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Abstract

In this paper, we study the effect of the release of emission information on housing prices. The main event under study is the release of the first wave of data from the European Pollutant Release and Transfer Register (E-PRTR) publishing emission quantities for the reporting year 2007. We base our analysis on quarterly house prices at the German postal code level for the years 2004-2011 and provide, to the best of our knowledge, the first analysis outside the US on this research question. We estimate a differences-in-differences model and find no significant effect of the release of emission information on the value of houses in affected postal code areas when controlling for observable differences in land use, prevalence of housing types, tax revenues and other postal code area characteristics by means of propensity score matching. This result survives several robustness checks. We conclude that disclosing the first wave of E-PRTR emissions had no robust impact on housing prices.

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1 Introduction

According to the concept of "regulation by information", the mere provision of information can generate community pressure on polluters to reduce their emissions as households respond to the information. While there is evidence that households adjust their behavior to reduce the negative consequences for their health when provided with information on water quality (Graff Zivin et al., 2011) or ambient ozone (Neidell, 2009, Moretti and Neidell, 2011), empirical studies on the most prominent program established on this concept, the US-American Toxics Release Inventory (TRI), have yielded mixed results. Sanders (2013) is most similar to our analysis. Sanders analyzes the effect of an enlargement in the TRI database using a large set of postal codes from multiple states and finds a significant and negative impact on affected postal codes. We look at the revelation of emissions information in Germany and in doing so provide what seems to be the first attempt in Europe to assess the impact of large scale publications of pollution information on house prices. Our definition of treatment differs from Sanders' approach and we are fortunate to have a more detailed data set describing the characteristics of postal code areas to address the issue of finding comparable treatment and control groups in our sample. Our results show the importance of controlling for such observable differences.

Despite the weak evidence base supporting the effectiveness of the TRI, several other countries have launched similar registers, also in Europe. The main event under study is the first wave of data from the European Pollutant Release and Transfer Register (E-PRTR), released in 2009 and reporting on pollutant emissions from 2007. The E-PRTR replaced its predecessor, the European Pollutant Emission Register (EPER), and included an expanded set of both emissions and facilities. Following its initial data release the E-PRTR received a considerably larger amount of media attention than its predecessor. The pollutants covered in the new register are emitted to one of three media: air, water or soil with approximately 60 pollutants in each group and with some degree of overlap. E-PRTR emissions data is collected yearly with a delay of approximately 2 years. So far, comprehensive data releases have taken place in 2009, 2010, 2011 and 2012.

We base our analysis on quarterly house prices at the German postal code level ("Postleitzahlen") for the years 2004-2011. 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. It relies on several assumptions concerning market extent and the identification of an appropriate control group. The control group should be identical to the treatment group in the absence of treatment for the treatment effect to be accurately identified. We collect a large data set on land use characteristics and combine it with socio-economic information on municipalities which are spatially assigned to individual postal code areas. These data indicate substantial systematic differences between the treated postal code areas and the untreated areas in the full data and reveal substantial differences between treated postal code areas in the former Eastern and Western Germany. Based on our data on the observable characteristics we match our treated postal code areas to suitable controls. With matching both the size and significance of the treatment effects in either region are dramatically reduced and we are unable to find any effect of the information revelation.

We carry out a number of robustness checks based on our treatment definition. Our main treatment definition may be too broad as small emissions are treated as equal to large emissions (Sanders (2013) emphasizes non-linear effects in emission quantities). To better capture the quantity emitted, we redefined the treatment variable to indicate quartiles of toxicity weighted emissions. We approximate toxicity by the reporting thresholds for the register. These thresholds are publicly available and send a signal about the danger associated with the emission. No significant effect was found after matching was used. Additional robustness checks concern the distance to emissions and narrowing down the treatment definition to concern only those postal codes with urban area within 500 m of an emission. In sum, our results suggest that disclosing the first wave of E-PRTR emissions had no significant impact on average housing prices in Germany at the postal code level once we account for observable characteristics of the postal code areas.

2 Related Literature and Background

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. Housing markets are often used for non-market valuation purposes including a large literature on housing prices and environmental amenities using e.g. the hedonic model (Palmquist, 2004). Much of this literature focuses on the impact of air pollution measures on housing prices or on localized amenities and disamenities such as power plants (Davis, 2011) and Superfund sites (Mastromonaco, forthcoming).[1] In the last decade, a number of papers on environmental valuation using a quasi-experimental approach have emerged (e.g. 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 while the hedonic model aims to recover a marginal willingness to pay measure from the slope of the hedonic price function, the quasi-experimental approach recovers a capitalization effect. Kuminoff and Pope (2011) emphasize that several assumptions are required to interpret the capitalized effect as an estimate of households' average marginal willingness to pay for the amenity.

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

There are several studies which look at the effect of providing pollution information on housing prices. Pope (2008) looks at the introduction of disclosure laws requiring sellers to provide information about airport noise exposure to buyers. The effects on housing prices in the United States of making emission data from the Toxic Release Inventory (TRI) public has already been evaluated by several empirical studies. While Bui and Mayer (2003) find no significant effects of TRI releases on the housing market at the county level, Sanders (2013) finds evidence of a negative impact of reported TRI emissions on housing prices using a nation-wide postal code based approach and conducting an event-study based on the extension of the TRI pollutant reporting definitions in 1998. There are also papers based on micro-level data. Oberholzer-Gee and Mitsunari (2006) find a negative effect of emissions at short distances (< 1 mile) from the emitter. Currie et al. (2013) look at both health effects from residing near polluting facilities and effects of the opening and closing of polluting facilities registered in the TRI on housing prices. Using micro data on individual transactions, they also find a significant effect on house prices, albeit at the very local level within 0.5 miles of the facility. Thus, several of these existing studies find both statistically and economically significant effects of exposure to pollution on the housing price. To the best of our knowledge, we are the first to look at the effect of the E-PRTR on house prices.

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 view 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. In 2003, the UNECE Pollutant Release and Transfer Register protocol was signed resulting in the establishment of the European Pollutant Release and Transfer Register (E-PRTR). 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.

While the predecessor, the EPER, lived a relatively quiet life,[2] the launch of the E-PRTR in 2009 was heavily publicized. Several major German newspapers announced the launch of the German E-PRTR website

[2]The EPER made Europe-wide pollution data for the year 2001 available in 2004 and pollution 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).

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.[3] The launch was also accompanied by an official conference in Berlin and the introduction of a more professional website layout. The website itself is centered around a convenient database hosted on the servers of the European Environment Agency (EEA) and was featured in a number of popular magazines. Furthermore, maps with the graphical depiction of core pollution areas and point sources on the website made the information more accessible to people not familiar with the subject or not interested in filtering through extensive micro data.

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. Altogether it seems reasonable that the information released on June 3rd 2009 should be considered news to the German households. While they likely had beliefs about the level of pollution in their area, the release of E-PRTR pollution data provided them with the opportunity to update their beliefs and adjust behavior if deemed necessary. Hence, we treat the release of the E-PRTR information in the second quarter of 2009 as the pivotal event in our analysis.

3 Method

Our approach is based on differences in differences as we look at the evolution of house prices over time in different postal code areas. We restrict the data on housing prices (Y) to a time interval covering two years before and after the release of the data as suggested by Sanders (2013). Given our quarterly data, we are left with 16 observations for each postal code area. We include a shift dummy variable ($Post$) which is set to 1 for all quarters after the release of the emissions data and a dummy variable for treatment (T). We estimate the following model with postal code fixed effects (α_i^4) and time by state fixed effects (α_{ts}^5):

$$Y_{its} = \alpha^0 + \alpha_s^1 Post_{it} State_s + \alpha^2 T_i + \alpha^3 Post_{it} T_i + \alpha_i^4 + \alpha_{ts}^5 State_s + \varepsilon_{its}$$

First, the appropriate definition of treatment status (T) is crucial to our study and we test a number of different definitions. In the E-PRTR data, 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. We refine these treatment definitions to address the concern that quantity emitted may be important in section

[3]Examples of comprehensive newspaper articles on the newly available E-PRTR data include Abendblatt (2009) and TAZ (2009).

6. When performing a fixed effects regression, the treatment dummies are dropped because of their time invariance and time by state fixed effects are included to control for state-specific time trends.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.

Second, the extent of the market is important in determining the appropriate capitalization effect if there is heterogeneity in preferences in different housing markets. Treating large geographic areas (e.g. the whole USA) as a single market is not unusual in the quasi-experimental hedonic literature (e.g.Greenstone and Gallagher (2008), Sanders (2012)). Gamper-Rabindran and Timmins (2013) find that there is considerable heterogeneity in the capitalization of clean-ups of hazardous waste across the USA. Their findings suggest that pooling data across regions may be misleading. Given the German history and the resulting very different economic conditions in the former Eastern and Western Germany, we estimate our model for each of these two regions separately.

Third, we need to rule out systematical differences between control and treatment group, in particular in the general housing market trend. If treatment status is determined at least in parts 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 the use of propensity 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 a location. The market definition discussed above can also be seen as narrowing down the relevant control group to compare to the treated postal code areas to control for (regional) differences in terms of unobservable characteristics.[4]

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 should be affected differently than the control areas. It could be 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 for a postal code area in our matching procedure.

[4]This point is made in a recent paper by Abbott and Klaiber (2013) in which they use matching to account for observable characteristics, but use spatial proximity to define comparable units in terms of unobservable characteristics.

4 Data

4.1 Housing Data

We use the "F&B Wohn-Preis-Index" on the postal code level with quarterly data for the past 10 years (2002Q2-2012Q1) which has been purchased from F&B GmbH, Hamburg. 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 terrace 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 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[5] and have been summarized in F+B (2012).

The baseline index used is normalized to 100 in 2004Q2 for each postal code and describes the development in housing prices within each separate postal code relative to the housing price index at this fixed point in time. We compared the 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 house price data.

4.2 Pollution data

4.2.1 Facility reports

Pollution data has been taken from the website of the European Pollutant Release and Transfer Register (E-PRTR). The database itself is maintained by the European Environment Agency[6] and the tables used list pollution data from point sources on the facility level for all European countries reporting to the E-PRTR in absolute quantities. The database contains releases into air, water and soil as well as transfers to external waste treatment facilities. The reports differentiate between 96 pollutants, out of which 70 actually occurred in Germany in the reports for 2007.

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

[6] 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-6

In total, there have been 26,832 pollutant point source releases and 4,704 waste transfers reported for all of Germany and all 6 reporting years together. Out of these, 826 entries had to be dropped because of apparently faulty data submission, restricted information due to confidentiality claims and issues with double entries. For the year 2007, there were 4,727 point source releases and 952 waste transfers reported for 1,976 individual facilities. For our analysis we exclude reports on CO_2 as this substance does not pose a local threat to nearby households. 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 less concerns within the local community than the direct release of pollutants into the local environment.

4.2.2 Facility locations

The E-PRTR database also contains Gauss-Krüger coordinates (WGS84) of each facility. We use a geographic information system (ArcGIS) to display the locations and to attribute it to the corresponding postal code area. Shape files for ArcGIS have been provided by GfK GeoMarketing and contain the full set of 8,212 German postal code areas and the approximately 12,000 municipalities in Germany as of January 2012.[7]

The location of emissions by postal code areas is displayed in red in Figure 1. The visual representation shows that emissions are not spread out evenly across Germany. There are several emissions in well-known industrial areas such as e.g. the Ruhr valley, as well as in certain areas in the former German Democratic Republic. There are in total 1,118 postal code areas, which contain a point source according to the data set published in 2009.

[7]Interestingly, looking at the 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.

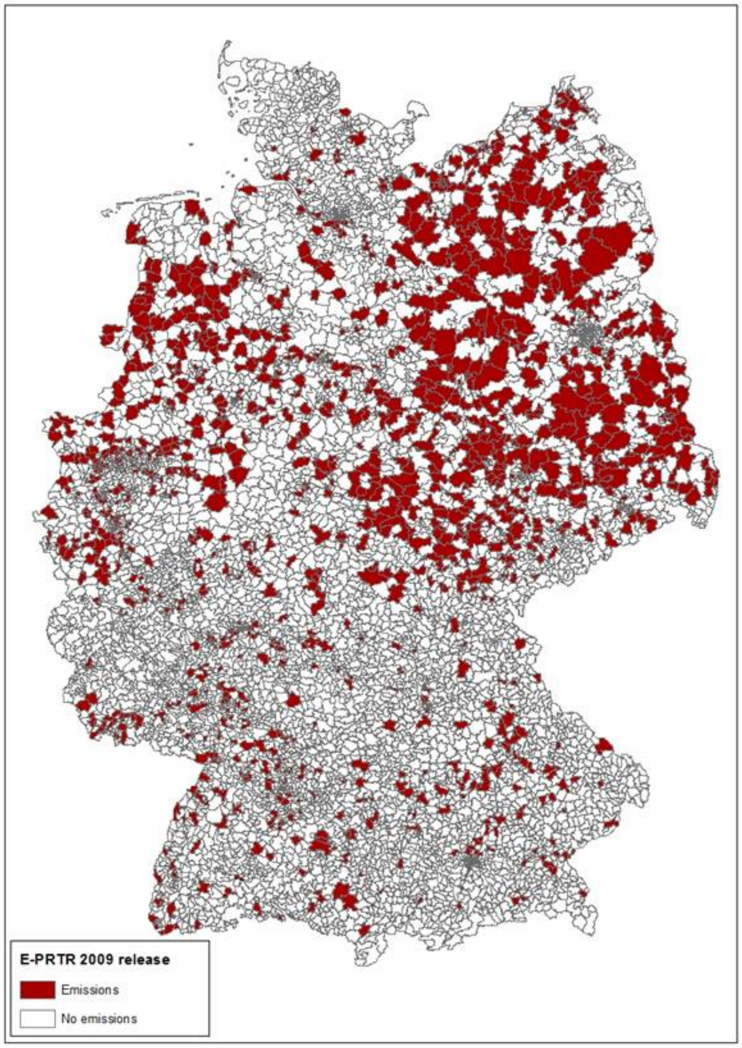


Figure 1: Postal code areas with emissions

4.3 Data on postal code areas

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. 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 such as urban area, infrastructure, natural areas etc. 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, where the different categories of land use are demonstrated for the postal code covering the centre 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.

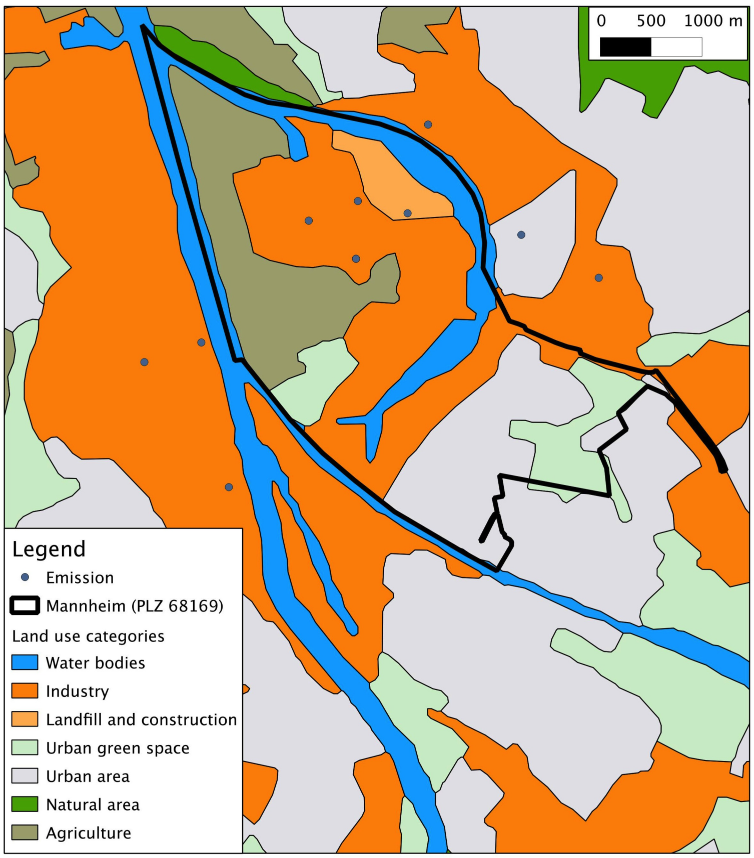


Figure 2: Land use in Mannheim, Germany

4.3.2 Municipality Data

At the municipality level we have access to the 2009 wave of the INKAR[8] database provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development. These data describe

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

the demographic, economic and social composition of municipalities. Among other things these data contain information about the unemployment rate, prevalent type of housing, age composition and population size as well as tax revenues at the municipality level. A list of variables in our data set can be found in Tables 2 and 3.

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.[9] Our sample in the estimations using matching was therefore reduced to 8,171 postal code areas.

5 Results

5.1 Full Sample

We estimate the model with postal code fixed effects and state-specific time trends (implemented as quarterly dummies and post dummies). 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% for the subsequent two-year-period. In the aggregate, housing prices in the treated postal codes rose just as strongly as non-treated ones (column 1 in Table 1). We proceed to look at the former Eastern and Western Germany separately (columns 2 and 3 in Table 1). The results differ a great deal between the two regions. Even with state-specific time trends 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.

[9] Over the last years there have been several municipal reforms merging and dividing municipalities. Since our INKAR data is from 2009 we had to match municipalities from then to present municipal structures and then to the postal code areas. Since no old shape files were available for municipalities, some municipalities were lost in the first step of this process.

Table 1: Panel estimates, full sample

Full data	Full sample (1)	Western Germany (2)	Eastern Germany (3)
Post*T	0.053	0.236 **	-0.399 ***
	(0.081)	(0.091)	(0.166)
Constant	95.791 ***	95.893 ***	95.303 ***
	(0.0259)	(0.029)	(0.059)
Postal code FE	Yes	Yes	Yes
State-specific Post	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes
R^2	0.394	0.387	0.424
Observations	8212	6799	1413
Treated observations (T=1)	1118	741	377

Note. Dependent variable is house price index; clustered standard errors in parantheses.
*/**/*** Significant at the 5%/1%/0.1% level.

5.2 Matching

The underlying assumption in the differences in differences approach is that the treatment and the control group have the same observable and unobservable characteristics except for the fact that the treatment group was exposed to treatment. If 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. Given that we have constructed a data set describing the characteristics of the postal code areas, we can check if this assumption holds for observable variables. If the treatment group and control group are similar in terms of observable characteristics it seems more likely that they should also be similar in terms of unobservable characteristics. We compared the means in the two populations and tested if they were significantly different. For a large number of the characteristics this turned out to be the case as is shown in Tables 2 and 3.

Table 2: Mean characteristics of treatment and control group before matching.

Western Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	5.5	4.3	58.6	19.14	0.0
- long term	29.2	27.9	10.6	3.39	0.0
- long term, change	-24.3	-26.3	5.0	1.54	0.1
Employed in the primary sector	1.0	1.7	-29.6	-8.16	0.0
- secondary sector	37.2	38.7	-8.7	-2.62	0.0
- tertiary sector	61.8	59.6	12.8	3.89	0.0
Commuters into municipality	62.6	66.5	-32.7	-10.13	0.0
Commuters out of municipality	60.2	73.3	-62.3	-19.44	0.0
Total tax revenues	674.5	598.5	22.6	6.99	0.0
Population density	866.6	490.8	45.7	14.48	0.0
Value added tax revenues	45.9	30.6	57.1	17.91	0.0
Commercial tax revenues	450.1	314.1	27.9	8.80	0.0
Income tax revenues	333.6	340.8	-8.9	-2.73	0.0
Distance to freeway	10.5	14.7	-38.4	-10.90	0.0
Distance to airport	47.1	58.6	-43.2	-12.76	0.0
Distance to fast trains	17.9	23.8	-38.4	-11.65	0.0
Distance to large urban center	20.9	28.1	-39.1	-12.17	0.0
Distance to medium urban center	5.1	10.4	-66.9	-19.20	0.0
Access to European neighbors	236.7	245.0	-31.0	-9.41	0.0
Newly constructed buildings	1.8	1.8	-5.0	-1.51	0.1
Share of single/two family housing	81.0	87.9	-54.8	-17.73	0.0
- multiple family housing	19.0	12.2	54.8	17.73	0.0
Small apartments	7.2	6.1	27.0	8.22	0.0
Large apartments	46.9	55.3	-55.6	-17.60	0.0
Size of postal code area (km^2)	48.8	35.0	19.5	6.48	0.0
pct_agriculture	47.9	54.0	-23.5	-7.26	0.0
pct_urban area	19.4	13.3	31.0	9.29	0.0
pct_water bodies	1.7	1.3	11.9	3.42	0.0
pct_natural areas	21.3	28.3	-33.1	-9.87	0.0
pct_industrial areas	6.7	1.7	56.5	22.17	0.0
pct_land fills etc.	0.8	0.2	32.5	13.35	0.0

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.

Table 3: Mean characteristics of treatment and control group before matching.

Eastern Germany					
Variable	Treated	Control	%bias	t	$p > \|t\|$
Unemployment level	10.4	9.8	23.2	3.97	0.0
- long term	28.7	27.3	10.8	1.76	0.1
- long term, change	-49.5	-50.8	4.8	0.79	0.4
Employed in the primary sector	5.0	3.3	29.2	4.91	0.0
- secondary sector	33.7	30.2	23.3	3.69	0.0
- tertiary sector	61.2	66.5	-31.1	-4.94	0.0
Commuters into municipality	61.4	54.2	43.4	6.55	0.0
Commuters out of municipality	65.5	56.8	35.0	5.34	0.0
Total tax revenues	381.2	386.0	-1.9	-0.31	0.8
Population density	345.7	1013.9	-61.1	-8.71	0.0
Value added tax revenues	32.0	33.6	-10.0	-1.68	0.1
Commercial tax revenues	223.7	219.3	1.6	0.27	0.8
Income tax revenues	150.4	167.4	-36.2	-5.53	0.0
Distance to freeway	16.6	16.0	4.5	-0.73	0.5
Distance to airport	74.3	63.0	24.9	4.01	0.0
Distance to fast trains	26.5	20.9	30.7	4.94	0.0
Distance to large urban center	34.6	25.8	38.5	6.20	0.0
Distance to medium urban center	9.6	9.0	12.3	2.01	0.0
Access to European neighbors	267.7	259.0	19.9	3.27	0.0
Newly constructed buildings	1.0	1.2	-8.1	-1.76	0.2
Share of single/two family housing	80.4	74.4	40.6	6.37	0.0
- multiple family housing	19.6	25.6	-40.6	-6.37	0.0
Small apartments	6.6	8.4	-46.8	-7.01	0.0
Large apartments	36.1	32.2	33.7	5.41	0.0
Size of postal code area (km^2)	139.3	54.3	84.9	16.46	0.0
pct_agriculture	60.8	42.7	66.3	10.45	0.0
pct_urban area	9.3	25.4	-68.0	-9.84	0.0
pct_water bodies	2.1	1.7	7.5	1.23	0.2
pct_natural areas	22.7	23.5	-3.7	-0.58	0.6
pct_industrial areas	3.2	3.5	-4.3	-0.70	0.5
pct_land fills etc.	1.0	0.4	28.0	5.43	0.0

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.

These tables also reveal the stark differences between former Eastern and Western Germany. Generally speaking, the postal code areas in the treatment group in Western Germany have fewer commuters out of the municipality, lower distance to medium sized urban centers, 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 form large urban centers and from main line train stations. So where treatment in Western Germany is associated with the prevalence of industry, this seems to be less the case in Eastern Germany. 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 have a larger share of landfills than the untreated postal code areas. Overall, this is consistent with the treated postal code areas being less attractive than the postal code areas for which no emission information had to be reported. These differences mirror the findings in Bui and Mayer (2003) when looking at the characteristics of affected counties in Massachusetts. In fact, the authors find fairly similar systematic differences between the counties subject to emissions registered in the TRI and those without emissions. 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.

The idea underlying the matching approach is to find control units which are in fact comparable to the treatment group in terms of relevant observable characteristics. We use propensity score matching which aims to identify those postal code areas, which have equal likelihood of being treated, as far as this can be predicted given observable variables. Our choice of characteristics upon which to base the matching procedure was based on which characteristics could be expected to affect the evolution of residential housing prices. Generally speaking, a probit or a logit is estimated with the treatment indicator as the dependent variable. Then, observations are matched based on their propensity score, i.e. the likelihood of treatment. Our propensity score matching uses the user written procedure psmatch2 for Stata. We employ nearest neighbor matching to identify the relevant control group based on the observable characteristics of the postal code areas. A logit model including the covariates was estimated for each region.[10] Several of the covariates were highly significant reflecting the different characteristics discussed above. We imposed common support for the matched sample. This reduced the sample by 2 postal code areas in Western Germany. In Eastern Germany, common support results in the loss of 13 postal code areas. 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 odds ratio 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 (A.2 and A.3). We also include figures displaying the evolution in average prices in the matched control and treatment group in the appendix (A.4).

The control and the treatment group in each region are shown in Figure 3. It is clear that both the treatment and the control postal code areas are scattered across each of the regions, i.e. although spatial

[10] 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 urban land use out of the logit models used for matching.

proximity is not directly a condition for matching, the outcome is not a control group spatially distinct from the treatment group.

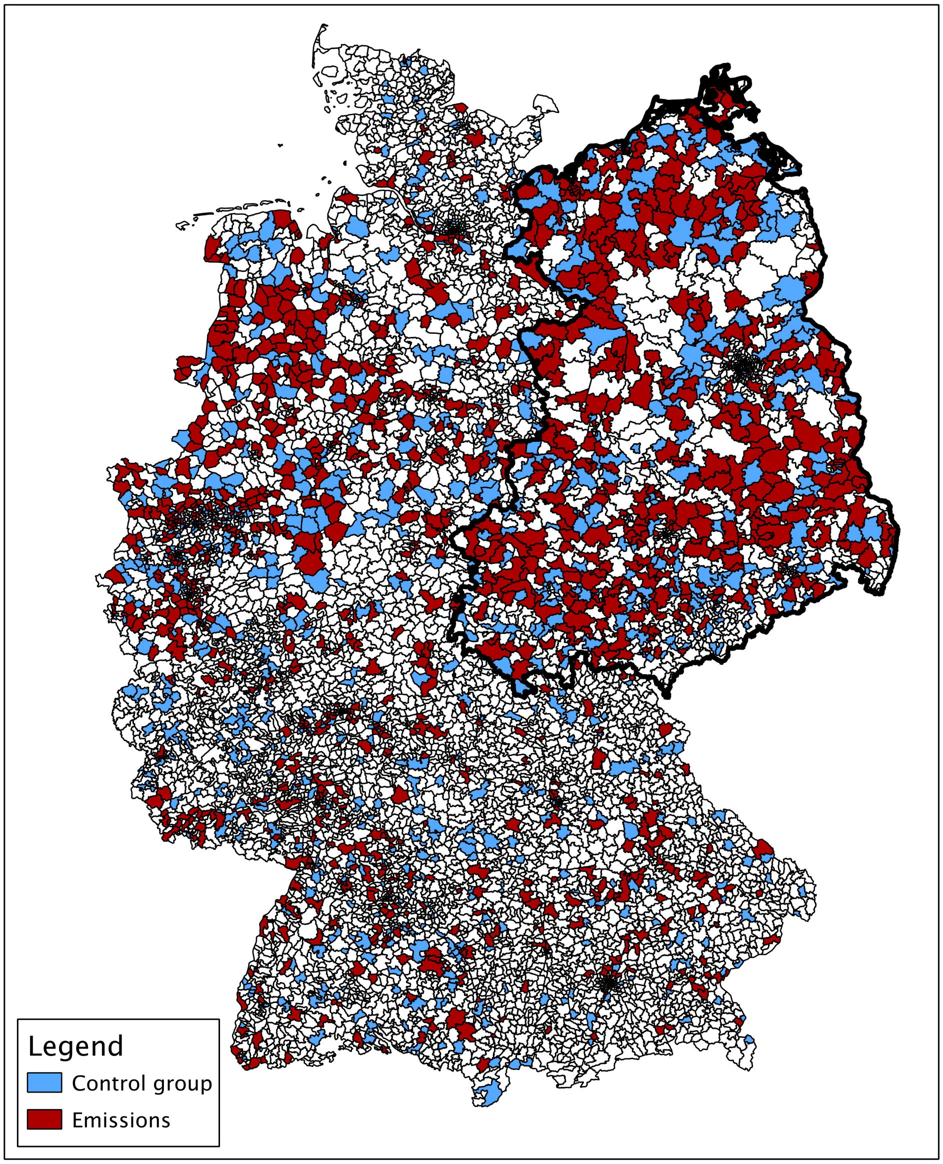


Figure 3: Treatment and control groups with matching

We carried out the differences in differences estimation using our matched samples but otherwise with the same specification as in Table 1. The results of the estimation with matching are given in Table 4 where we also report the previous results for convenience of the reader. The main coefficient for post treatment is markedly reduced towards zero in comparison with the coefficient from the unmatched sample estimation 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. Furthermore, when the standard errors are calculated with clustering at the postal code level, the treatment effect is no longer significant at at any conventional level for either of the regions. 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.

Table 4: Panel estimates, matched samples

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*T	0.237 **	-0.046	-0.399 ***	0.170
	(0.090)	(0.131)	(0.166)	(0.240)
Constant	95.893 ***	96.376 ***	95.303 ***	94.966 ***
	(0.029)	(0.057)	(0.060)	(0.091)
Postal code FE	Yes	Yes	Yes	Yes
State-specific Post	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes
R^2	0.393	0.440	0.403	0.243
Observations	6799	1319	1413	568
Treated observations (T=1)	741	739	377	350

Note. Dependent variable is house price index; clustered standard errors in parantheses.
*/**/*** Significant at the 5%/1%/0,.1% level.

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 introduce buffers to allow for an expanded treatment effect on postal code areas within 500 m of a facility. Third, as our housing price index concerns residential property, we estimate a model where we limit the treatment definition to only those postal code areas where urban area or urban green space was within 500 m of an emitter facility. Summarizing, 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 a postal code area. The robustness checks are described in more detail below.[11]

[11] 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.

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. Sanders (2013) looks at quartiles of emitted quantities to address the concern that the quantity emitted may be important. We follow this approach and aggregate the emissions of different substances to a measure of total weighted 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. For severity we use the reporting thresholds from the E-PRTR as a proxy. These thresholds are lower for more potent substances such as benzene or dioxin than for less potent substances such as nitrogen oxides. The thresholds are publicly available and as no toxicity measure is contained within the E-PRTR we believe that this measure captures well the level of information easily available to households.[12]

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 all emissions within the postal code area weighted by their corresponding reporting thresholds. 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:

$$Y_{its} = \alpha^0 + \alpha_s^1 Post_{it} State_s + \sum_{j=1}^{4} \left[\alpha_j^2 T_j + \alpha_j^3 Post_{it} T_j\right] + \alpha_i^4 + \alpha_{ts}^5 State_s + e_{its}$$

The coefficients of interest are now the α_j^3 as they correspond to the interaction of the shift dummy variable ($Post$) and the treatment dummy (T_j) with respect to each of the $j = 1, 2, 3, 4$ quartiles. The results are shown in Table 5. For Western Germany in the full sample without matching again a positive treatment effect is found. 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. With matched samples however, no significant effect is found at all for the information release. Summarizing, the results from the main specifications are confirmed in this robustness check. We also carried out analysis 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.[13]

[12]The reporting thresholds are an imperfect proxy for toxicity. They are not directly intended to capture toxicity but rather to ensure that as many emissions are covered by the register as possible. Still, when looking across the table of thresholds and the substances, there is a clear pattern that lower thresholds are associated with substances generally perceived as being dangerous.

[13]A table of these results is available from the authors upon request.

Table 5: Quartiles of emissions

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*TQ1	0.003	-0.355	-0.438	0.160
	(0.189)	(0.213)	(0.248)	(0.297)
Post*TQ2	0.038	-0.239	-0.537 *	0.0430
	(0.201)	(0.222)	(0.246)	(0.298)
Post*TQ3	0.442 **	0.133	-0.299	0.203
	(0.157)	(0.184)	(0.305)	(0.370)
Post*TQ4	0.350 *	0.130	-0.138	0.450
	(0.140)	(0.166)	(0.405)	(0.449)
Constant	95.893 ***	96.376 ***	95.303 ***	94.966 ***
	(0.029)	(0.057)	(0.059)	(0.091)
Postal code FE	Yes	Yes	Yes	Yes
State-specific Post	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes
R^2	0.393	0.442	0.424	0.244
Observations	6799	1319	1413	568
Treated observations (T=1)	741	739	377	350

Note. Dependent variable is house price index; clustered standard errors in parantheses.
*/**/*** Significant at the 5%/1%/0.1% level.

6.2 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.[14] 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. Looking at the results in Table 6, the new treatment definition does not

[14] This includes emissions from 13 additional facilities located in neighbouring countries but close enough to the border to affect German postal code areas.

Table 6: Treatment based on buffers

	Western Germany		Eastern Germany	
	Full sample	Matched sample	Full sample	Matched sample
Post*T	0.408 ***	0.206	-0.286	0.112
	(0.0801)	(0.116)	(0.154)	(0.211)
Constant	95.893 **	96.365 ***	95.303 ***	94.975 ***
	(0.029)	(0.049)	(0.059)	(0.080)
Postal code FE	Yes	Yes	Yes	Yes
State-specific Post	Yes	Yes	Yes	Yes
State specific trends	Yes	Yes	Yes	Yes
R^2	0.388	0.439	0.424	0.319
Observations	6799	1920	1413	683
Treated observations (T=1)	1127	1124	458	428

Note. Dependent variable is house price index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

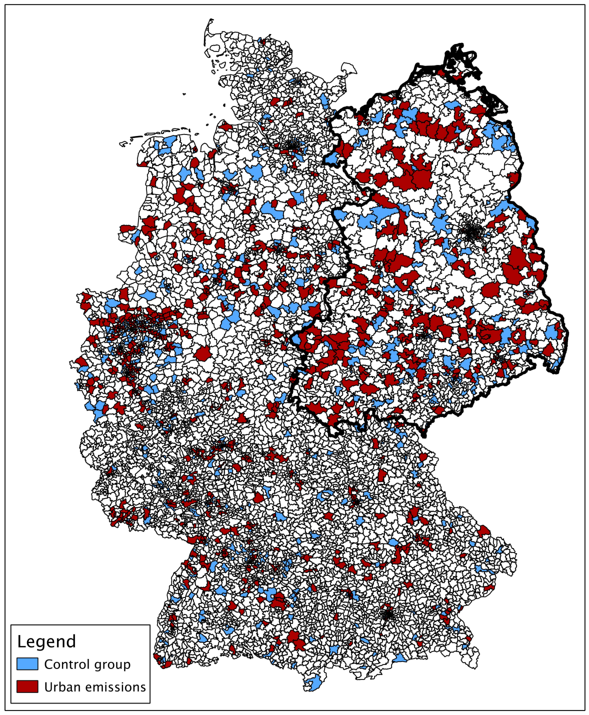
change the estimates substantially. Overall, previous results are confirmed showing that they did not suffer from a bias due to emitters located close to the border of the postal code areas.

6.3 Urban areas only

In a last robustness check, the sample is reduced to those areas that contain urban parts, i.e. areas labelled 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. Compared to the definition without a buffer the reduction is by about 40 %. Since we are restricting attention to postal code areas where non-industrial urban areas are in close proximity to emissions, this treatment definition should be the most likely to show an effect of treatment of all the specifications that we looked at. In total there are 826 affected postal code areas with the urban treatment definition. Their spatial distribution is seen in figure 4.

Estimations are carried out for the full sample divided into Eastern Germany and Western Germany. Additionally, matching is carried out using propensity scores based on the extensive data collected characterizing a postal code area. 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.5 for a comparison of charactersitics pre- and post-matching). Two matching definitions are used: Match A and Match B. B is like A, but excludes all postal code areas from the control group, which

Figure 4: Map of treated areas and controls



had emissions in 2009 that were not near urban areas. The results are seen in table 7. For the matched samples, no significant effect could be found in either Western Germany or Eastern Germany.

Table 7: Results: Differences-in-differences estimation

	Western Germany			Eastern Germany		
	Full	Matched A	Matched B	Full	Matched A	Matched B
Post*T	0.319 **	-0.0635	-0.110	-0.396 *	-0.153	-0.271
	(0.099)	(0.154)	(0.165)	(0.185)	(0.257)	(0.269)
Constant	95.89 ***	96.71 ***	96.69 ***	95.30 ***	94.98 ***	95.19 ***
	(0.029)	(0.064)	(0.066)	(0.059)	(0.104)	(0.110)
Postal code FE	X	X	X	X	X	X
State-specific Post	X	X	X	X	X	X
State-specific trends	X	X	X	X	X	X
Number of postal code areas	6799	1071	995	1413	390	348
Treated	603	603	603	223	215	215
R^2	0.387	0.463	0.466	0.424	0.327	0.357

Note. Dependent variable is house price index; clustered standard errors in parentheses.
Matched A: Propensity score matching of treated and untreated postal code areas within region
Matched B: As A but excluding areas with emissions outside urban areas
*/**/*** Significant at the 5%/1%/0.1% level.

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. We collected a sizable data set characterizing the areas under study in order to facilitate identification of a suitable control group. Postal code areas with and without emissions are found to be quite different on average. Moreover, the characteristics of postal code areas with emissions differ vastly between the former Eastern and Western Germany. Our analysis hints at the importance of also considering the market in which capitalization takes place as a way to control for unobservable differences in addition to observable characteristics.

A possible threat to recovering an effect 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 quite limited. This data set may just be too crude to capture effects at the very local scale. Oberholzer-Gee and Mitsunari (2006) find a robust effect on house prices only within half a mile of the polluting facility with their micro-data on individual transactions. Currie et al. (2013), using a very detailed dataset of housing transactions and openings and closings of polluting facilities, identify an effect on house prices within 1 mile of the facility with the largest impact found within half a mile of the facility. Our house price index concerns the price of the average house in a postal code area. Gamper-Rabindran and Timmins (2013) emphasize that undesirable neighbors are 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 can not be ruled out based on our analysis.

Our findings do not necessarily imply that 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. A possible explanation is, that households already have a good idea about the amount of pollution in the area in which they live before buying their homes and therefore pollution from emitters in the area is already capitalized in the prevailing housing prices. In this case, the data available on the E-PRTR website might not have been real news for households living in areas with high pollution levels. 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. 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 heightened awareness of these issues now than in the early days of the TRI and the published information is spread also by environmental NGOs. This is evidenced by the existence of e.g. top 10-lists of worst polluters in the US. Recent research by Schlenker and Scorse (2012) suggests that companies react to their placement on such scorecards perhaps in anticipation of community pressure.

“Regulation by information” may be a useful policy tool but the prerequisite is that people are aware and capable of understanding the information provided to them. In the US state of California disclosure laws make realtors liable in cases where homeowners were not informed prior to purchase about exposure of their property to undesirable substances/neighbors. In Germany no such policy is in place and there is no incentive for a realtor or owner to inform potential buyers or tenants of the less attractive aspects of a property.

References

Joshua K. Abbott and H. Allen Klaiber. The value of water as an urban club good: A matching approach to community-provided lakes. *Journal of Environmental Economics and Management*, 65(2):208–224, 2013.

Hamburger Abendblatt. EU stellt Schadstoffquellen in Europa online. pages Issue: 11/10/2009, p. 29, 2009. Axel Springer Verlag.

J. Angrist and J. Pischke. *Mostly harmless econometrics: an empiricist's companion.* Princeton University Press, 2009.

Linda T. M. Bui and Christopher J. Mayer. Regulation and capitalization of environmental amenities: Evidence from the toxic release inventory in massachusetts. *The Review of Economics and Statistics*, 85 (3):693–708, August 2003.

Janet Currie, Lucas Davis, Michael Greenstone, and Reed Walker. Do housing prices reflect environmental health risks? evidence from more than 1600 toxic plant openings and closings. NBER Working Paper 18700, January 2013.

Lucas Davis. The effect of health risk on housing values: Evidence from a cancer cluster. *American Economic Review*, 94(5):1693–1704, 2004.

Lucas Davis. The effect of power plants on local housing prices and rents. *Review of Economics and Statistics*, 93(4):1391–1402, 2011.

Entsorga. Blick in die Zukunft. page Issue: 06/21/2004, 2004.

F+B. F+B-Wohn-Index Deutschland - Methodiksteckbrief, 2012. F+B GmbH.

S. Gamper-Rabindran and Christopher Timmins. Does cleanup of hazardous waste sites raise housing values? *Journal of Environmental Economics and Management*, 65(3):345–360, 2013.

J Graff Zivin, M Neidell, and W Schlenker. Water quality violations and avoidance behavior: Evidence from bottled water consumption. *American Economic Review Papers and Proceedings*, 101:448–453, 2011.

Michael Greenstone and Justin Gallagher. Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, 123(3):951–1003, August 2008.

Nicolai V. Kuminoff and Jaren C. Pope. Do ”capitalization effects” for public goods reveal the public's willingnes to pay? Unpublished manuscript, 2011.

Leigh Linden and Jonah E. Rockoff. Estimates of the impact of crime risk on property values from megan's laws. *The American Economic Review*, 98(3):1103–1127, 2008.

Raplph Mastromonaco. Hazardous Waste Hits Hollywood: Superfund and Housing Prices in Los Angeles. *Environmental and Resource Economics*, forthcoming.

Enrico Moretti and Matthew Neidell. Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *Journal of Human Resources*, 46(1):154–175, 2011.

Matthew Neidell. Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations. *Journal of Human Resources*, 44(2):450–478, 2009.

Felix Oberholzer-Gee and Miki Mitsunari. Information regulation: Do the victims of externalities pay attention? *Journal of Regulatory Economics*, 30:141–158, 2006.

Raymond B Palmquist. *Handbook of Environmental Economics*, volume 2, chapter Property Value models. Elsevier North Holland, 2004.

Christopher F. Parmeter and Jaren C. Pope. Quasi-experiments and hedonic property value methods. Written for the Handbook on Experimental Economics and the Environment, Edward Elgar Publishers. Editors: John A. List and Michael K. Price, January 2009.

Jaren C. Pope. Buyer information and the hedonic: The impact of a seller disclosure on the implicit price for airport noise. *Journal of Urban Economics*, 63(2):498 – 516, 2008.

Nicholas J Sanders. Housing markets and public information on local amenities: Evidence of non-linear response to information shocks. Unpublished manuscript, 8 2013.

Wolfram Schlenker and Jason Scorse. Does being a top 10 worst polluter affect environmental releases? evidence from the u.s. toxic release inventory. Unpublished manuscript, 2012.

TAZ. Interessantes über Umweltsuender aus der Nachbarschaft - Ab sofort kann im Internet jeder nachgucken, mit welchen Schadstoffen Unternehmen die Umwelt belasten. pages Issue: 06/06/2009, p. 8, 2009. Contrapress.

Charles Tiebout. A pure theory of local expenditures. *Journal of Political Economy*, 64(5):416–424, 1956.

A Appendix

A.1 Logit estimations for propensity score matching

Table 8: Logit estimates for matching, part I

Treatment status	Western Germany		Eastern Germany	
	no buffer	500 m buffer	No buffer	500 m buffer
Unemployment	0.0676	0.0899 *	0.0026	0.0079
	(0.0466)	(0.0398)	(0.0458)	(0.0435)
Long term unempl.	-0.0108	-0.0129 *	0.0046	0.0050
	(0.0065)	(0.0055)	(0.0138)	(0.0132)
Change in l.t. unempl.	0.0004	-0.0000	0.0045	0.0002
	(0.0021)	(0.0018)	(0.0073)	(0.0070)
New construction	0.0506	0.0486	-0.0346	0.0084
	(0.0354)	(0.0294)	(0.0655)	(0.0505)
Secondary sector employment	0.0277	0.0255	0.0067	-0.0053
	(0.0246)	(0.0204)	(0.0176)	(0.0168)
Tertiary sector employment	0.0010	0.0022	-0.0089	-0.0167
	(0.0251)	(0.0208)	(0.0183)	(0.0174)
Commuters into area	0.0047	0.0075	0.0152	0.0214
	(0.0062)	(0.0053)	(0.0122)	(0.0115)
Commuters out of area	-0.0124 *	-0.0059	-0.0255 *	-0.0293 **
	(0.0055)	(0.0047)	(0.0121)	(0.0114)
Total tax revenues	0.0013 *	0.0017 *	-0.0000	0.0001
	(0.0006)	(0.0007)	(0.0008)	(0.0009)
Population density	0.0001	-0.0001	-0.0006 **	-0.0004 *
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Value-added tax revenues	0.0063	0.0032	-0.0102	-0.0135
	(0.0032)	(0.0029)	(0.0084)	(0.0081)
Commercial tax revenues	-0.0008	-0.0010 *	0.0002	0.0000
	(0.0005)	(0.0005)	(0.0008)	(0.0008)
Income tax revenues	-0.0056 ***	-0.0044 ***	0.0055	0.0057
	(0.0012)	(0.0011)	(0.0034)	(0.0031)
Distance to highway	-0.0048	-0.0076	-0.0117	-0.0071
	(0.0056)	(0.0048)	(0.0076)	(0.0072)
Distance to airport	-0.0039	-0.0057 *	0.0008	-0.0025
	(0.0027)	(0.0023)	(0.0026)	(0.0025)
Distance to train station	-0.0017	-0.0028	0.0022	0.00063
	(0.0039)	(0.0034)	(0.0056)	(0.0053)
ll	-1913.8	-2516.7	-611.4	-708.5
Observations	6788	6788	1370	1370

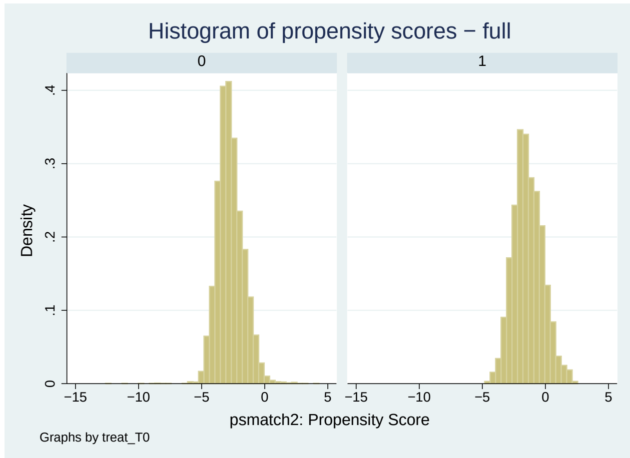
Note. Dependent variable is house price index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

Table 9: Logit estimates, part II

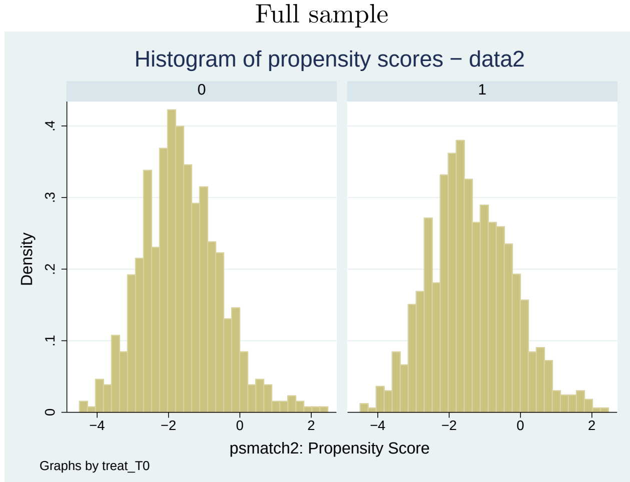
Treatment status	Western Germany		Eastern Germany	
	No buffer	500 m buffer	No buffer	500 m buffer
Distance to large urban center	-0.0047	-0.0081 *	0.0012	-0.0010
	(0.0039)	(0.0034)	(0.0053)	(0.0050)
Distance to medium urban cent.	-0.0527 ***	-0.0593 ***	-0.0274 *	-0.0346 **
	(0.0090)	(0.0079)	(0.0125)	(0.0120)
Distance to European center	-0.0047	-0.0017	0.0011	0.0041
	(0.0033)	(0.0028)	(0.0028)	(0.0027)
Apartment buildings	-0.0057	0.0158	0.0151	-0.0011
	(0.0114)	(0.0096)	(0.0168)	(0.0157)
Small apt.	-0.0204	-0.0158	-0.0163	-0.0082
	(0.0223)	(0.0187)	(0.0443)	(0.0402)
Large apt.	-0.0179	-0.0074	0.0056	-0.0018
	(0.0111)	(0.0094)	(0.0185)	(0.0175)
Size of postal code area	1.27e-08 ***	1.16e-08 ***	1.05e-08 ***	1.05e-08 ***
	(1.31e-09)	(1.18e-09)	(1.18e-09)	(1.18e-09)
Land use agriculture	0.0169 ***	0.0090 **	0.0218 ***	0.0139 **
	(0.0034)	(0.0028)	(0.0065)	(0.0052)
Land use water	0.0571 ***	0.0454 ***	0.0278	0.0076
	(0.0109)	(0.0096)	(0.0171)	(0.0158)
Land use natural area	0.0061	-0.0003	0.0002	-0.0010
	(0.0038)	(0.0030)	(0.0073)	(0.0058)
Land use industry	0.0589 ***	0.0511 ***	0.0592 ***	0.0409 ***
	(0.0061)	(0.0055)	(0.0124)	(0.0099)
Land use landfills	0.151 ***	0.196 ***	0.170 ***	0.166 ***
	(0.0228)	(0.0254)	(0.0376)	(0.0383)
Constant	-0.618	-1.709	-2.887	-1.532
	(2.903)	(2.400)	(2.612)	(2.467)
ll	-1913.8	-2516.7	-611.4	-708.5
Observations	6788	6788	1370	1370

Note. Dependent variable is house price index; clustered standard errors in parentheses.
*/**/*** Significant at the 5%/1%/0.1% level.

A.2 Distribution of propensity scores

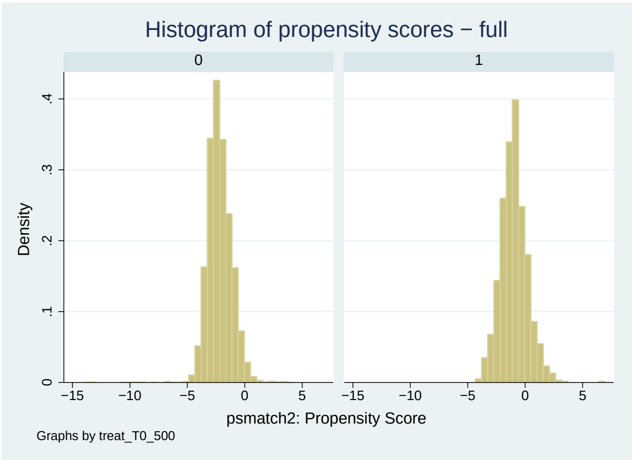


Full sample

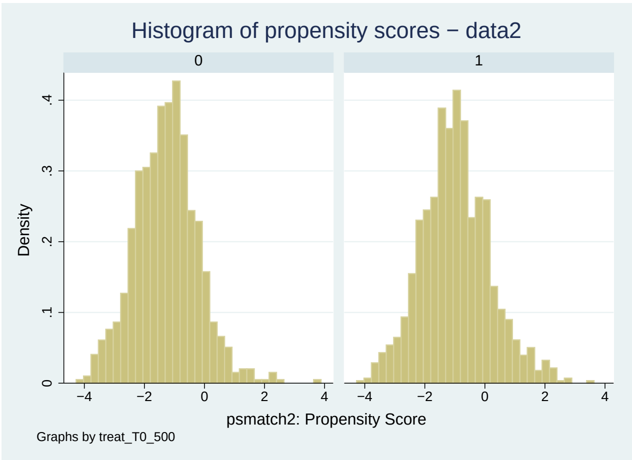


Matched sample

Figure 5: Propensity scores, Western Germany, no buffer

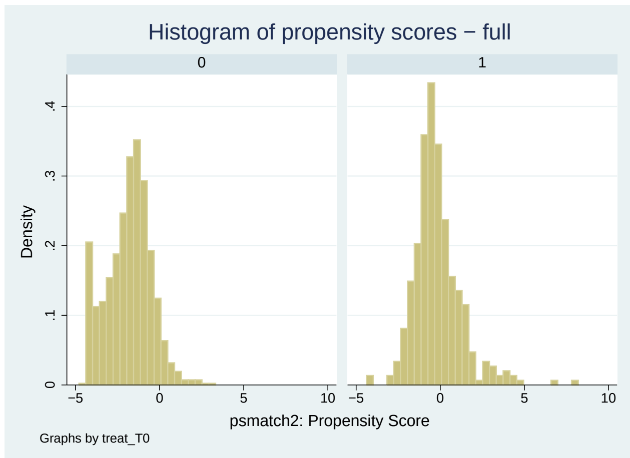


Full sample

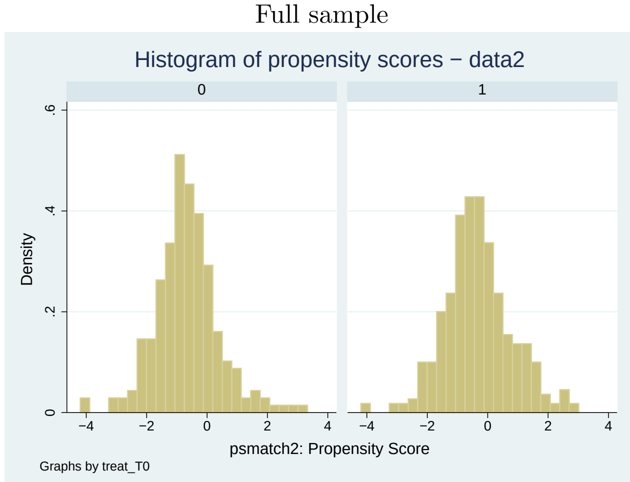


Matched sample

Figure 6: Propensity scores, Western Germany, 500 m buffer

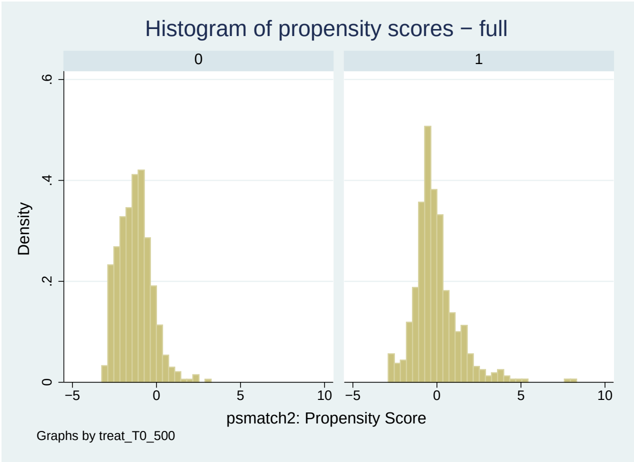


Full sample

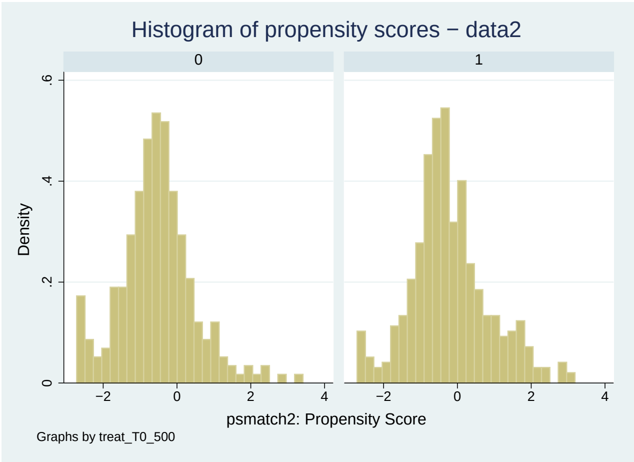


Matched sample

Figure 7: Propensity scores, Eastern Germany, no buffer



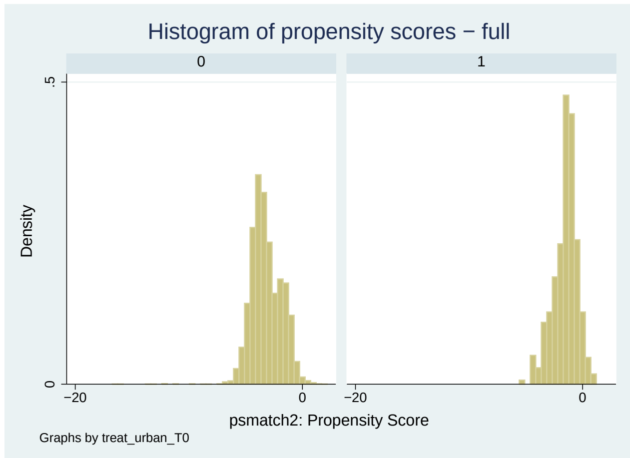
Full sample



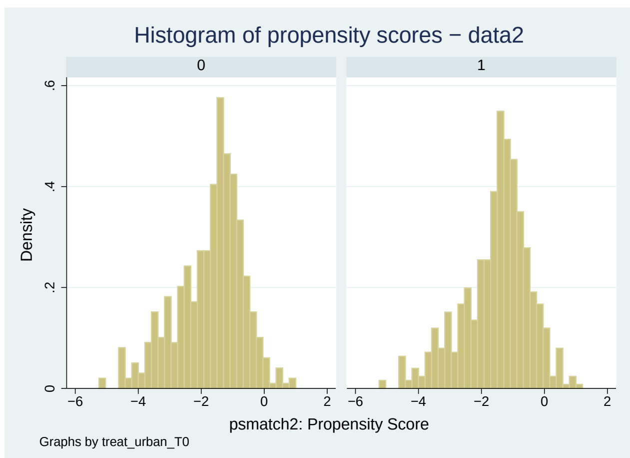
Matched sample

Figure 8: Propensity scores, Eastern Germany, 500 m buffer

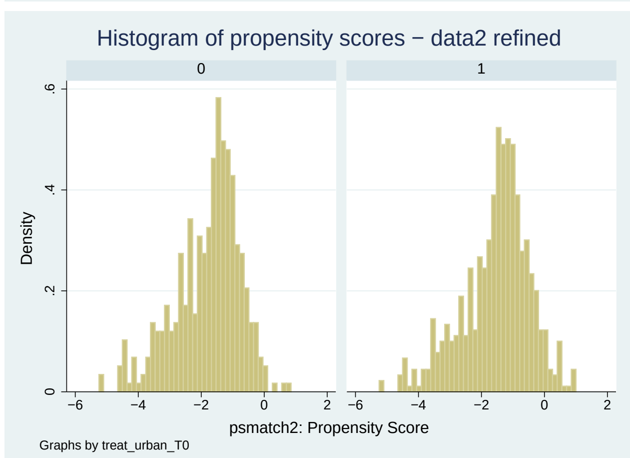
A.3 Histograms urban area only



Full sample

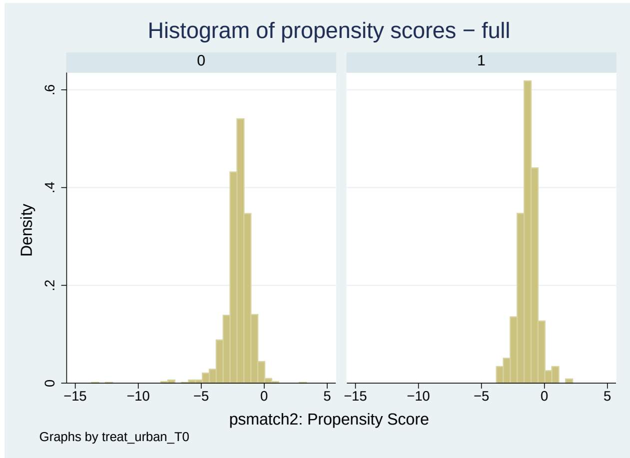


Match A

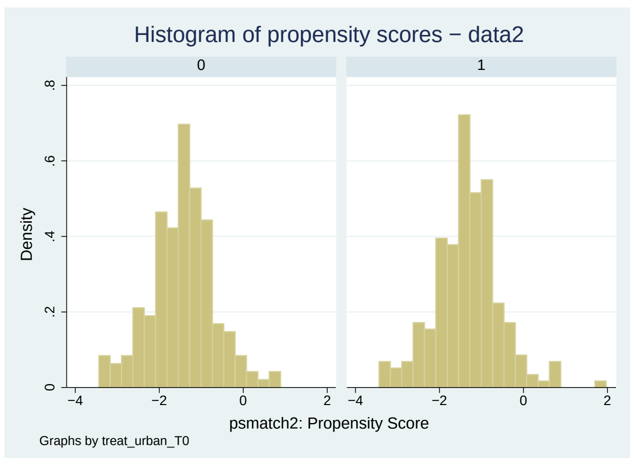


Match B

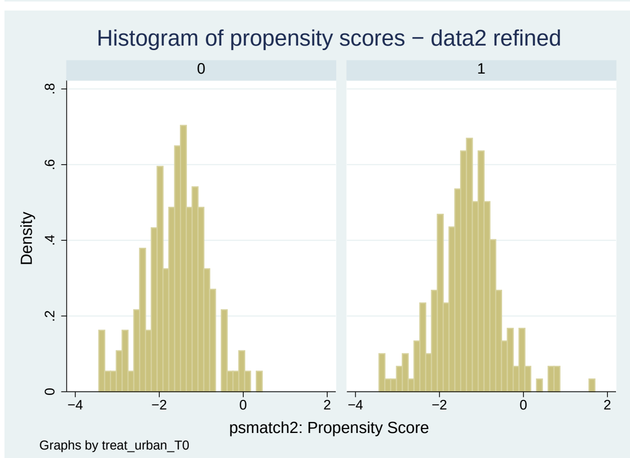
Figure 9: Histograms of propensity scores, urban area, Western Germany



Full sample



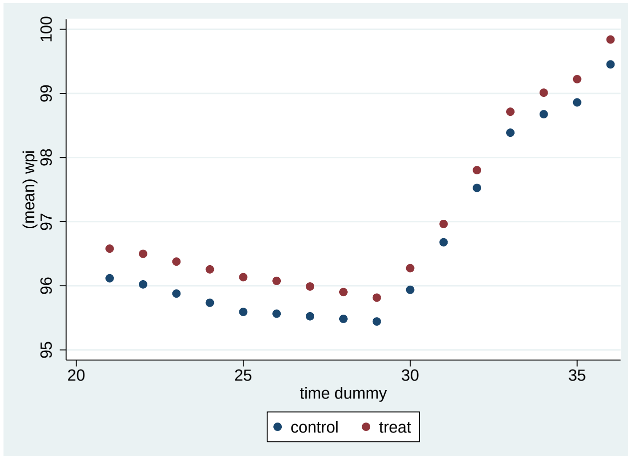
Match A



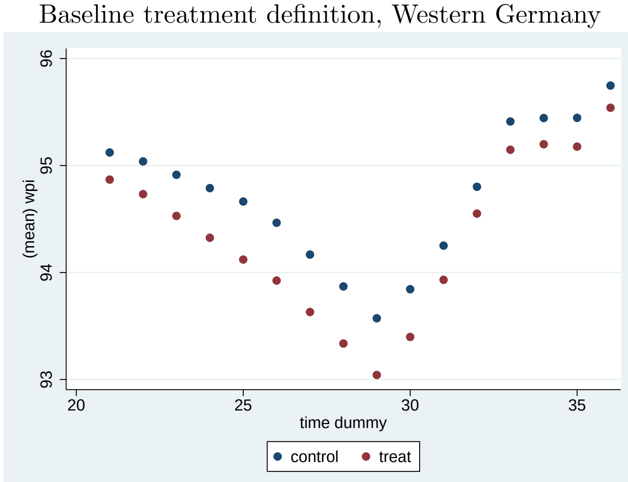
Match B

Figure 10: Histograms of propensity scores, urban area, Eastern Germany

A.4 House price index for matched control and treatment group



Baseline treatment definition, Western Germany



Baseline treatment definition, Eastern Germany

Figure 11: Evolution in mean price index, control and treatment groups

A.5 Characteristics post matching, treatment and control group

Table 10: Treatment and control group before and after matching, Eastern Germany

Variable	Unmatched Matched	Mean Treated	Control	% reduction %bias	—bias—	t-test t	p¿—t—
Unemployment	Unmatched	10.436	9.822	23.2		3.97	0
	Matched	10.388	10.17	8.2	64.5	1.01	0.311
Unempl. longt.	Unmatched	28.701	27.262	10.8		1.76	0.079
	Matched	29.008	28.492	3.9	64.1	0.51	0.608
ΔUnempl. longt.	Unmatched	-49.518	-50.771	4.8		0.79	0.431
	Matched	-49.134	-49.827	2.7	44.7	0.36	0.722
Construction	Unmatched	1.055	1.188	-8.1		-1.21	0.225
	Matched	1.049	1.141	-5.7	30.3	-1.08	0.282
Empl. secondary	Unmatched	33.746	30.154	23.3		3.69	0
	Matched	33.798	34.536	-4.8	79.5	-0.64	0.52
Empl. tertiary	Unmatched	61.207	66.49	-31.1		-4.94	0
	Matched	61.201	60.826	2.2	92.9	0.3	0.762
Commute in	Unmatched	61.367	54.199	43.4		6.55	0
	Matched	61.66	62.708	-6.3	85.4	-1.02	0.306
Commute out	Unmatched	65.479	56.832	35		5.34	0
	Matched	65.712	66.634	-3.7	89.3	-0.58	0.561
Tax rev.	Unmatched	381.24	386.05	-1.9		-0.31	0.759
	Matched	383.4	424.32	-15.9	-750.8	-1.12	0.264
Pop. density	Unmatched	345.65	1013.9	-61.1		-8.71	0
	Matched	355.5	321.35	3.1	94.9	0.75	0.454
VAT rev.	Unmatched	32.039	33.641	-10		-1.68	0.094
	Matched	32.135	32.556	-2.6	73.8	-0.34	0.737
Corp. tax rev.	Unmatched	223.72	219.31	1.6		0.27	0.789
	Matched	226.94	258.59	-11.6	-617.6	-0.89	0.373
Income tax rev.	Unmatched	150.4	167.4	-36.2		-5.53	0
	Matched	150.7	150.81	-0.2	99.3	-0.04	0.969
Dist. Autobahn	Unmatched	16.594	16.017	4.5		0.73	0.466
	Matched	16.458	14.209	17.4	-289.8	2.49	0.013
Dist. airport	Unmatched	74.282	62.992	24.9		4.01	0
	Matched	74.257	72.842	3.1	87.5	0.41	0.679
Dist. train st.	Unmatched	26.531	20.906	30.7		4.94	0
	Matched	26.167	24.805	7.4	75.8	1.03	0.303
Dist. large urb.	Unmatched	34.645	25.833	38.5		6.2	0
	Matched	34.067	31.843	9.7	74.8	1.39	0.166
Dist. medium urb.	Unmatched	9.687	8.580	12.3		2.01	0.045
	Matched	9.868	9.390	5.3	56.8	0.71	0.476
Dist. Europe	Unmatched	267.73	258.96	19.9		3.27	0.001
	Matched	268.5	265.31	7.2	63.6	0.98	0.328

Table 10: Treatment and control group before and after matching, Eastern Germany (cont.)

	Unmatched	Mean			% reduction	t-test	
Variable	Matched	Treated	Control	%bias	—bias—	t	p¿—t—
Share multiple family home	Unmatched	19.648	25.563	-40.6		-6.37	0
	Matched	19.725	19.445	1.9	95.3	0.28	0.776
Small apt.	Unmatched	6.633	8.403	-46.8		-7.01	0
	Matched	6.637	6.596	1.1	97.6	0.18	0.858
Large apt.	Unmatched	36.079	32.247	33.7		5.41	0
	Matched	36.105	36.213	-0.9	97.2	-0.13	0.898
Postal code size	Unmatched	1.40E+08	5.40E+07	84	0.5	16.2	0
	Matched	1.20E+08	1.20E+08	4.7	94.5	0.64	0.52
pct_agri	Unmatched	60.322	42.302	66		10.19	0
	Matched	60.235	60.458	-0.8	98.8	-0.13	0.9
pct_water	Unmatched	2.103	1.815	6.5		1.05	0.295
	Matched	2.130	2.137	-0.2	97.4	-0.02	0.982
pct_nat	Unmatched	22.893	23.187	-1.4		-0.22	0.828
	Matched	22.524	22.789	-1.3	9.6	-0.19	0.85
pct_ind	Unmatched	3.296	3.601	-4.1		-0.64	0.521
	Matched	3.401	3.429	-0.4	90.8	-0.05	0.961
pct_dep	Unmatched	0.954	0.363	27.3		5.23	0
	Matched	0.988	1.009	-1	96.4	-0.1	0.918

Table 11: Treatment and control group before and after matching, Western Germany

	Unmatched	Mean		% reduction		t-test	
Variable	Matched	Treated	Control	%bias	—bias—	t	p¿—t—
Unemployment	Unmatched	5.548	4.374	57.8		15.66	0
	Matched	5.548	5.530	0.9	98.4	0.16	0.871
Unempl. longt.	Unmatched	29.175	27.982	9.2		2.49	0.013
	Matched	29.175	29.56	-3	67.8	-0.54	0.589
ΔUnempl. longt.	Unmatched	-24.406	-26.128	4.3		1.12	0.263
	Matched	-24.406	-23.486	-2.3	46.6	-0.44	0.658
Construction	Unmatched	1.728	1.827	-6.7		-1.72	0.086
	Matched	1.728	1.774	-3.2	53	-0.66	0.511
Empl. secondary	Unmatched	38.336	38.432	-0.6		-0.15	0.882
	Matched	38.336	38.892	-3.4	-476.6	-0.64	0.521
Empl. tertiary	Unmatched	60.622	59.916	4.3		1.09	0.277
	Matched	60.622	60.11	3.1	27.5	0.58	0.559
Commute in	Unmatched	61.863	66.291	-37.6		-9.67	0
	Matched	61.863	61.383	4.1	89.2	0.77	0.444
Commute out	Unmatched	59.227	72.557	-64		-16.41	0
	Matched	59.227	58.797	2.1	96.8	0.39	0.697
Tax rev.	Unmatched	668.48	604.06	19		4.95	0
	Matched	668.48	661.35	2.1	88.9	0.28	0.782
Pop. density	Unmatched	822.78	520.09	36.8		9.69	0
	Matched	822.78	791.69	3.8	89.7	0.67	0.503
VAT rev.	Unmatched	46.508	31.524	55.8		14.57	0
	Matched	46.508	45.55	3.6	93.6	0.63	0.531
Corp. tax rev.	Unmatched	451.21	322.66	25.9		6.96	0
	Matched	451.21	443.29	1.6	93.8	0.23	0.816
Income tax rev.	Unmatched	325.38	341.33	-20		-5.09	0
	Matched	325.38	322.85	3.2	84.1	0.63	0.528
Dist. Autobahn	Unmatched	11.075	14.347	-28.8		-6.99	0
	Matched	11.075	11.897	-7.2	74.9	-1.55	0.121
Dist. airport	Unmatched	48.457	57.707	-34.3		-8.49	0
	Matched	48.457	49.835	-5.1	85.1	-1.02	0.308
Dist. train st.	Unmatched	18.985	23.299	-27.6		-7.01	0
	Matched	18.985	19.984	-6.4	76.8	-1.2	0.231
Dist. large urb.	Unmatched	22.622	27.438	-25.4		-6.72	0
	Matched	22.622	23.36	-3.9	84.7	-0.74	0.46
Dist. medium urb.	Unmatched	5.217	10.04	-60		-14.49	0
	Matched	5.217	5.145	0.9	98.5	0.2	0.845
Dist. Europe	Unmatched	238.62	244.18	-20.7		-5.3	0
	Matched	238.62	239.89	-4.7	77.2	-0.91	0.361

Table 11: Treatment and control group before and after matching, Western Germany (cont.)

Variable	Unmatched Matched	Mean Treated	Control	% reduction %bias	—bias—	t-test t	p¿—t—
Share multiple family home	Unmatched	18.294	12.683	44.7		11.96	0
	Matched	18.294	17.85	3.5	92.1	0.63	0.53
Small apt.	Unmatched	6.992	6.161	20.6		5.2	0
	Matched	6.992	6.963	0.7	96.5	0.14	0.891
Large apt.	Unmatched	47.549	54.707	-47.3		-12.45	0
	Matched	47.549	48.267	-4.7	90	-0.87	0.382
Postal code size	Unmatched	4.90E+07	3.50E+07	35		10.18	0
	Matched	4.90E+07	5.20E+07	-9.6	72.6	-1.47	0.141
pct_agri	Unmatched	49.477	53.452	-15.4		-3.94	0
	Matched	49.477	50.089	-2.4	84.6	-0.44	0.657
pct_water	Unmatched	1.943	1.259	17.2		4.22	0
	Matched	1.943	1.757	4.7	72.8	0.82	0.415
pct_nat	Unmatched	21.381	27.809	-30.7		-7.58	0
	Matched	21.381	21.971	-2.8	90.8	-0.56	0.577
pct_ind	Unmatched	7.325	1.964	56.8		19.74	0
	Matched	7.325	6.486	8.9	84.3	1.27	0.206
pct_dep	Unmatched	0.852	0.256	35.6		10.95	0
	Matched	0.852	0.894	-2.5	93	-0.29	0.772

Table 12: *Urban:* 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	10.604	9.870	28.7		3.92	0
	Matched	10.604	10.631	-1.1	96.3	-0.11	0.915
Unempl. longt.	Unmatched	28.353	27.511	6.3		0.85	0.396
	Matched	28.353	28.259	0.7	88.7	0.07	0.945
ΔUnempl. longt.	Unmatched	-49.846	-50.55	2.8		0.36	0.715
	Matched	-49.846	-50.123	1.1	60.6	0.11	0.914
Construction	Unmatched	0.835	1.212	-26.3		-2.84	0.005
	Matched	0.835	0.782	3.7	85.8	0.84	0.403
Empl. secondary	Unmatched	32.133	30.914	7.8		1.03	0.304
	Matched	32.133	33.37	-7.9	-1.5	-0.84	0.4
Empl. tertiary	Unmatched	63.99	65.295	-7.5		-1	0.319
	Matched	63.99	62.306	9.7	-29	1.01	0.312
Commute in	Unmatched	56.375	56.047	1.9		0.24	0.808
	Matched	56.375	57.642	-7.3	-286	-0.83	0.409
Commute out	Unmatched	57.672	59.394	-6.6		-0.87	0.386
	Matched	57.672	59.868	-8.5	-27.6	-0.94	0.345
Tax rev.	Unmatched	382.59	385.18	-1.2		-0.14	0.891
	Matched	382.59	374.1	3.9	-227.4	0.57	0.568
Pop. density	Unmatched	702.45	861.88	-13.1		-1.67	0.095
	Matched	702.45	583.22	9.8	25.2	1.18	0.24
VAT rev.	Unmatched	34.804	32.921	11.8		1.62	0.105
	Matched	34.804	34.469	2.1	82.2	0.22	0.828
Corp. tax rev.	Unmatched	230.11	218.68	4.9		0.57	0.568
	Matched	230.11	226.45	1.6	68	0.19	0.853
Income tax rev.	Unmatched	156.41	164.11	-16.1		-2.05	0.041
	Matched	156.41	151.48	10.3	36	1.21	0.227
Dist. Autobahn	Unmatched	15.424	16.309	-7		-0.92	0.356
	Matched	15.424	16.123	-5.5	21	-0.54	0.587
Dist. airport	Unmatched	67.318	65.735	3.5		0.46	0.645
	Matched	67.318	65.573	3.8	-10.2	0.44	0.657
Dist. train st.	Unmatched	22.716	22.337	2		0.27	0.786
	Matched	22.716	24.315	-8.5	-322.1	-0.88	0.379
Dist. large urb.	Unmatched	29.347	27.948	5.9		0.8	0.424
	Matched	29.347	31.119	-7.5	-26.7	-0.75	0.452
Dist. medium urb.	Unmatched	7.638	9.103	-16.6		-2.19	0.029
	Matched	7.638	8.212	-6.5	60.8	-0.68	0.496
Dist. Europe	Unmatched	263.63	260.85	6.1		0.85	0.395
	Matched	263.63	266.69	-6.7	-9.9	-0.74	0.462

Table 12: *Urban:* Treatment and control group before and after matching (A), Eastern Germany (cont.)

	Unmatched	Mean		% reduction		t-test	
Variable	Matched	Treated	Control	%bias	—bias—	t	p¿—t—
Share multiple family home	Unmatched	24.656	23.873	5.1		0.69	0.493
	Matched	24.656	23.415	8.1	-58.4	0.88	0.379
Small apt.	Unmatched	7.639	7.989	-8.8		-1.12	0.262
	Matched	7.639	7.281	9	-2.6	1.03	0.303
Large apt.	Unmatched	32.865	33.336	-4.1		-0.54	0.588
	Matched	32.865	33.542	-5.9	-43.8	-0.62	0.539
Postal code size	Unmatched	1.10E+08	7.00E+07	42	0.4	6.35	0
	Matched	1.10E+08	1.10E+08	4.3	89.9	0.36	0.721
pct_agri	Unmatched	54.254	45.741	28.6		3.85	0
	Matched	54.254	57.807	-11.9	58.3	-1.29	0.196
pct_water	Unmatched	1.66	1.935	-6.3		-0.82	0.41
	Matched	1.66	1.687	-0.6	90.3	-0.07	0.945
pct_nat	Unmatched	18.53	23.962	-26.6		-3.32	0.001
	Matched	18.53	18.888	-1.7	93.4	-0.2	0.839
pct_ind	Unmatched	4.831	3.277	18.8		2.7	0.007
	Matched	4.831	4.006	10	46.9	0.93	0.354
pct_dep	Unmatched	0.764	0.475	13.9		2.09	0.037
	Matched	0.764	1.068	-14.7	-5.1	-1.13	0.257

Table 13: *Urban:* 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	6.093	4.346	87		21.62	0
	Matched	6.093	6.051	2.1	97.6	0.34	0.731
Unempl. longt.	Unmatched	31.961	27.737	33.4		8.1	0
	Matched	31.961	31.905	0.4	98.7	0.07	0.941
ΔUnempl. longt.	Unmatched	-17.896	-26.728	22.5		5.25	0
	Matched	-17.896	-18.372	1.2	94.6	0.22	0.827
Construction	Unmatched	1.617	1.836	-16.6		-3.44	0.001
	Matched	1.617	1.638	-1.6	90.3	-0.36	0.722
Empl. secondary	Unmatched	34.984	38.755	-23.1		-5.32	0
	Matched	34.984	34.702	1.7	92.5	0.3	0.763
Empl. tertiary	Unmatched	64.436	59.561	29.7		6.87	0
	Matched	64.436	64.723	-1.7	94.1	-0.3	0.762
Commute in	Unmatched	60.001	66.374	-54.4		-12.78	0
	Matched	60.001	60.098	-0.8	98.5	-0.14	0.885
Commute out	Unmatched	53.129	72.854	-96.1		-22.54	0
	Matched	53.129	52.395	3.6	96.3	0.61	0.542
Tax rev.	Unmatched	682.45	604.12	26.1		5.5	0
	Matched	682.45	676.61	1.9	92.5	0.38	0.704
Pop. density	Unmatched	1117.7	498.05	72.2		18.44	0
	Matched	1117.7	1091.2	3.1	95.7	0.5	0.62
VAT rev.	Unmatched	52.248	31.298	78.7		18.8	0
	Matched	52.248	51.51	2.8	96.5	0.46	0.646
Corp. tax rev.	Unmatched	474.37	323.25	34.4		7.47	0
	Matched	474.37	468.35	1.4	96	0.26	0.793
Income tax rev.	Unmatched	333.8	340.16	-8.3		-1.85	0.064
	Matched	333.8	331.7	2.7	67	0.52	0.605
Dist. Autobahn	Unmatched	9.887	14.39	-40.7		-8.81	0
	Matched	9.887	9.474	3.7	90.8	0.78	0.433
Dist. airport	Unmatched	43.852	57.951	-52.9		-11.88	0
	Matched	43.852	45.043	-4.5	91.5	-0.79	0.43
Dist. train st.	Unmatched	14.825	23.606	-57.1		-13.16	0
	Matched	14.825	14.561	1.7	97	0.31	0.759
Dist. large urb.	Unmatched	17.361	27.844	-57.1		-13.5	0
	Matched	17.361	16.927	2.4	95.9	0.41	0.681
Dist. medium urb.	Unmatched	2.967	10.152	-98		-19.99	0
	Matched	2.967	2.612	4.8	95.1	1.15	0.252
Dist. Europe	Unmatched	233.51	244.56	-41.6		-9.66	0
	Matched	233.51	235.02	-5.7	86.3	-1	0.318

Table 13: *Urban:* 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—
Share multiple family home	Unmatched	23.388	12.311	87.2		22.1	0
	Matched	23.388	23.487	-0.8	99.1	-0.13	0.9
Small apt.	Unmatched	8.105	6.071	49.5		11.71	0
	Matched	8.105	8.287	-4.4	91	-0.77	0.444
Large apt.	Unmatched	41.457	55.142	-94.8		-22.28	0
	Matched	41.457	41.087	2.6	97.3	0.44	0.657
Postal code size	Unmatched	3.60E+07	3.60E+07	-0.4		-0.11	0.915
	Matched	3.60E+07	3.80E+07	-4	-808	-0.58	0.563
pct_agri	Unmatched	40.287	54.26	-54		-12.78	0
	Matched	40.287	40.747	-1.8	96.7	-0.3	0.766
pct_water	Unmatched	1.632	1.304	8.8		1.85	0.065
	Matched	1.632	1.627	0.1	98.5	0.02	0.982
pct_nat	Unmatched	20.441	27.755	-34.5		-7.88	0
	Matched	20.441	19.959	2.3	93.4	0.4	0.691
pct_ind	Unmatched	8.422	1.983	68.6		21.7	0
	Matched	8.422	7.366	11.2	83.6	1.51	0.132
pct_dep	Unmatched	0.811	0.273	30.1		9	0
	Matched	0.811	0.542	15	50.1	2.18	0.029