Standard errors clustered at the federal state level in parentheses. First stage regressions yield highly significant coefficients for the relevant instruments and the reported F-Statistics.

A.2 Appendix - Chapter Two

A.2.1 Data on postal code area sociodemographic characteristics

Sources for the INKAR database include statistical records on the German federal and state level as well as individual data collections of Federal Ministries, the Eurostat Regio database, GfK (Gesellschaft für Konsumforschung) records, official tax records and the accessibility model of the BBSR (Bundesinstitut für Bau-, Stadt- und Raumforschung). The variables in the data set are described in Table A.8. The INKAR data we use is the 2010 publication, which contains information about the municipalities at the end of 2008.

The data on postal code characteristics is available at the municipal level ("Gemeinde") and for aggregated municipalities (so-called "Gemeindeverbände"), but the unit of analysis is a postal code area as mentioned in the main text. Unfortunately, these two spatial entities do not perfectly overlap. As a result we used GIS software to match postal code areas to municipalities based on the spatial overlay of the two entities. For this purpose we combined a postal code area shape file with a shape file of 11,329 municipalities, both provided by GfK GeoMarketing GmbH as of 2012. A number of municipal reforms have led to restructuring of a few hundred municipalities between 2008 and 2012. As a result, we were unable to merge sociodemographic data to a small number of postal code areas. In total we were able to match 8,194 out of our 8,212 postal code areas to an INKAR unit.

The spatial overlay analysis was done based on urban area in the municipalities as the INKAR data mainly refers to sociodemographic data such as unemployment levels, tax revenues, and the prevalence of types of residential buildings. Each urban area was identified by the municipality code within which it lay. The postal code area was then allocated to the municipality with the largest share of urban area within the postal code area. Almost 300 postal code areas contained no urban areas. These were matched based on the simple spatial overlap to the municipality with the largest share of the postal code area. Once this allocation was complete based on the 2012 municipalities, we used information on changing municipalities from the German Statistical authorities (Destatis) to trace the municipalities that changed back to their 2008 identification number. For the 8,194 postal code areas thus matched to the INKAR units, 4,618 where allocated to a single municipality and 3,576 to an aggregate ("Gemeindeverband").

Table A.8: INKAR 2010 Indicators used for matching

Label	INKAR 2010 Indicator	Description	Unit	Time Period
Unemployment Level	Arbeitslosigkeit	Fraction of unemployed (total) with respect to employable populace (aged 15-65)	%	2008
- long term	Langzeitarbeitslose	Fraction of long-term unemployed with respect to total number of unemployed	%	2008
- long term, change	Entwicklung Langzeitarbeitslose	Change in the number of long-term unemployed (1yr or more)	%	2003-2008
- long term	Langzeitarbeitslose	Fraction of long-term unemployed with respect to total number of unemployed	%	2008
Employed in the primary sector	Beschäftigte Primärer Sektor	Fraction of SVs in the primary sector	%	2008
- secondary sector	Beschäftigte Sekundärer Sektor	Fraction of SVs in the secondary sector	%	2008
- tertiary sector	Beschäftigte Tertiärer Sektor	Fraction of SVs[121] in the tertiary sector	%	2008
Commuters into municipality	Einpendler	Fraction of outgoing commuters to total number of employed residents	%	2008
Commuters out of municipality	Auspendler	Fraction of incoming commuters to total number of locally employed SVs	%	2008
Total tax revenues	Steuereinnahmen	Total average tax revenues per citizen in 2008	Euro	2008
Population density	Einwohnerdichte	Population density per km^2	decimal	2008
Value added tax revenues	Umsatzsteuer	Average yearly Value Added Tax (VAT) per citizen	Euro	2008
Commercial tax revenues	Gewerbesteuer	Average yearly commercial tax per citizen	Euro	2008
Income tax revenues	Einkommensteuer	Average yearly income tax per citizen (as received by the local municipality)	Euro	2008
Distance to freeway	Erreichbarkeit von Autobahnen	Average travel time to nearest freeway entrance ramp (by car)	min	2010
Distance to airport	Erreichbarkeit von Flughäfen	Average travel time to nearest German international airport (by car)	min	2010
Distance to fast trains	Erreichbarkeit von IC/EC/ICE-Bahnhöfen	Average travel time to nearest German transregional train station (by car)	min	2010
Distance to large urban center	Erreichbarkeit von Oberzentren	Average travel time to the nearest regional center (by car)	min	2010
Distance to medium urban center	Erreichbarkeit von Mittelzentren	Average travel time to the nearest local town center or regional center (by car)	min	2010
Access to European neighbors	Erreichbarkeit europ. Agglomerationszentren	Average travel time to all 41 European metropolitan areas (by car and plane combined)	min	2007
Newly constructed buildings	Neubau Wohnungen je Einwohner	Completed apartments (in new buildings) per 1000 citizens	per 1000	2008
Share of single/two family housing	Ein- und Zweifamilienhäuser	Fraction of residential buildings with 1-2 apartments	%	2008
-multiple family housing	Mehrfamilienhäuser	Fraction of residential buildings with 5+ apartments	%	2008
Small apartments	Anteil 1- und 2-Raum-Wohnungen	Fraction of apartments with 1-2 rooms	%	2008
Large apartments	Anteil 5- und mehr Raum-Wohnungen	Fraction of apartments with 5+ rooms	%	2008
	Bevölkerungsentwicklung	Change in population (total)	%	2003-2008

[121] Abbreviation for "Sozialversicherungspflichtig Angestellte" (Registered employees subject to social insurance contributions).

A.2.2 Construction of Weighted Emission Scores

In order to create postal code quantiles with respect to the severity of treatment (relative severity of emitted substances) we add up the individual emission reports for each postal code weighted by their emission thresholds. For the E-PRTR data release in 2009 this is done according to the following formula:

$$WeightedEmissionScore_i(2009) = \sum_{f_i=1}^{F_i} \left[\sum_{p=1}^{P} \frac{Quantity_{p,f_i}(2007)}{Threshold_p} \right] \tag{A.5}$$

Here, $f_i = 1, ..., F_i$ denotes the individual facilities in the respective postal code while $p = 1, ..., P$ denotes all substances listed in the database with $Quantity_{p,f_i}(2007)$ being the reported quantity of an individual substance by the respective facility for the year 2007. This emission quantity is weighted by the reporting threshold defined in the E-PRTR regulations. Overall, this measure is a good proxy for the severity of emissions recorded for a certain postal code. As the reporting thresholds are reasonable proxies for toxicity and are also available to the public as possible guidelines for interpreting the values in the database, this aggregate measure constitutes a sound basis for creating treatment quantiles. A few examples of computed Weighted Emission Scores are presented in Figure A.8 below.

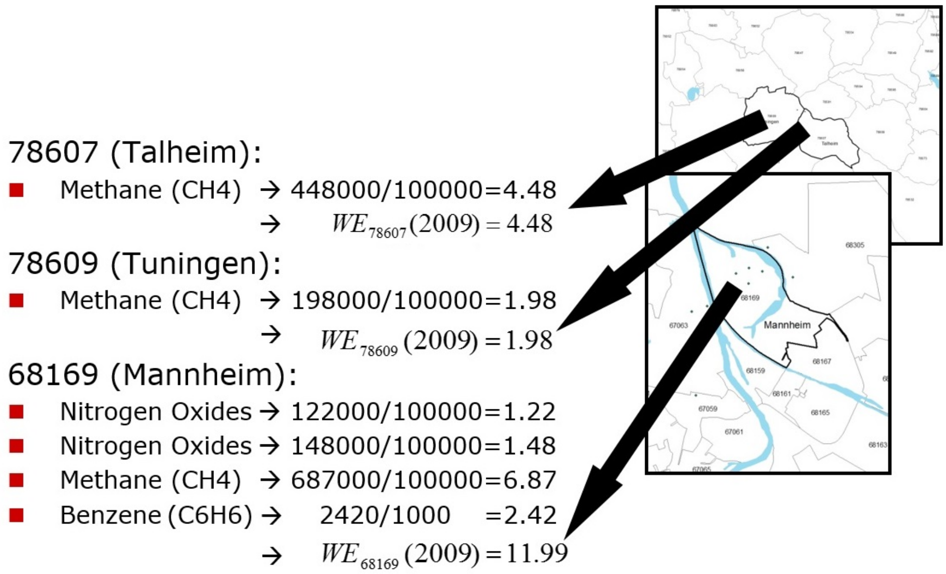


Figure A.8: Examples for the construction of Weighted Emission Scores

A.2.3 Logit estimations for propensity score matching

Table A.9: Logit estimates for matching, part I

Treatment status	Western Germany		Eastern Germany	
	No buffer	500 m buffer	No buffer	500 m buffer
Unemployment	0.0753	0.0853*	-0.0106	0.00257
	(0.0416)	(0.0353)	(0.0408)	(0.0385)
Long term unempl.	-0.0117	-0.0138*	0.00993	0.00806
	(0.00648)	(0.00551)	(0.0136)	(0.0130)
Change in l.t. unempl.	0.000381	0.0000277	0.00124	-0.00195
	(0.00207)	(0.00176)	(0.00723)	(0.00694)
New construction	-0.0144	-0.0155	-0.0489	-0.0130
	(0.0320)	(0.0268)	(0.0561)	(0.0451)
Secondary sector employment	0.0190	0.0225	-0.00373	-0.0111
	(0.0216)	(0.0180)	(0.0165)	(0.0156)
Tertiary sector employment	-0.00624	0.000278	-0.0167	-0.0198
	(0.0222)	(0.0185)	(0.0169)	(0.0161)
Commuters into area	0.00677	0.00910	0.0175	0.0226*
	(0.00588)	(0.00509)	(0.0115)	(0.0108)
Commuters out of area	-0.0142**	-0.00790	-0.0256*	-0.0287**
	(0.00522)	(0.00452)	(0.0115)	(0.0108)
Total tax revenues	0.000747	0.00121**	-0.000142	-0.00000669
	(0.000417)	(0.000448)	(0.000710)	(0.000695)
Population density	-0.0000113	-0.000137	-0.000624**	-0.000303
	(0.000136)	(0.000113)	(0.000222)	(0.000184)
Value-added tax revenues	0.00462	0.00249	-0.0101	-0.0126
	(0.00270)	(0.00241)	(0.00706)	(0.00676)
Commercial tax revenues	-0.000446	-0.000819*	0.000404	0.000189
	(0.000372)	(0.000368)	(0.000736)	(0.000718)
Income tax revenues	-0.00411***	-0.00335***	0.00782*	0.00694*
	(0.00100)	(0.000874)	(0.00373)	(0.00344)
Distance to highway	-0.00497	-0.00761	-0.00827	-0.00734
	(0.00558)	(0.00485)	(0.00766)	(0.00727)
Distance to airport	-0.00351	-0.00553*	-0.00146	-0.00443
	(0.00278)	(0.00235)	(0.00319)	(0.00297)
Distance to train station	-0.00195	-0.00287	0.00175	-0.000664
	(0.00388)	(0.00340)	(0.00542)	(0.00513)
ll	-1926	-2526.4	-624.5	-708.5
Observations	6791	6788	1402	1370

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Table A.10: Logit estimates, part II

Treatment status	Western Germany		Eastern Germany	
	No buffer	500 m buffer	No buffer	500 m buffer
Distance to large urban center	-0.00367	-0.00746*	-0.000606	-0.00194
	(0.00385)	(0.00334)	(0.00527)	(0.00498)
Distance to medium urban cent.	-0.0528***	-0.0588***	-0.0241	-0.0300*
	(0.00904)	(0.00791)	(0.0125)	(0.0119)
Distance to European center	-0.00571	-0.00268	0.00471	0.00774
	(0.00354)	(0.00296)	(0.00594)	(0.00550)
Apartment buildings	-0.00465	0.0167	0.00927	-0.00547
	(0.0114)	(0.00956)	(0.0168)	(0.0156)
Small apt.	-0.0236	-0.0201	-0.0285	-0.00827
	(0.0220)	(0.0184)	(0.0437)	(0.0395)
Large apt.	-0.0181	-0.00805	-0.00421	-0.00521
	(0.0108)	(0.00909)	(0.0179)	(0.0168)
Size of postal code area (m^2)	1.29e-08***	1.17e-08***	1.10e-08***	1.06e-08***
	(1.30e-09)	(1.18e-09)	(1.18e-09)	(1.17e-09)
Land use agriculture	0.0113***	0.00983***	0.0213***	0.0130***
	(0.00257)	(0.00216)	(0.00441)	(0.00389)
Land use water	0.0497***	0.0445***	0.0316	0.0102
	(0.0106)	(0.00937)	(0.0169)	(0.0160)
Land use natural area	-0.00509	0.00137	-0.00119	-0.00379
	(0.00400)	(0.00315)	(0.00769)	(0.00597)
Land use industry	0.0530***	0.0520***	0.0587***	0.0395***
	(0.00564)	(0.00534)	(0.0116)	(0.00974)
Land use landfills	0.144***	0.198***	0.173***	0.166***
	(0.0230)	(0.0257)	(0.0380)	(0.0385)
Constant	0.945	-1.141	-3.009	-2.168
	(2.650)	(2.207)	(2.689)	(2.541)
ll	-1926	-2526.4	-624.5	-724.9
Observations	6791	6788	1402	1402

Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

A.2.4 Development of Housing Prices in Germany

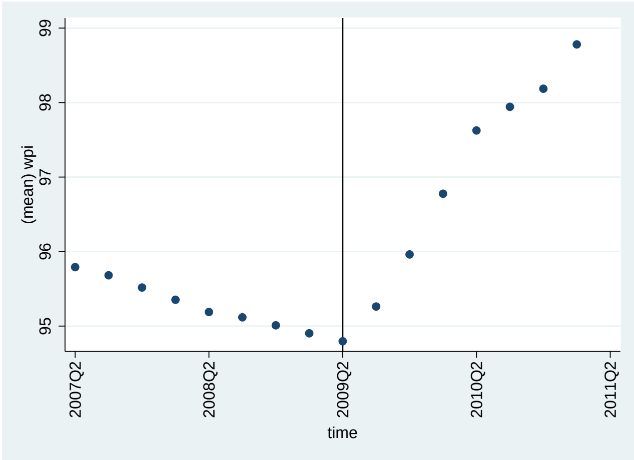


Figure A.9: Price trends (House Price Index), unmatched sample

A.2.5 Testing the common trend assumption

The common trend assumption is tested by estimating the following regression setup:

$$
\begin{aligned}
Y_{it} = \quad & \beta^0 + \beta^1(1 - Post_t) \cdot t + \beta^2 Post_t \cdot t + \beta^3(1 - Post_t) \cdot Treated_i \cdot t \\
& + \beta^4 Post_t \cdot Treated_i \cdot t + \beta^5 Post_t \cdot Treated_i + \beta^6 Post_t + \beta_i^7 + \varepsilon_{it}
\end{aligned} \tag{A.6}
$$

The main coefficient of interest is the one for a possible trend divergence prior to treatment for the treatment group (β^3, “Pre-Trend*Treatment” in Table A.11). Given the graphical representation of the trends in housing prices, a linear trend model is the preferable choice for our analysis. A sharp turn in the development of German housing prices can be seen to coincide roughly with the publication of the first E-PRTR wave and is not restricted to either of the groups but a universal feature of housing prices in Germany, which can be explained by the notion that there has been a surge in housing prices after the recent financial crisis due to other investment options

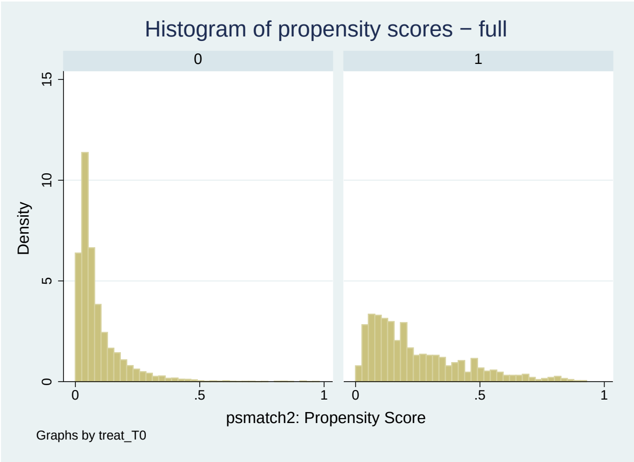
Table A.11: Common trend regressions

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Pre-Trend	-0.138***	-0.094***	-0.075***	-0.196***
	(0.005)	(0.011)	(0.014)	(0.024)
Post-Trend	0.612***	0.599***	0.525***	0.386***
	(0.007)	(0.021)	(0.019)	(0.037)
Pre-Trend*Treatment	0.037*	-0.006	-0.148***	-0.024
	(0.013)	(0.020)	(0.024)	(0.031)
Post-Trend*Treatment	0.015	-0.016	-0.188***	-0.036
	(0.018)	(0.028)	(0.037)	(0.050)
Post*Treatment	0.249	-0.154	-1.020***	-0.099
	(0.129)	(0.192)	(0.211)	(0.292)
Postal code FE	Yes	Yes	Yes	Yes
R^2	0.317	0.377	0.169	0.114
Observations	6799	1312	1413	595
Treated observations	741	727	377	368

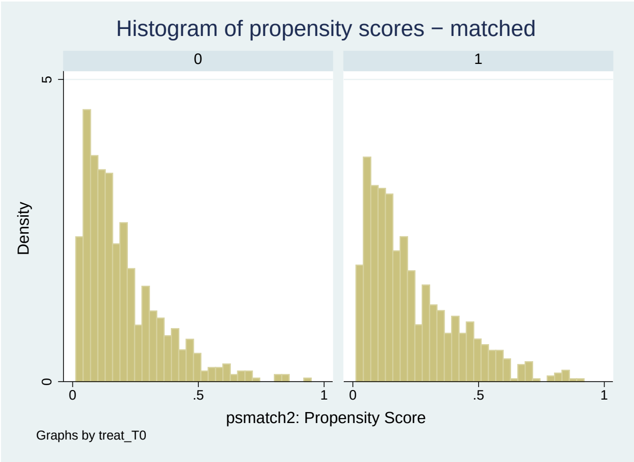
Note. Dependent variable is House Price Index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level. Matched sample based on nearest neighbor matching.

becoming less attractive. Most importantly, we observe in Table A.11 that the common trend assumption holds for both parts of Germany after the matching procedure has been completed. Any pre-treatment trend differences that may have prevailed in the unmatched sample between treatment and control group are eliminated by nearest neighbor matching. It is also worth noting that in the matched sample there is no significant trend differential after 2009Q2, which already indicates that the treatment (consisting of at least one E-PRTR report within a postal-code) may have had little effect on the trend in housing prices.

A.2.6 Histograms of propensity scores

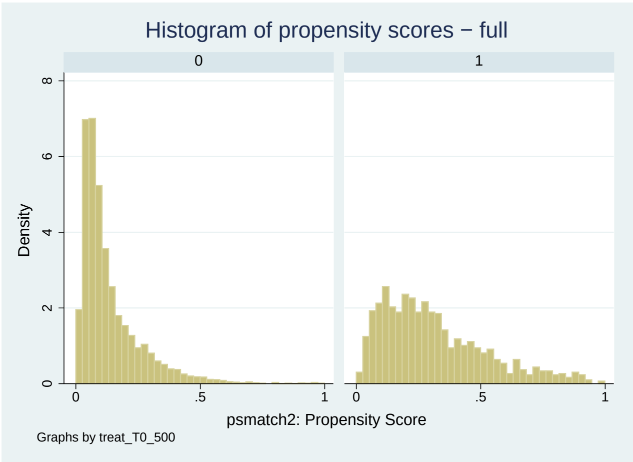


Full sample

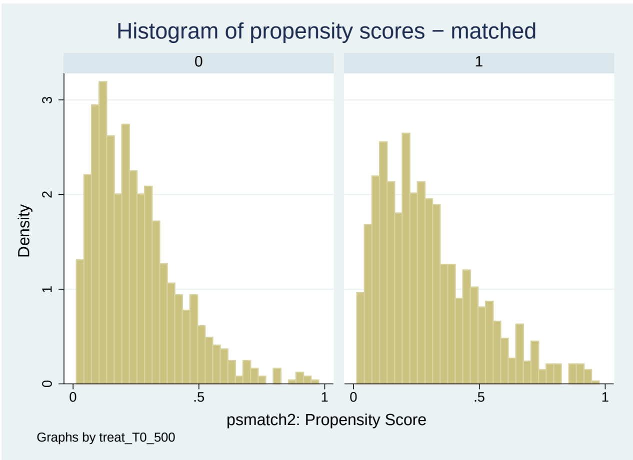


Matched sample

Figure A.10: Propensity scores, Western Germany, no buffer

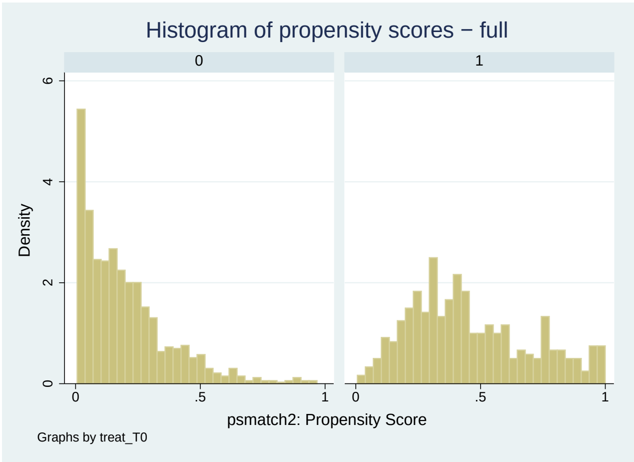


Full sample

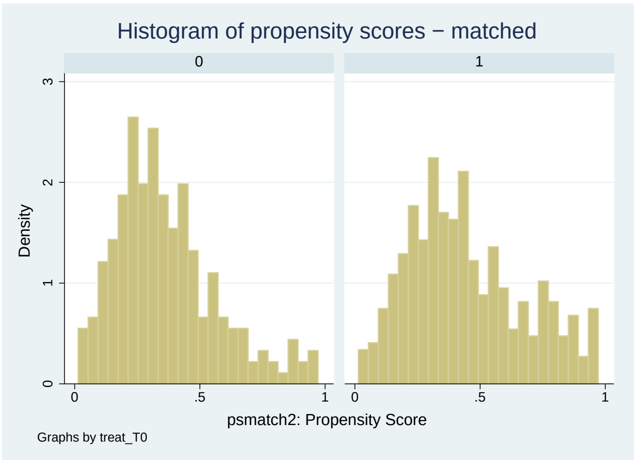


Matched sample

Figure A.11: Propensity scores, Western Germany, 500 m buffer

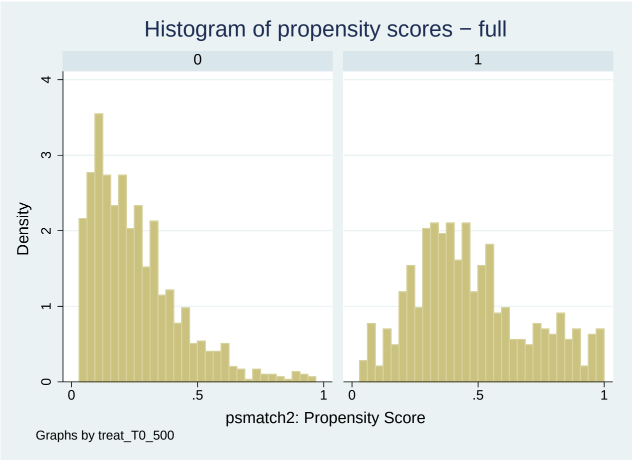


Full sample

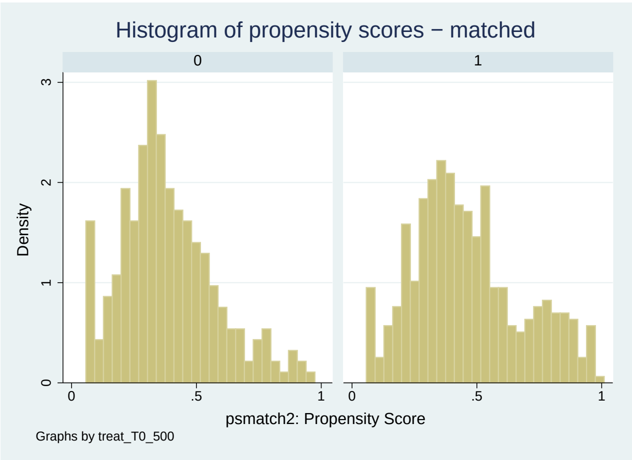


Matched sample

Figure A.12: Propensity scores, Eastern Germany, no buffer



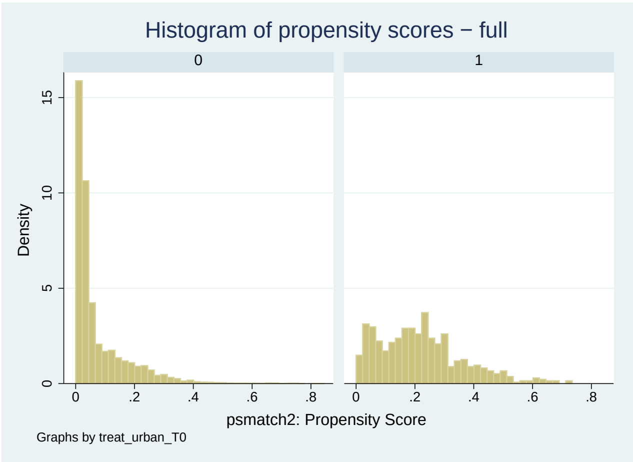
Full sample



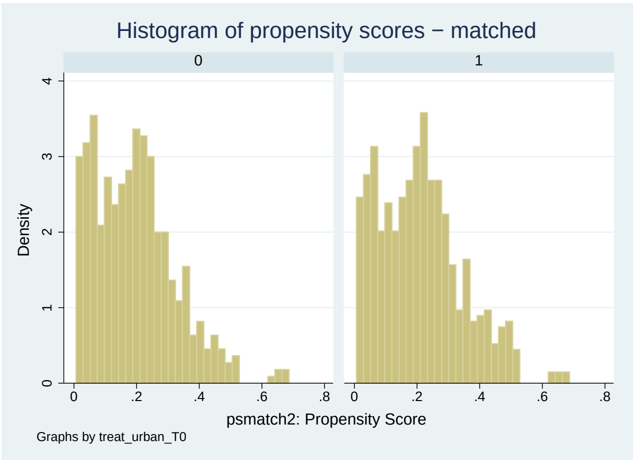
Matched sample

Figure A.13: Propensity scores, Eastern Germany, 500 m buffer

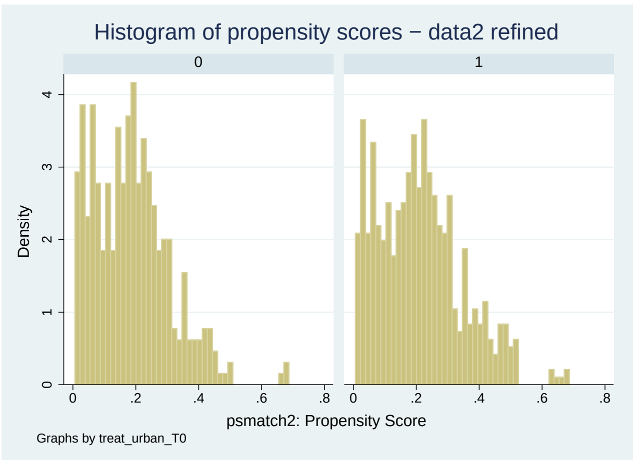
A.2.7 Histograms of propensity scores (urban areas only)



Full sample

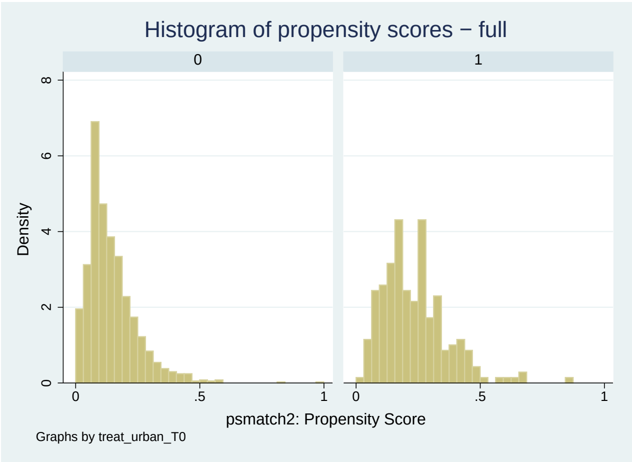


Match A

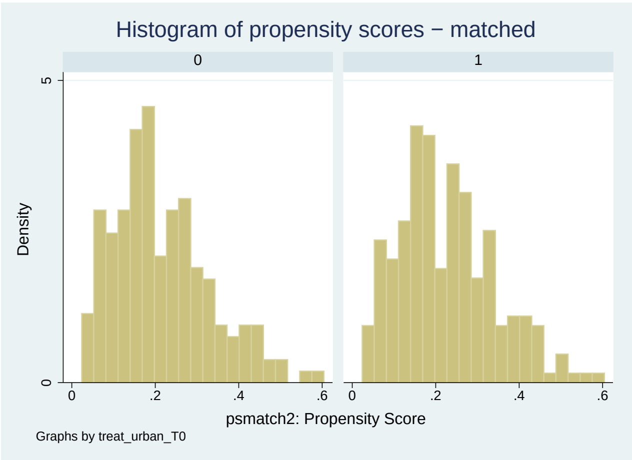


Match B

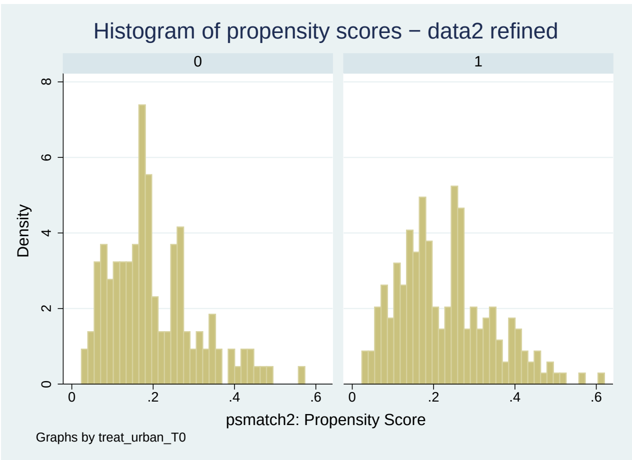
Figure A.14: Histograms of propensity scores, urban areas, Western Germany



Full sample



Match A



Match B

Figure A.15: Histograms of propensity scores, urban areas, Eastern Germany

A.2.8 Geographical distribution of treatment and control group (matched sample)

This figure is the corrected version released as erratum on the Springer website "Erratum to: The Effect of Emission Information on Housing Prices: Quasi-Experimental Evidence from the European Pollutant Release and Transfer Register". It depicts the control and treatment group counties contained in the matched sample[122].

[122] Quote from the website (https://link.springer.com/article/10.1007%2Fs10640-016-0100-9): "The authors would like to replace Fig. 13 in the original article with the below figure. Due to a misspecification in the corresponding shape file the original figure may have given the impression that the treatment and control groups were not cleanly separated. Figure 13 clearly demonstrates the spatial distribution and the correct separation of these groups."

Figure A.16: Treatment and control groups with NN matching (Corrected)

A.2.9 Geographical distribution treatment and control group (matched sample, urban areas only)

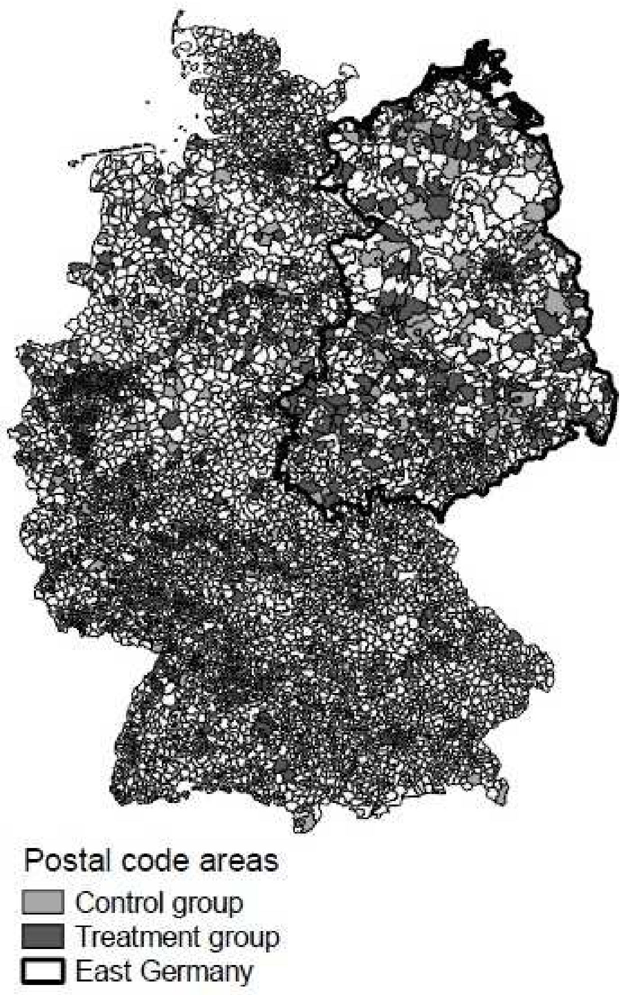


Figure A.17: Map of treated areas and matched controls, urban areas

A.2.10 Mean characteristics and bias comparison for treatment and control group (urban areas only)

Table A.12: Urban areas only: Treatment and control group before and after matching (A), Western Germany

Variable	Unmatched Matched	Mean Treated	Mean Control	% reduction %bias	% reduction $\|bias\|$	t-test t	t-test p>$\|t\|$
Unemployment	Unmatched	5.70	3.92	83.20		20.83	0.00
	Matched	5.67	5.68	-0.60	99.20	-0.10	0.92
Unempl. longt.	Unmatched	31.96	27.75	33.30		8.08	0.00
	Matched	31.83	31.97	-1.10	96.80	-0.17	0.86
ΔUnempl. longt.	Unmatched	-17.90	-26.72	22.50		5.24	0.00
	Matched	-18.04	-16.56	-3.80	83.30	-0.63	0.53
Construction	Unmatched	2.03	2.46	-26.50		-5.65	0.00
	Matched	2.04	2.01	1.60	93.90	0.34	0.73
Empl. secondary	Unmatched	35.45	39.36	-24.20		-5.52	0.00
	Matched	35.36	36.10	-4.60	81.20	-0.79	0.43
Empl. tertiary	Unmatched	63.55	58.34	32.10		7.38	0.00
	Matched	63.63	62.97	4.10	87.30	0.69	0.49
Commute in	Unmatched	59.83	66.25	-54.70		-12.87	0.00
	Matched	59.91	59.81	0.90	98.40	0.15	0.89
Commute out	Unmatched	52.93	72.77	-96.20		-22.57	0.00
	Matched	53.19	52.12	5.20	94.60	0.88	0.38
Tax rev.	Unmatched	782.01	672.32	33.10		7.32	0.00
	Matched	781.88	769.49	3.70	88.70	0.77	0.44
Pop. density	Unmatched	1118.60	498.16	72.30		18.49	0.00
	Matched	1104.30	1142.10	-4.40	93.90	-0.66	0.51
VAT rev.	Unmatched	51.83	30.69	76.10		18.20	0.00
	Matched	51.44	51.66	-0.80	98.90	-0.13	0.89
Corp. tax rev.	Unmatched	523.36	334.41	46.40		10.95	0.00
	Matched	521.91	509.35	3.10	93.40	0.58	0.56
Income tax rev.	Unmatched	362.25	363.82	-1.90		-0.41	0.68
	Matched	362.89	362.55	0.40	78.60	0.07	0.94
Dist. Autobahn	Unmatched	9.89	14.45	-40.90		-8.80	0.00
	Matched	9.97	10.02	-0.40	99.10	-0.08	0.94
Dist. airport	Unmatched	43.85	58.06	-53.10		-11.89	0.00
	Matched	44.13	43.95	0.70	98.80	0.12	0.90

Table A.12: Urban areas only: Treatment and control group before and after matching (A), Western Germany (cont.)

Variable	Unmatched Matched	Mean Treated	Control	% reduction %bias	$\|bias\|$	t-test t	p> $\|t\|$
Dist. train st.	Unmatched	14.83	23.63	-57.20		-13.18	0.00
	Matched	15.04	14.80	1.50	97.30	0.27	0.79
Dist. large urb.	Unmatched	17.36	27.90	-57.20	.-13	51.0	00.
	Matched	17.62	17.76	-0.80	98.70	-0.13	0.90
Dist. medium urb.	Unmatched	2.97	10.20	-96.50	.-19	52.0	00.
	Matched	3.03	2.77	3.40	96.50	0.80	0.43
Dist. Europe	Unmatched	233.51	244.78	-42.60	.-9	96.0	00.
	Matched	233.84	233.85	-0.10	99.90	-0.01	0.99
Share multiple family home	Unmatched	23.44	12.33	87.20	.	22.11	0.00
	Matched	23.22	24.02	-6.30	92.80	-0.97	0.33
Small apt.	Unmatched	8.10	6.07	49.50		11.72	0.00
	Matched	8.11	8.46	-8.40	83.00	-1.36	0.17
Large apt.	Unmatched	41.39	55.08	-94.70		-22.26	0.00
	Matched	41.61	40.94	4.70	95.10	0.79	0.43
Postal code size (km^2)	Unmatched	36.00	37.00	-0.70		-0.17	0.87
	Matched	37.00	36.00	1.50	-122.40	0.23	0.82
pct_agri	Unmatched	40.29	54.25	-54.00		-12.76	0.00
	Matched	40.84	39.77	4.20	92.30	0.70	0.49
pct_water	Unmatched	1.63	1.31	8.70		1.84	0.07
	Matched	1.58	1.35	5.90	32.00	1.13	0.26
pct_urban	Unmatched	25.53	13.25	59.70		14.44	0.00
	Matched	25.49	26.71	-5.90	90.10	-0.88	0.38
pct_ind	Unmatched	8.42	1.98	68.60		21.71	0.00
	Matched	7.83	7.03	8.50	87.60	1.27	0.21
pct_dep	Unmatched	0.81	0.27	30.10		9.00	0.00
	Matched	0.81	0.57	13.70	54.60	1.99	0.05

Table A.13: Urban areas only: Treatment and control group before and after matching (A), Eastern Germany

Variable	Unmatched Matched	Mean Treated	Control	% reduction %bias	$\|bias\|$	t-test t	p>$\|t\|$
Unemployment	Unmatched	10.70	9.99	25.40		3.51	0.00
	Matched	10.67	10.68	-0.60	97.50	-0.07	0.95
Unempl. longt.	Unmatched	28.60	27.56	7.70		1.05	0.29
	Matched	28.83	29.55	-5.50	29.40	-0.56	0.58
ΔUnempl. longt.	Unmatched	-49.91	-50.59	2.70		0.36	0.72
	Matched	-49.45	-48.08	-5.40	-99.20	-0.56	0.57
Construction	Unmatched	1.26	1.70	-25.20		-2.86	0.00
	Matched	1.27	1.25	0.90	96.30	0.15	0.88
Empl. secondary	Unmatched	32.35	31.00	8.70		1.16	0.25
	Matched	32.36	31.76	3.90	55.50	0.42	0.68
Empl. tertiary	Unmatched	62.95	64.43	-8.50		-1.14	0.25
	Matched	62.88	63.61	-4.20	50.50	-0.45	0.65
Commute in	Unmatched	57.18	56.32	5.00		0.65	0.51
	Matched	57.15	58.05	-5.20	-4.40	-0.57	0.57
Commute out	Unmatched	58.66	59.99	-5.10		-0.68	0.50
	Matched	58.84	58.53	1.20	76.40	0.13	0.90
Tax rev.	Unmatched	423.67	414.18	3.50		0.43	0.67
	Matched	424.38	404.25	7.50	-112.20	1.16	0.25
Pop. density	Unmatched	680.52	847.17	-13.90		-1.80	0.07
	Matched	689.64	659.45	2.50	81.90	0.29	0.77
VAT rev.	Unmatched	35.17	33.60	9.10		1.27	0.21
	Matched	35.09	36.93	-10.70	-17.60	-1.15	0.25
Corp. tax rev.	Unmatched	253.71	238.44	5.70		0.70	0.49
	Matched	254.77	236.32	6.90	-20.90	1.01	0.32
Income tax rev.	Unmatched	158.64	165.89	-14.40		-1.86	0.06
	Matched	158.83	158.46	0.70	95.00	0.08	0.93
Dist. Autobahn	Unmatched	15.79	16.74	-7.50		-1.00	0.32
	Matched	15.71	15.81	-0.70	90.30	-0.08	0.94
Dist. airport	Unmatched	68.71	66.93	4.00		0.54	0.59
	Matched	68.77	72.52	-8.40	-110.30	-0.90	0.37
Dist. train st.	Unmatched	23.46	23.10	1.90		0.26	0.79
	Matched	23.20	22.18	5.40	-179.30	0.57	0.57
Dist. large urb.	Unmatched	30.47	28.86	6.80		0.93	0.35
	Matched	30.22	29.40	3.50	48.70	0.36	0.72
Dist. medium urb.	Unmatched	8.13	9.40	-14.30		-1.92	0.06
	Matched	8.28	8.05	2.50	82.60	0.27	0.79
Dist. Europe	Unmatched	271.49	265.42	17.60		2.28	0.02
	Matched	271.57	272.59	-3.00	83.20	-0.34	0.73

Table A.13: Urban areas only: Treatment and control group before and after matching (A), Eastern Germany (cont.)

Variable	Unmatched Matched	Mean Treated	Control	% reduction %bias	$\|bias\|$	t-test t	p>$\|t\|$
Share multiple family home	Unmatched	24.26	23.73	3.50		0.47	0.64
	Matched	24.28	24.61	-2.20	37.10	-0.23	0.82
Small apt.	Unmatched	7.51	7.91	-10.20		-1.33	0.18
	Matched	7.52	7.48	1.00	90.20	0.11	0.91
Large apt.	Unmatched	33.07	33.42	-3.00		-0.41	0.68
	Matched	33.07	32.91	1.40	54.10	0.15	0.88
Postal code size (km^2)	Unmatched	110.00	70.00	43.00	0.10	6.53	0.00
	Matched	110.00	110.00	0.40	99.10	-0.04	0.97
pct_agri	Unmatched	54.99	46.03	30.10		4.12	0.00
	Matched	54.70	57.40	-9.10	69.90	-0.99	0.32
pct_water	Unmatched	1.71	1.90	-4.50		-0.60	0.55
	Matched	1.72	1.36	8.30	-85.30	0.99	0.32
pct_urban	Unmatched	17.02	22.02	-19.10		-2.44	0.02
	Matched	17.29	16.55	2.80	85.10	0.34	0.73
pct_ind	Unmatched	4.68	3.22	17.90		2.61	0.01
	Matched	4.76	4.44	3.90	78.40	0.37	0.71
pct_dep	Unmatched	0.77	0.47	14.70		2.24	0.03
	Matched	0.79	0.51	13.30	9.30	1.42	0.16

A.2.11 Summary of mean comparisons and regression results

Table A.14: ATET vs regression coefficients (full and matched sample)

	Full sample		Full sample	
	Entire Germany		West Germany	East Germany
ATET	0.0005		0.217**	-0.425*
	(0.083)		(0.090)	(0.169)
Post*Treatment	0.053		0.236**	-0.399*
	(0.081)		(0.091)	(0.166)
Obs (T/C)	8212 (1118/7094)		6799 (741/6058)	1413 (377/1036)
	Full sample (with 500 m buffers)		Full sample (urban areas only)	
	West Germany	East Germany	West Germany	East Germany
ATET	0.368***	-0.332*	0.287***	-0.397**
	(0.078)	(0.160)	(0.097)	(0.185)
Post*Treatment	0.408***	-0.286	0.319**	-0.396*
	(0.080)	(0.154)	(0.099)	(0.185)
Obs (T/C)	6799 (1127/5672)	1413 (458/955)	6799 (603/6196)	1413 (223/1190)
	Nearest neighbour matching (NN)		NN (with 500 m buffers)	
	West Germany	East Germany	West Germany	East Germany
ATET	-0.069	-0.063	-0.010	-0.002
	(0.136)	(0.232)	(0.117)	(0.224)
Post*Treatment	-0.074	-0.084	-0.011	-0.000
	(0.138)	(0.233)	(0.117)	(0.228)
Obs (T/C)	1312 (727/585)	595 (368/227)	1917 (1105/812)	710 (447/263)
	NN (urban areas only, Match A)		NN (urban areas only, Match B)	
	West Germany	East Germany	West Germany	East Germany
ATET	-0.113	-0.290	-0.094	-0.372
	(0.154)	(0.270)	(0.163)	(0.310)
Post*Treatment	-0.118	-0.285	-0.080	-0.350
	(0.156)	(0.273)	(0.164)	(0.307)
Obs (T/C)	1070 (591/479)	400 (219/181)	991 (591/400)	357 (219/138)
	Radius matching		Mahalanobis matching	
	West Germany	East Germany	West Germany	East Germany
ATET	0.036	0.125	-0.0017	-0.164
	(0.114)	(0.211)	(0.131)	(0.225)
Post*Treatment	0.041	0.121	-0.0018	-0.113
	(0.113)	(0.213)	(0.131)	(0.216)
Obs (T/C)	5617 (612/5005)	1140 (317/823)	1342 (727/615)	615 (368/247)

ATET: Treatment effects measured in differences in House Price Index (pre-post) including state fixed effects. Robust standard errors in parentheses.

Regressions: Dependent variable is the House Price Index. Clustered standard errors in parentheses.

*/**/*** Significant at the 5%/1%/0.1% level.

A.3 Appendix - Chapter Three

A.3.1 E-PRTR: Industry Classifications

Facility-level emission reports in the register are either identified by the NACE1.1 code of the main economic activity (EPER) or by the NACE2.0 code (E-PRTR). I use the correspondence tables available from EUROSTAT to convert all entries to three digit NACE1.1 codes. This is done because conversions between NACE2.0 and NACE1.1 are unambiguous at the three digit level and because the research project in Chapter 1 requires merging information at the NACE1.1 level corresponding to the WZ93 classifications used in DFS[123].

In ambiguous cases, I consider the E-PRTR text entries "MainEconomic Activity", "MainSubEconomicActivity" and "FirmName" (in this order) for manual assignment. For the cases that do not yield a unique NACE1.1 code and for the frequent misreportings in EPER that provide only a more general (e.g. two digit) classification, I refer to the description fields in the conversion tables to manually assign the most fitting code. This results in a uniquely identified correspondence table after the codes 284 ("Forging, pressing, stamping and roll forming of metal; powder metallurgy") and 285 ("Treatment and coating of metals") have been assigned to code 287 ("Manufacture of other fabricated metal products") and after code 275 ("Casting of metals") has been changed to 271 ("Manufacture of basic iron and steel and of ferro-alloys") in order to correspond with DFS trade flows.

[123]For the supplementary analysis presented in Chapter 3.4.2, I limit trade flow data from COMTRADE to the manufacturing categories $WZ93 \in [150, ..., 369] \setminus [231, 232, 233]$ in accordance with the research presented in Chapter 1 and combine these with E-PRTR totals. This requires linking SITC (rev. 3/4) codes to WZ93 categories. EUROSTAT correspondence tables can be obtained from the website (https://ec.europa.eu/eurostat/de/web/nace-rev2/correspondence_tables).

A.3.2 EPER vs. E-PRTR

While the reporting requirements have changed between the two register versions, the substances (NO_X, SO_X, $PM10$) and the manufacturing industries evaluated in Chapter 1 and Chapter 3.4.2 have not been subject to changes in thresholds. These have remained at 100,000kg for NO_X, at 150,000kg for SO_X and at 50,000kg per year for $PM10$ over the course of the sample period[124]. Therefore, no limitations exist for the comparison of reported EPER and E-PRTR values.

Capacity exemptions and the relevant facility definitions have also remained unchanged across the manufacturing sectors under study[125]. Thus, EPER and E-PRTR records can be combined within the framework of Chapter 3.4.2 to analyze trends in industry emissions between 2001 and 2008.

[124] The validity of comparisons over time and register versions for other pollutants has to be checked by consulting the guidance document European Union (2006a) available online (http://prtr.ec.europa.eu/docs/en_prtr.pdf).

[125] According to European Union (2006a), changes in capacity thresholds have only occurred for waste treatment sites, landfills closed before 07/2001 and the incineration of non-hazardous wastes. Under E-PRTR regulation, certain types of facilities for the chemical protection of wood, intensive aquaculture and the coloring of ships have been added to the portfolio of reporting facilities but none of these report emission quantities for the pollutants under study in Germany during the period of observation.

A.3.3 Visual Example of Grid Aggregation

Figure A.18 contains the heat map of the underlying $7 \times 8km^2$ OI raster with shading according to deciles in NO_2 concentration changes over the period of observation in Chapter 1 along with the target choropleth map of German counties shaded according to the county-level deciles.

Pollutant concentrations are inherently normalized as they are densities measured in $\mu g/m^3$ which represent absolute quantities normalized by the height of the air column and the ground area $((\mu g/m) \cdot (1/m^2))$. It can be seen that colour gradients are usually smooth and that patterns at the grid-level carry over into the county features of the target layer.

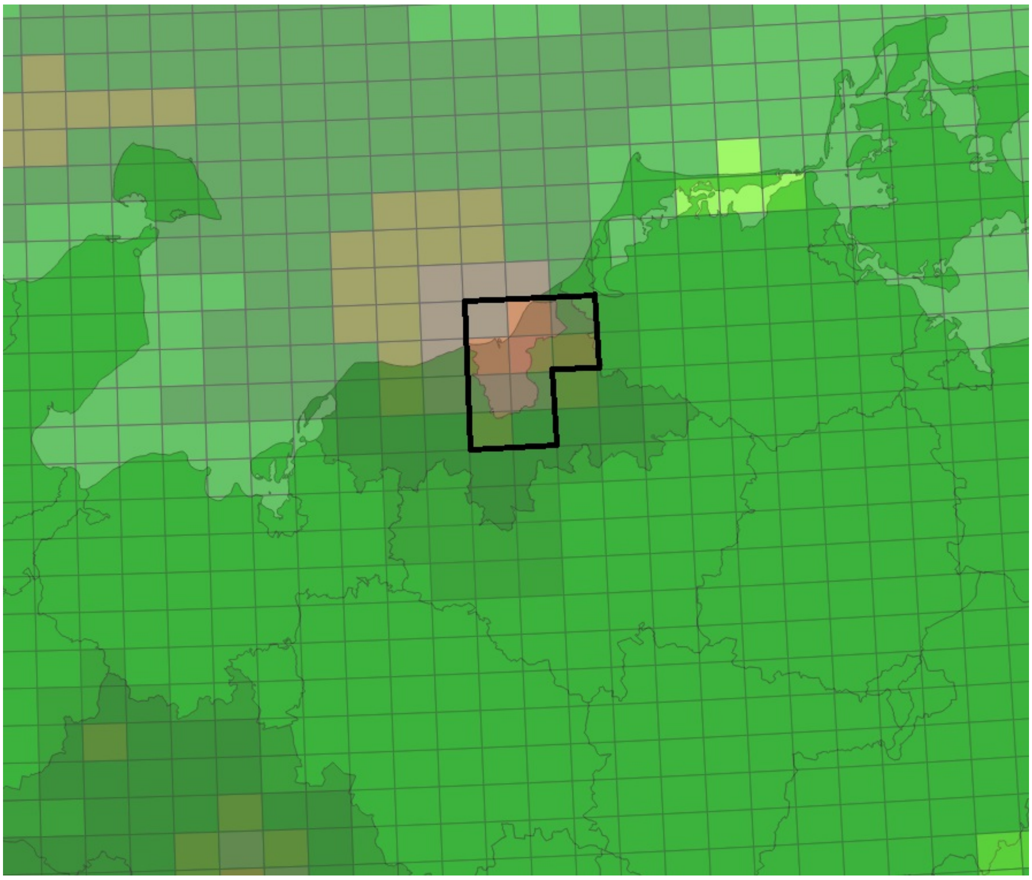


Figure A.18: Choropleth Map: Aggregation via unweighted overlaps