ECONSTOR Make Your Publications Visible.

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

König, Christian

Article — Published Version Neighbourhood structure and environmental quality: A fine-grained analysis of spatial inequalities in urban Germany

Urban Studies

Provided in Cooperation with:

WZB Berlin Social Science Center

Suggested Citation: König, Christian (2024) : Neighbourhood structure and environmental quality: A fine-grained analysis of spatial inequalities in urban Germany, Urban Studies, ISSN 1360-063X, Sage, Thousand Oaks, CA, Vol. 61, Iss. 10, pp. 1968-1989, https://doi.org/10.1177/00420980231224224

This Version is available at: https://hdl.handle.net/10419/313528

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.



WWW.ECONSTOR.EU

https://creativecommons.org/licenses/by/4.0/

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



Article

Urban Studies

Urban Studies 2024, Vol. 61(10) 1968–1989 © Urban Studies Journal Limited 2024 © Article reuse guidelines: sagepub.com/journals-permissions DOI: 10.1177/00420980231224224 journals.sagepub.com/home/usj

Neighbourhood structure and environmental quality: A fine-grained analysis of spatial inequalities in urban Germany

Christian König

WZB, Germany

Abstract

Urban environments are characterised by sparsity of space, elevated levels of air pollution and limited exposure to natural environments. Yet, residential environmental quality varies substantially both between and within cities. This study combines information on the socio-economic and demographic composition of 243,607 urban neighbourhoods with administrative and remote sensing data on the spatial distribution of industrial plants and urban green space to investigate patterns of environmental inequality in urban Germany at unprecedented levels of spatial granularity. It disentangles neighbourhood disadvantages experienced by foreign minorities (nonnationals) from those experienced by low-income households in order to assess the plausibility of economic explanations of residential sorting. The high level of spatial granularity makes it possible to examine patterns of environmental inequality not only between the relatively large areas that have been used as units of analysis in previous work but also within them, while reducing the threat of ecological bias. Results indicate that non-nationals are more likely to be exposed to industrial air pollution and less likely to live close to green spaces. This association holds even after adjusting for neighbourhood income composition and in fixed-effects specifications that restrict the analysis to within-city variation. I find no evidence for environmental inequality by socio-economic status. Exploratory sub-sample analyses show that neighbourhood disadvantages for non-nationals are higher in cities characterised by high levels of anti-foreigner sentiment, pointing towards housing market discrimination as a potentially important driver of foreign residents' neighbourhood disadvantage.

Keywords

environmental justice, inequality, land use, method, neighbourhood, race/ethnicity, residential sorting and segregation

Corresponding author: Christian König, WZB Berlin Social Science Center, Dynamics of Social Inequalities, Reichpietschufer 50, Berlin 10785, Germany.

Email: christian.koenig@wzb.eu

摘要

城市环境的特点是空间稀少、空气污染严重、接触自然环境的机会有限。然而,城市之间和城市内部的居 住环境质量差异很大。本研究将 243,607 个城市街区的社会经济和人口构成信息与工业厂房和城市绿地空 间分布的行政和遥感数据相结合,以前所未有的空间粒度级别考察德国城市环境不平等的模式。本文将外 国少数民族(非国民)所经历的邻里劣势与低收入家庭所经历的邻里劣势区分开来,以评估住宅分类的经 济解释的合理性。高级别的空间粒度使得我们不仅可以考察先前研究中用作分析单位的相对较大区域之间 的环境不平等模式,还可以考察这些区域内部的环境不平等模式,同时减少生态偏倚的威胁。结果表明, 非国民更有可能受到工业空气污染的影响,并且更少居住在靠近绿色空间的地方。即使在针对街区收入构 成进行调整,以及遵照固定效应规范将分析限制在城市的内部变化后,这种关联仍然成立。我们没有发现 任何证据表明社会经济地位造成环境不平等。探索性子样本分析表明,在反外国人情绪高涨的城市中,非 国民的邻里劣势更为严重,这表明住房市场歧视是造成外国居民邻里劣势的潜在重要驱动因素。

关键词

环境正义、不平等、土地利用、方法、邻里、种族/民族、住宅分类和隔离

Received September 2022; accepted November 2023

Introduction

Urbanisation has led individuals worldwide to reside in densely populated areas marked by sparsity of space, elevated air pollution and limited exposure to nature. Residential environments vary substantially both between and within cities. Scholars have emphasised the role of residential segregation in processes of stratification, operating through differences in locational attainment such as school quality or public service provision (Alba and Logan, 1993; Massey et al., 1987).

Residential environmental quality is one crucial dimension of spatial inequality in urban settings that has been shown to affect health and life chances more broadly. Studies have demonstrated robust associations and plausibly causal effects of environmental quality on physical health (Currie, 2013; Currie and Walker, 2011), mental health (Engemann et al., 2019; Roberts et al., 2019) and other key outcomes, such as educational performance (Heissel et al., 2022), crime (Bondy et al., 2020; Manduca and Sampson, 2019) and inter-generational economic mobility (Colmer and Voorheis, 2020; Manduca and Sampson, 2019; O'Brien et al., 2018).

Research on *environmental inequality* (EI) examines differences in exposure to environmental 'goods' and 'bads' according to socio-economic status and ethno-racial background (Ash and Fetter, 2004). Previous, predominantly North American, work has shown that socio-economically disadvantaged households and members of racial and ethnic minorities are disproportionately affected by environmental hazards and have lower access to natural environments at their place of residence (Ard, 2015; Ash and Boyce, 2018; Banzhaf et al., 2019; Crowder and Downey, 2010).

The present paper adds to an emerging body of EI literature focusing on Germany (e.g. Diekmann et al., 2023; Jünger, 2021; Rüttenauer, 2018), (i) by analysing patterns of EI in urban Germany at unprecedented levels of spatial granularity and (ii) by exploring two possible mechanisms underlying residential sorting: income inequality and housing market discrimination resulting from anti-foreigner sentiment. I combine data on demographic and socio-economic composition for all 243,607 urban German neighbourhoods (containing around 65 households, on average) with industrial pollution register data as well as remote sensing green space data. These two dimensions of environmental quality are well-suited to studying neighbourhood disadvantages of non-nationals, defined as the neighbourhoods' proportion of residents without German citizenship, and low-income households because they can be precisely located.

Results indicate that non-nationals are more likely to be exposed to industrial air pollution and less likely to live close to green spaces. Notably, this association holds even after adjusting for neighbourhood income composition and in fixed-effects specifications that restrict the analysis to within-city variation. I find no evidence for EI by socioeconomic status. Further sub-sample analyses suggest that neighbourhood disadvantages for non-nationals are higher in cities with higher levels of anti-foreigner sentiment, suggesting that housing market discrimination might contribute to neighbourhood disadvantages of foreign residents.

This study contributes to previous literature on EI in several ways: First, it disentangles potential neighbourhood disadvantages experienced by non-national residents from those experienced by low-income households to assess the plausibility of economic explanations of residential sorting.

Second, it contributes to the still limited literature on EI in Germany (Diekmann et al., 2023; Jünger, 2021; Rüttenauer, 2018).The utilisation of neighbourhood-level data warrants an examination of EI patterns not only between the relatively large areas (e.g. municipalities, counties) that have served as units of analysis in previous work but also within them. I exploit important within-area variation that would be masked by spatial aggregation in the case of coarser spatial data. If EI occurred only between cities, this could be driven by the (historical) sorting of minorities into more industrialised cities. However, this explanation does not convincingly account for within-city EI. Scrutinising potential between-city variations, I also conduct exploratory sub-sample analyses to investigate differences in EI based on city-level contexts.

Third, the high level of spatial granularity reduces the risk of ecological bias. Ecological bias arises due to within-area variability in exposures and confounders, which tends to be smaller in more confined and homogenous spatial units. Typically, spatial aggregation of data is carried out according to administrative units whose division does not prioritise grouping individuals or areas with constant or even similar exposures. However, aggregating across larger geopolitical units (e.g. US states or counties. German districts or municipalities etc.) may dilute or even conceal important local nuances and anomalies.

Finally, the analyses use a comparatively spatial treatment assignment precise approach. Environmental quality measures are assigned to neighbourhoods based on their distance to industrial facilities and green spaces, which - together with the very fine-grained neighbourhood data - addresses important limitations of previously used approaches (e.g. unit-hazard coincidence approach). This distance-based approach entails creating circular buffers with a certain diameter around each neighbourhood, defining 'proximity'. I conduct all analyses for a range of buffer sizes to account for the arbitrary choice of buffer size in distancebased approaches, ensuring a comprehensive exploration of proximity and exposure to green spaces and industrial facilities.

Theory and background

Theoretically, EI has often been attributed to two broad classes of causal mechanisms: selective siting and selective migration. Selective siting means that environmental hazards are disproportionately placed in areas with lower socio-economic status and higher minority shares. Selective migration, by contrast, means that residential sorting emerges as a post-siting process following changes in neighbourhood environmental quality (Mohai and Saha, 2015). Disentangling the (dynamic) processes of siting and sorting is generally difficult with cross-sectional data. Investigating selective siting, in particular, necessitates longitudinal data due to the typically prolonged nature of changes in land use patterns compared to households moving to different neighbourhoods. Consequently, the focus of this paper is directed towards residential sorting. In the following, I will discuss three major types of sorting processes.

Socio-economic explanations of residential sorting

Economic explanations of residential sorting and environmental inequality propose that more affluent households move into more desirable and less polluted neighbourhoods, while low-income households are drawn towards neighbourhoods with lower environmental quality where housing prices are more affordable.

Evidence indeed suggests that environmental goods, such as trees and open spaces, increase housing value, whereas environmental bads like landfills, roads or proximity to high voltage lines negatively affect selling prices (Bolitzer and Netusil, 2000; Cavailhès et al., 2009; Sirmans et al., 2005). Previous studies have demonstrated the sensitivity of housing prices to air pollution (Chay and Greenstone, 2005) and the presence of green spaces (Panduro et al., 2018).

The racial income inequality hypothesis (Crowder and Downey, 2010) posits that ethnic and racial minorities reside in lowerquality neighbourhoods because they have, on average, fewer economic resources. Rüttenauer and Best (2021) investigate the socio-economically selective in- and outmigration of neighbourhoods affected by industrial plant openings and closings. They show that municipalities' average income decreases after plant openings, but find no effect of facility closures on an area's socioeconomic composition. Akee et al. (2019) found that Black people, Native Americans and Hispanics in the US - as compared to White people and Asians – have significantly lower average incomes and are also highly immobile in terms of overall economic mobility. Giesecke et al. (2017), in their examination of poverty risk by migration background in Germany, found that individuals with a migration background face twice the risk of poverty compared to individuals without a migration background.

If economic disadvantage is the main driver of ethno-racial differences in neighbourhood attainment, non-nationals' neighbourhood disadvantage should vanish once adjusting for income at the neighbourhood level.

Preference-based explanations of residential sorting

Although group-level differences in preferences are beyond the scope of this study, persistent residential segregation could be a realisation thereof. If ethnic minorities are less bothered by low environmental quality at the place of residence (e.g. due to lower environmental awareness or because they apply higher thresholds for hazardous exposure) this could explain their tendency to move into environmentally less attractive neighbourhoods.

Alternatively, EI by ethno-racial background might be rooted in minorities having

different preferences for neighbourhood characteristics that happen to be correlated with low environmental quality. For ethnic minorities, residing with co-ethnics has been shown to influence internal location and migration decisions (Mossaad et al., 2020). Ethnic networks are believed to equip marginalised immigrant groups with employment and housing opportunities that may not be available elsewhere. Wiedner et al. (2022) demonstrated that ethno-religious infrastructures in Germany indeed increase immigrants' life satisfaction but are often located in socio-economically disadvantaged inner city areas. As residents of inner-city areas frequently contend with elevated levels of pollution, location-dependent social and network resources could partly reproduce EI by ethno-racial background, once

Discrimination-based explanation of residential sorting

established.

Finally, neighbourhood disadvantages of migrants and non-nationals might be due to ethnic or racial discrimination in the housing market, pushing them into less desirable neighbourhoods irrespective of their income. Housing choices of ethnic minorities and individuals without German citizenship are restricted, if access to living space is denied by private landlords and real estate agents. Experimental studies have indeed shown discrimination against members of ethnic or racial minorities as potential tenants (Auspurg et al., 2017; Massey and Lundy, 2001; Yinger, 1986, 1995). The role of landlords and rental agents as gatekeepers affecting patterns of residential sorting is likely to be more relevant in countries with large shares of rental housing. In 2021, more than half of the German population (50.9%) lived in rental housing, representing the largest rental housing sector in Europe (Eurostat, 2022).

The extent of housing market discrimination is likely to vary across different local contexts. Racial prejudice and anti-foreigner sentiment have been suggested to increase discrimination against minorities (Bobo and Zubrinsky, 1996). This could be attributed to prejudiced attitudes towards outgroup populations by gatekeepers who discriminate to avoid dealing with them, or due to agents' and landlords' expectations of prejudiced customers and tenants which they might hope to appease by restricting minority access (Page, 1995).

Audit studies indeed suggest that, all else being equal, agent and customer prejudice are linked to elevated housing market discrimination (Ondrich et al., 1999; Page, 1995). Evidence for Germany is limited to a few cities and rather mixed. Auspurg et al. (2017) found that discrimination against Turkish residents was strongest in neighbourhoods with high shares of Turkish residents. Müller (2015), in contrast, found that city districts of Berlin with relatively high shares of migrant residents tended to treat ethnic minority applicants more equally with regard to invitations to view a flat.

If housing market discrimination partly explains neighbourhood EI, I expect neighbourhood disadvantages of non-nationals to be stronger in areas with high levels of local anti-foreigner sentiment. To shed light on the plausibility of discrimination-based explanations, I employ sub-sample analysis by city-level anti-foreigner sentiment, proxied by right-wing votership (see Measures Section below).

Environmental inequality in Germany

Most earlier studies for Germany either focus on single cities or regions (Diekmann et al., 2023; Flacke et al., 2016; Kabisch and Haase, 2014; Raddatz and Mennis, 2013; Schüle et al., 2017) or employ subjective measures of pollution exposure (Kohlhuber et al., 2006). Rüttenauer (2018) provided a first nation-wide assessment of the sociospatial distribution of industrial air pollution using objective data. He found that the share of minorities within a census tract positively correlates with pollution exposure. While not directly accounting for income, housingrelated control variables are included but do a poor job in explaining minorities' neighbourhood disadvantage, casting doubt on the racial income inequality hypothesis. A recent study by Jünger (2021) investigates socio-economic and ethnic disparities regarding land use by combining land use data with German survey data. He finds that low-income migrants are particularly likely to live in areas with limited access to green space and high levels of soil sealing. Diekmann et al. (2023) investigated exposure to noise from road traffic and aviation, finding small to moderate effects of income and non-Western migration background on noise exposure. The evidence with regard to the role of economic resources in residential sorting, thus, remains mixed, while other structural factors have received even less attention.

Against this background, the paper seeks to further our understanding of EI in urban Germany (i) by studying neighbourhood environmental disadvantage at higher spatial resolution than previous studies and (ii) by exploring two possible underlying mechanisms: income inequality and discrimination resulting from anti-foreigner sentiment (proxied by right-wing vote shares).

Methods

Data

The following analyses use geo-referenced data on neighbourhood composition, industrial air pollution and land use in urban areas, supplemented by further municipality-level information.¹

I focus on urban areas for two reasons: first, because these are the areas where natural environments are scarce, potentially showing marked inequalities; and second, high-quality land use data employed here is not available for all Germany, but only for so-called functional urban areas (FUAs). According to the EU-OECD definition (Dijkstra et al., 2019), a FUA comprises a city (i.e. a municipality whose majority of residents live in contiguous, high density grid cells with at least 50,000 inhabitants) and its commuting zone. Commuting zones contain a city's surrounding travel-to-work areas where at least 15% of employed residents are working in a city. Figure S1 in the Online Supplemental Material illustrates the designation of urban cores (henceforth also referred to as cities) and commuting zones (periphery) based on the EU-OECD definition. I restrict the main analyses to the urban cores but will point the interested reader to supplementary analyses based on commuting zones and entire FUAs.

Infas360 provides socio-economic and demographic information for all German neighbourhoods in 2017. The neighbourhood units are based on administrative settlement blocks (Siedlungsblöcke) from the digital landscape model by the Federal Agency for Cartography and Geodesy (Bundesamt für Kartographie und Geodäsie, BKG). This dataset allows for an unprecedented level of spatial granularity in analysing EI in Germany. Note, however, that data at this granularity is the result of small estimation techniques using both area administrative and privately purchased data, a general limitation compared to similarly fine-grained administrative data – which is unavailable for Germany. Infas360 intersects neighbourhood polygons with gridded data $(1 \text{ km} \times 1 \text{ km})$ from the 2011 census to obtain within-district and -municipality distributions. Together with annually updated administrative data at these higher levels, projections are performed to obtain finegrained data in more recent years. Refer to the Measures subsection below for details on key variables.

Germany comprises roughly 2 million neighbourhoods and 41 million households. Neighbourhoods located in cities sum up to 243,607 neighbourhoods containing 39% (16 million) of all households.

Data on industrial air pollution is obtained from the European Pollution Release and Transfer Register (E-PRTR, European Commission, 2006). Industrial plants are obliged to disclose information on pollutants released to air, water and soil, subject to pollutant-specific reporting thresholds. The E-PRTR covers 91 key pollutants including heavy metals, pesticides, dioxins and other chemicals, as well as greenhouse gases. The empirical analyses are restricted to air pollutants directly relevant to health. Greenhouse gases like carbon dioxide (CO₂) and methane (CH₄) are excluded, as their inhalation is not considered an immediate carcinogenic or non-carcinogenic health risk (California Environmental Protection Agency, 2022). Following the restrictions above, the 2017 dataset contains 1256 facilities reporting emissions to air, with 862 located within 3 km buffer distance of FUAs and 350 are located within buffer distance of cities.

Data on land use in FUAs, including green space, is obtained from the Urban Atlas 2018 (European Environment Agency, 2020), offering high-resolution data derived from satellite imagery.² For this study, the following land use categories related to urban green space are merged: 'Green urban areas', 'Sports and leisure facilities', 'Forests' and 'Herbaceous vegetation associations'. Other types (e.g. arable land, permanent crops and pastures) are excluded, as their benefits and desirability are potentially ambiguous. Access to these open spaces may not be freely available, and they may also be associated with noise or odours.

Municipality-level information is gathered from the Statistical Offices of the Federal States³ and the Federal Institute for Research on Building, Urban Affairs and Spatial Development.⁴

Spatial treatment assignment

When working with geographic information system (GIS) data, there are different approaches of exposure assignment.⁵ Simple spatial coincidence techniques assume that exposure to environmental hazards is confined to the boundaries of predetermined geographic units, such as counties, municipalities or census tracts (Chakraborty et al., 2011). Studies employing this unit-hazard coincidence approach typically classify populations residing in spatial units that host an environmental hazard as exposed and compare them to residents in non-host units. This is problematic because hazards near the edge of a host unit could equally or even more strongly affect neighbouring non-host units and because it assumes uniform exposure within host units. While the use of highresolution data helps alleviate false positives (i.e. areas considered exposed without being substantially affected), it increases the risk of false negatives, as only a limited population is regarded as exposed.

Therefore, I employ a distance-based approach to spatial treatment assignment using buffer analysis which entails generating circular polygons around geographical point locations or areas. This approach rests on the idea that environmental features of neighbouring and other close-by units are likely to affect the quality of life of residents in a unit under study (local spillovers). It offers a more accurate geographic representation of exposure to environmental factors, as it recognises that their effects are not confined solely to host units. Previous studies have used buffers of various sizes to identify exposed units and populations, ranging from a few 100 m up to 5 km in the case of industrial pollution (Mohai and Saha, 2006, 2007; Pastor et al., 2004; Walker et al., 2005) and from 0 to 1000 m with regard to green space exposure (Cohen-Cline et al., 2015; Engemann et al., 2019; Jünger, 2021). The choice of buffer sizes is often insufficiently motivated and, at times, arbitrary. To ensure that results do not hinge on measurement choices, I employ a range of buffer sizes representing reasonable measures of proximity and exposure.

While distance-based approaches provide a more precise approximation of exposure, they come with inherent limitations: discrete buffers remain a fuzzy proxy for exposure, since dispersal of pollutants is likely to occur gradually and asymmetrically, influenced by factors like topography and prevailing wind direction (Chakraborty et al., 2011).

Analyses of industrial exposures will be run for 1, 2 and 3 km buffers around industrial facilities. I further include a set of 'exclusion rings' (0, 500, 1000 m), representing buffers around the treatment buffer that are excluded from the sample in order to prevent areas of unclear exposure to attenuate potentially substantive patterns of EI.

For the green space analyses, I start with the surface shares of the neighbourhood areas themselves that are covered by green space (0 m of buffering) and then continue to draw buffers of 250 m, 500 m and 750 m in diameter around each neighbourhood for green space assignment. Due to the construction of the green space variable as the surface share covered by green space, increasing buffer sizes only alter neighbourhoods' green space exposure at the margin. In contrast to the assignment of air toxins, there are no binary non-treated/treated jumps at the margin (i.e. no need to apply 'exclusion rings'). Figure 1 visualises the different layers of spatial data and the buffer approach to spatial treatment assignment.



Figure 1. Visualisation of the spatial data and the approach to spatial treatment assignment underlying the subsequent analyses. The city district of Berlin–Spandau serves as an example only. Panel (a) shows the area's neighbourhood units (grey). Panel (b) highlights one specific neighbourhood (black) to illustrate the construction of circular buffers determining exposure to green spaces (dashed line) and industrial sites (solid line) around that neighbourhood. Panel (c) adds spatial information on green spaces (dotted areas) and industrial plants (crosses).

Measures

Outcomes: Neighbourhood-level shares of nonnationals and low-income households. The neighbourhood share of non-national residents, defined as the proportion of inhabitants without a German citizenship, is the main dependent variable. Estimations at the neighbourhood level are derived from administrative data on non-nationals at the municipality and district level for 2017, which are then distributed across neighbourhoods using gridded census data from 2011.

The main analyses are additionally run using the neighbourhood share of lowincome households, defined by a monthly household income of 1500 EUR or less (after taxes), as dependent variable. This measure relies on administrative data regarding income shares typically spent on housing by different income groups, along with neighbourhood-level housing price data. It is adjusted for housing type, the distribution of age and household size at the neighbourhood level, and then calibrated with annual income survey data (CASA-Monitor).

Neighbourhood environmental quality variables. The two explanatory variables of interest are exposure to industrial air pollution and access to green space.

Exposure to industrial air pollution is measured by two variables: a binary variable indicating whether a neighbourhood is exposed to at least one large industrial plant and the natural logarithm of the toxicityweighted amount of all pollutants emitted by any industrial plant within the buffer.

For the latter, non-exposed neighbourhoods are assigned the minimum positive exposure value observed in the data to prevent issues during subsequent log-transformation (due to $\lim_{x\to 0^+} \ln(x) = -\infty$).⁶ Consequently, the regression coefficient of the binary exposure variable indicates estimated mean differences

in outcomes between non-exposed and minimally exposed neighbourhoods. The coefficient of the adjusted and log-transformed variable estimates differences in outcomes associated with different levels of air pollution exposure among neighbourhoods in proximity of at least one industrial site. A one-unit increase in the toxicity-weighted pollution variable is equivalent to a 2.7-fold increase in exposure.⁷

This approach is preferable to using $\ln(x + z)$, where x is the toxicity-weighted amount of pollution and z some 'small' constant (e.g. 1, 0.1 or 0.001). Unlike the approach of using $\ln(x + 1)$, for instance, the method employed here avoids arbitrarily setting the difference in exposure between non-exposed and minimally exposed units by choosing a small constant. Additionally, it avoids imposing any unjustified assumptions on the functional form of the relationship between these groups of neighbourhoods.

Collapsing exposure to different toxins into a single index of pollution exposure requires pollutant-specific toxicity weights. Here, I use the inverse of the pollutantspecific threshold for reporting set by E-PRTR legislation. These thresholds consider pollutant-specific adverse effects on human health and the environment, making their inverse a suitable proxy of pollutants' toxicity.

The green space variable is more straightforward. Simple buffers are drawn around every neighbourhood in the sample, and access to urban green space is then constructed as the buffer area surface share covered by green space.

Neighbourhood-level controls. To examine whether potential disadvantages for nonnationals can be attributed to group-level differences in economic resources, I control for the neighbourhood income composition (share of low-income households). Neighbourhood age structure – measured as the share of residents age 65 or older – is likely to be a confounder, being associated with citizenship in the sense that non-nationals, on average, are younger than the majority population (Statistisches Bundesamt. 2018). Moreover, age is linked to the level of neighbourhood environmental quality through population growth of inner city areas, driven by economic, social and educational possibilities, and the fact that young households are particularly attracted by these amenities (Kabisch and Haase, 2011; Moos, 2016). Family structure - that is, the share of households with underage children - should be controlled for, as family status might affect migration decisions. Families may require more space and have stronger preferences for natural environments.

vote Municipality-level moderator: right-wing share. To shed light on the plausibility of discrimination-based explanations, I exploit regional variation in EI and municipalitylevel anti-foreigner sentiment in an exploratory sub-sample analysis. As I do not obtain a direct measure of anti-foreigner sentiment, I use municipality-level right-wing votership (votes for the Alternative für Deutschland, AfD) during the 2017 general elections as a proxy measure. Based on data from 12 European countries including Germany, Semyonov et al. (2006) show that political orientation (i.e. support of right-wing ideologies) is among the strongest predictors of anti-foreigner sentiment (alongside economic vulnerability).

Municipality-level controls. Population density is a likely confounder, as urbanity is associated with both the level of environmental quality and the sociodemographic composition of neighbourhoods. Controlling for municipalities' distance to the German border accounts for the possibility that large industrial facilities are more frequently located near the border due to lower levels of local opposition (NIMBYism). Moreover, areas close to the border might exhibit different shares and compositions of nonnational residents due to cross-border commuters. Finally, per capita income tax revenue adjusts for income at the city level, not least to test whether differences in EI by city-level right-wing votership are merely an artefact of city-level economic vulnerability.

Descriptive statistics

Table S1 of the Online Supplemental Material shows descriptive statistics for key variables weighted by the number of house-holds per neighbourhood. The final data set contains 243,607 neighbourhoods in urban cores (cities). The average neighbourhood contains around 65 households, is roughly 1.9 *ha* large. Relative to 1 km^2 census grid cells, the neighbourhood data is distinctly more disaggregated, not to mention even larger units such as city districts or municipalities. For reference, the average urban census grid cell from the 2011 census contained around 841 households and was 100 *ha* (1 km^2) large.⁸

Neighbourhoods in cities accommodate 17% of non-nationals and 35% of lowincome households on average. Five percent of all neighbourhoods are exposed to at least one plant within 1 km. The share of exposed neighbourhoods increases with larger buffers (20% in the case of a 2 km buffer, 37% in the case of a 3 km buffer). Similarly, the average number of plants and the toxicityweighted amount of pollution increase with buffer size. The latter ranges from 0 to 6.58 (1 km buffer). Note that this implies a wide range of pollution exposure, as this variable has been log-transformed to account for skewedness. The most exposed neighbourhoods are exposed to toxicity-weighted pollution around 720 times larger than the neighbourhood with the lowest positive amount of exposure $(2.72^{6.58} \approx 723.5)$. Neighbourhoods' green space coverage varies considerably from basically no green space within the buffer area to almost entirely green neighbourhood buffer areas. The mean share of green space within the neighbourhood areas themselves is notably lower compared to other buffer specifications. This discrepancy arises from the fact that neighbourhood areas are best described as dense urban fabric, typically featuring few green spaces. The introduction of buffers leads to a clear increase of green space. Surface shares covered by green space tend to increase with buffer size, but remain rather similar across the buffer specifications.

Statistical approach

Whether non-national residents are disproportionately affected by low levels of environmental quality is assessed with a series of weighted bi- and multivariate regressions that are run separately for the different dimensions of environmental quality. First, I estimate bi-variate associations (M1) before step-wise introducing further neighbourhood-level controls (income. family and age composition; M2) and municipality-level controls (municipality size, distance to border and per capita income tax revenue; M3). The final model (M4) includes the full set of neighbourhood controls and municipality fixed effects to test whether inequalities persist within municipalities. Note that this final model does not include municipality-level controls as these do not vary within cities.

To examine EI by income, these models are also conducted using the share of lowincome households as the dependent variable. The key insights with regard to EI by income are briefly discussed in the Results section; corresponding plots and regression tables are part of the Online Supplemental Material. To investigate whether patterns of EI differ by local anti-foreigner sentiment, separate sub-sample analyses were run for neighbourhoods located in municipalities with low and high shares of right-wing (AfD) votes. The sub-sample analyses are based on M4 (i.e. including neighbourhood-level controls and municipality FEs). The results are supposed to provide some evidence on the plausibility of discriminatory explanations of EI with regard to non-nationals (e.g. housing market discrimination).

Previous studies on EI have used models with 'spatial lags' (i.e. Anselin and Bera, 1998; LeSage and Pace, 2009) to account for spatial autocorrelation and investigate spillover effects (e.g. Rüttenauer, 2018). I do not adopt this approach in the present study. The buffer-based approach to assignment of treatment (e.g. industrial pollution exposure) pursued here, in combination with small geo-spatial units such as neighbourhoods, is bound to create strong spatial autocorrelation in environmental quality variables by design because substantively meaningful buffers are much larger than the average neighbourhood. This leads to significant buffer overlap among adjacent neighbourhoods and consequently to spatial dependence. I discuss these issues in more detail in Section E in the Supplemental Material, where I also report results from models that include spatial lags. The main insight from this comparison is that models with spatial lags of environmental quality variables would lead to results that are less readily interpretable, yet qualitatively similar to those in the main article.

Results

Running different analyses for several buffer size and exclusion ring specifications leads to a considerable amount of results. Therefore, the first part of the results section is limited to a graphical presentation of results for



Figure 2. Main analyses for the neighbourhood-level share of non-nationals as dependent variable. Left column shows estimated coefficients from a series of OLS regressions: M1 is a bivariate regression; M2 adds neighbourhood-level controls (income, sex and age composition); M3 further controls for municipality size, income tax revenue and distance to border; M4 includes the full set of neighbourhood-level controls and municipality fixed effects. Right column shows predictions of non-nationals by neighbourhood environmental quality based on M4. Top row shows results with regard to exposure to industrial air pollution. Bottom row shows results with regard to green space access.

selected buffer specifications (2 km buffer without exclusion ring for industrial exposures, 500 m buffer for green spaces). Results across different buffer specifications follow thereafter.

Exposure to industrial air pollution

The top panel of Figure 2 depicts the relationship between exposure to industrial air toxins and the neighbourhood share of nonnationals. The left graph presents the regression coefficients alongside their 95% confiintervals dence for the four model specifications outlined above. Model 1 (M1) is a bi-variate regression of the share of nonnationals on exposure to industrial air pollution. Model 2 (M2) additionally controls for the neighbourhood income composition, as well as age and family structure. Model 3 (M3) further adjusts for municipality-level number of inhabitants, income tax revenue per capita and distance to the German border. Model 4 (M4) includes the full set of neighbourhood-level controls as well as municipality fixed effects. The right graph shows the prediction of the full model (M4). Recall that exposure to industry is measured with two variables: a binary exposure variable and the toxicity weighted amount of pollution. The binary exposure variable estimates differences in the share of nonnationals between non-exposed and minimally exposed neighbourhoods, represented by the dot and arrow at x equal to zero. The toxicity-weighted pollution coefficient estimates the link between the amount of pollution and the share of non-nationals for exposed neighbourhoods (conditional association), captured by the slope of the prediction.

The coefficient for the exposure indicator variable based on the bi-variate model (M1) indicates a 4.5 percentage points increase in

the share of non-nationals in minimally exposed neighbourhoods compared to nonexposed neighbourhoods. Conditional on being exposed, higher levels of toxicityweighted pollution are further associated with an even greater share of non-national residents. Overall, this bi-variate model predicts that the share of non-nationals in the most polluted neighbourhoods is about 14 percentage points higher than in neighbourhoods not exposed to any industry. Notably, including neighbourhood income composition and further neighbourhood controls (M2) results in largely unchanged outcomes, contradicting the idea that nonnationals' disproportionate exposure is driven by lower economic resources. Adding municipality-level controls only marginally attenuates the estimated coefficients (M3), suggesting that neighbourhood disadvantages of non-nationals cannot be substantially explained by their residence in larger – and potentially more polluted – cities.

Fixed effects results (M4) reveal that EI by citizenship occurs not only between cities, but persists when restricting the analysis to within-city variation. The (partial) associations between the pollution exposure variables and the share of non-nationals are slightly weaker than in Models 1–3 but remain substantial. The share of non-national residents in moderately exposed neighbourhoods is around 3.4 percentage points higher than in non-exposed ones. Elevated levels of toxicity-weighted pollution again appear to be associated with higher shares of non-nationals; however, the coefficient is no longer statistically significant.

To explore whether the results are specific to cities, I have also run the above analyses separately for commuting zones (periphery) and the entire FUAs (core and periphery). Results are displayed in the upper panel of Figure S3 in the Online Supplemental Material. Findings for the entire FUAs mirror those for the cities, with virtually identical differences between non-exposed and moderately exposed neighbourhoods and slope of the prediction. The level difference in the predictions makes intuitive sense, as the added peripheral areas typically exhibit fewer non-national residents. When restricting to the periphery, shares of nonnationals are still considerably higher in neighbourhoods exposed to industry. The amount of pollution, conditional on being exposed, is associated with relatively small increases in the share of non-nationals.

The same set of analyses using the share of low-income households as a dependent variable, indicates that the share of lowincome households actually tends to be lower in moderately exposed compared to non-exposed neighbourhoods. Including municipality fixed effects attenuates the coefficient to -1.4 percentage points, while the toxicity-weighted pollution coefficient becomes practically zero. Notably, industrial exposure regression coefficients in the case of low-income households lack statistical significance across all models.

Hence, I do not find clear patterns of environmental inequality by neighbourhood income composition. See Figure S2 and Tables S4 and S5 in the Online Supplemental Material for more detailed results.

Access to urban green space

Unlike exposure to industrial air pollution, access to green space is measured by a single variable: the proportion of the neighbourhood buffer area covered by green space. Residential green space is considered an environmental good. Higher levels of green space access, thus, represent elevated levels of residential environmental quality.

The bottom panels of Figure 2 depict regression results on the relationship between green space access and the share of non-nationals. In the bivariate analysis (M1), a one standard deviation increase in



Figure 3. Estimated regression coefficients of environmental quality variables from the full model (M4) for different buffer specifications.

Dependent variable: neighbourhood-level share of non-nationals. The two columns on the left are based on analyses of exposure to industrial air pollution, the right column is based on analyses of green space access.

green space correlates with a 1.6 percentage point (0.15 standard deviations⁹) decrease in the share of non-nationals. When adjusting for neighbourhood income, age and family composition (M2) this association is attenuated, but remains substantial. The association is remarkably robust to adding municipality-level controls (M3) and including municipality fixed effects (M4), indicating a substantial and statistically significant neighbourhood disadvantage for nonnationals. Importantly, unequal green space access is not primarily driven by nonnationals' selection into less green cities. The fixed effects specification predicts that, even within the same city, the share of nonnationals in the greenest neighbourhoods is around 9 percentage points lower than in the least green ones.

Online Figure S3 supplements the aforementioned estimates with identical analyses for the periphery and the overall FUAs. Even in suburban and rural areas surrounding cities, non-nationals reside in less green neighbourhoods, although disparities are substantially smaller than in urban cores. This aligns with expectations, given the prevalence of natural environments in more rural areas.

Regarding the neighbourhood share of low-income households, I do not find evidence of neighbourhood disadvantages in terms of green space access. If anything, lowincome households might be slightly more exposed to green spaces in cities, although these estimates are statistically insignificant.

Results across different buffer size specifications

The results presented above were derived from specific buffer size specifications (2 km buffer, 0 m exclusion ring for industrial exposure, 500 m buffer for green space access). I have estimated these models for a number of reasonable buffer size specifications to ensure that results are not crucially dependent on the choice of buffer size.

Comparing results across specifications, three observations stand out: first, the strength of the relationship between pollution and neighbourhood composition slightly diminishes with larger buffers. This can be seen in Figure 3 where coefficient



Figure 4. Sub-sample re-analysis of the association between the share of non-nationals and environmental quality.

Separate sub-sample analyses of municipalities with below- and above-median right-wing vote shares. The first two columns on the left are based on models with exposure to industrial pollution as the main independent variable for the 2 km buffer, 0 m exclusion ring specification. The right column is based on models with regard to green space access and the 500 m buffer specification. All coefficients are based on the full model including neighbourhood-level controls and municipality fixed effects (M4).

estimates for both the binary exposure indicator and the continuous pollution variable are slightly attenuated with increasing buffer size. This aligns with expectations, as neighbourhoods closest to an environmental hazard likely are the most affected. Second, statistical precision tends to increase with larger buffer sizes, an intuitive phenomenon, as larger buffers result in more observations in the treatment group. Third, the positive association between pollution exposure and the share of non-nationals in Figure 3 becomes more pronounced with the introduction and expansion of exclusion rings. This supports the argument that these areas can be considered areas of unclear exposure, which typically attenuate the strength of the relationship.

Regarding the spatial assignment of green space available to neighbourhoods, associations tend to increase with buffer size. As previously noted (refer to Online Supplemental Table S1), the average share of green space within neighbourhoods is low and exhibits limited variation, primarily comprising residential buildings. This may, in part, explain why inequalities become more pronounced when considering neighbourhoods' surrounding areas.

Effect heterogeneity by right-wing vote share

So far, the analysis has shown, (a) that nonnational residents face comparatively low levels of residential environmental quality and (b) that these patterns are not primarily due to the fact that non-nationals live in cities with lower overall environmental quality: marked environmental inequalities by citizenship are evident even within German cities.

To explore the potential of discriminatory explanations (e.g. in the housing market), I conducted municipality fixed effects estimations using two sub-samples of neighbourhoods located in cities with below and above median shares of right-wing votes during the 2017 general election.

Figure 4 demonstrates that neighbourhood disadvantages of non-national residents in Germany seem to be more pronounced in cities with high levels of antiforeigner sentiment.

In municipalities with high right-wing vote shares in the 2017 general election, moving from non-exposed to moderately exposed neighbourhoods is linked to a 4.5 percentage point increase in the share of non-nationals. In contrast, the estimated difference in the share of non-nationals between these types of neighbourhoods is only 2.6 percentage points in cities with relatively low right-wing vote shares. This pattern holds true for the toxicity-weighted amount of pollution, which is a stronger predictor of non-national residents in cities with high right-wing vote shares. Nevertheless, the estimated differences in coefficients fail to reach statistical significance.

With regard to green space presence, I find neighbourhood disadvantages by citizenship once more to be particularly strong in municipalities with high shares of rightwing votes. The estimated coefficient is almost twice as large as in municipalities with below-median right-wing vote shares. Here, the estimated difference in coefficients of 0.053 percentage points is statistically significant at the 95% level (*p*-value equal to 0.041).

Discussion

This study reveals that non-nationals in Germany experience disproportionately low levels of residential environmental quality. The associations between low environmental quality and the share of non-nationals hold net of the neighbourhood income composition which, notably, is not independently associated with lower environmental quality.

Comparing results from pooled and municipality fixed effects models shows that neighbourhood inequalities are unlikely to result from sorting of non-nationals into more polluted and less green cities. Even within a given German city, non-nationals face lower environmental quality on average.

Conducting analyses across various buffer specifications that have been applied in previous research corroborates the findings of socio-spatially unequal distribution of environmental goods and bads. Patterns of EI remained rather stable across the different specifications.

Housing market discrimination might limit housing choices of non-nationals, regardless of their income. The exploratory sub-sample analyses aim to assess the plausibility of discrimination-based explanations of residential sorting. Results indicate that non-nationals' neighbourhood disadvantage in terms of access to green space is larger in contexts of high right-wing votership. Nonnationals' neighbourhood disadvantages in terms of exposure to industrial toxins tend to show similar patterns, but are less pronounced and not statistically significant. While these analyses serve as a circumstantial test of discrimination-based mechanisms of sorting, the inability to directly distinguish discrimination from other factors that might prevent non-nationals from moving into cleaner neighbourhoods (e.g. anticipated discrimination or lack of perceived fit), warrants further investigation of the revealed patterns.

In summary, this paper provides proof of neighbourhood disadvantages for nonnationals that goes beyond group differences in financial resources, age, family formation and selection into municipalities, contradicting the ethnic income inequality hypothesis. The empirical insights point towards other important mechanisms of residential sorting such as housing market discrimination.

Conclusions

The study's findings on industrial exposure align with prior work by Rüttenauer (2018) who demonstrated a positive correlation between the presence of non-nationals in a census cell and exposure to industrial air pollution. The results further suggest that the presence of an industrial plant, even with moderate levels of toxic emissions, predicts the presence of non-national residents. The amount of toxic emissions moderately increases the share of non-nationals in a neighbourhood, once exposed. Apparently, the physical visibility of industrial sites reduces the attractiveness of neighbourhoods and triggers processes of residential sorting, somewhat independently of the levels of toxic emissions. This is in line with prior evidence (Currie et al., 2015; Rüttenauer and Best, 2021).

The study's results on green space access add to initial evidence on unequal land use exposures by Jünger (2021). Green space data in this study is limited to types of green spaces accessible to everybody and unambiguously fostering well-being (e.g. parks, forests), while more ambiguous green space types (e.g. arable land) are excluded. Green space presence might affect individuals (a) by reducing harm (e.g. reduced pollution, noise or heat), (b) by building capacities (e.g. promoting physical activity) and (c) by restoring capacities (e.g. aiding stress recovery) (Markevych et al., 2017). Notably, green space types considered here - focusing on accessibility and the absence of environmental hazards - align more with the first two mechanisms than the third: even the mere visual presence of other types of open space, accessible or not, might contribute to stress recovery, for instance.

I have considered two important dimensions of environmental quality: industrial air pollution and proximity to green space. The precise locatability is a notable advantage of these measures. In contrast, ambient air pollution data from sources like traffic and households relies on measurements from a coarse net of monitoring stations combined with geo-statistical modelling, resulting in coarser estimates of background pollution. Nevertheless, the results presented here cannot readily be extrapolated to other sources and dimensions of environmental quality.

The fine-grained socio-economic and demographic neighbourhood data comes with a number of limitations, being based on small area estimations combining administrative data and privately purchased information. It cannot be reproduced because the underlying algorithms are not fully public. Neighbourhood administrative data would be preferable in this regard, but is unavailable at this level of spatial granularity. Another limitation is that it involves data sources from different years, as small-scale estimates partly hinge on gridded data from the German census in 2011. This becomes more problematic in the case of substantial changes in a measure's within-municipality distribution between 2011 and 2017 and could be an issue with regard to the large inflow of non-nationals (relative to previous numbers) around 2015 in Eastern Germany.

In the absence of similarly fine-grained data from administrative sources, the data provides estimates for neighbourhood composition that may be useful for future crosssectional research on neighbourhood inequalities. Its utility for longitudinal analyses is limited due to forward projections based on less recent data involved in smallarea estimations.

The study's main outcome, the share of non-national residents, serves as a proxy for ethnic minorities. Ethnic minorities are particularly relevant in understanding neighbourhood and inequality segregation because they are among the groups most likely to face structural discrimination. However, since the Second World War, the German state has not gathered explicit data on ethnicity and race, but rather related data on foreigners, migrants and their descendants (Will, 2019). German citizenship does not clearly differentiate between natives born in Germany and newcomers. The categories of 'German citizens' and 'non-nationals' get more diverse as groups of 'German immigrants' (e.g. naturalised persons and late resettlers) and 'native foreigners' (children born to foreigners in Germany) are growing (Will, 2019). Unfortunately, reliable data on individuals with migration background at a high level of spatial granularity was not available.

In 2017, the group of non-nationals comprised 49% of the German residents with a migration background and most nonnationals (84%) have migrated themselves (Statistisches Bundesamt, 2018). Within this group, first generation immigrants are, thus, overrepresented compared to all individuals with migration background.

Using non-national residents may pose challenges for the sub-sample analyses. The neighbourhood disadvantages of nonnationals are particularly evident in municipalities with high levels of anti-foreigner sentiment. I cannot determine whether nonnationals across municipalities with varying degrees of anti-foreigner sentiment are comparable in terms of their individual background characteristics such as country of birth or level of education. If not, the findings regarding municipality-level anti-foreigner sentiment might (partly) be due to heterogenous non-national groups between cities.

Environmental hazards affect residents' health and well-being even at relatively low levels of pollution. Conversely, exposure to natural environments benefits health outcomes. While there is some overlap in the specific health outcomes affected by these two dimensions of environmental quality, they are not identical (König and Heisig, 2023). Expanding the scope of EI research to encompass environmental dimensions beyond (industrial) air pollution is crucial for future research on health inequalities. The paper's findings on differences in the extent of EI by local anti-foreigner sentiment suggest that a more detailed investigation of regional variation in EI as well as predictors thereof might be a fruitful avenue for future research.

Acknowledgements

Parts of this article were presented in seminars at the WZB Berlin Social Science Center and the University of Copenhagen as well as the ISA RC28 and ECSR 2021 annual conferences. I thank participants for their helpful feedback. I would like to thank the editor and three anonymous reviewers for their constructive feedback and timely handling of the manuscript. I am particularly indebted to Jan Paul Heisig, Heike Solga and Rourke O'Brien for their support and valuable feedback.

Declaration of conflicting interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Christian König D https://orcid.org/0000-0002-6764-7074

Supplemental material

Supplemental material for this article is available online.

Notes

- 1. Preparation and combination of different types of (geo-referenced) data as well as analyses have been carried out with R v4.1.2 (R Core Team, 2021) with extensive use of tidyverse (Wickham et al., 2019), sf (Pebesma, 2018), spdep (Bivand, 2022) and spatialreg (Bivand et al., 2021) packages.
- 2. Land uses are generally mapped if they cover at least 0.25 ha. Homogenous types of land

uses (e.g. green space) that are divided by roads can, however, further split into several polygons that are only required to cover at least 500 square meters to be mapped which must be considered very fine grained (roughly equal to a square of 22.3 m \times 22.3 m).

- Statistische Ämter des Bundes und der Länder, GENESIS-Datenbank Regionalstatistik.
- 4. Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR). Data access via Indikatoren und Karten zur Raum- und Stadtentwicklung (INKAR).
- 5. See Chakraborty et al. (2011) for a thorough discussion of different approaches.
- 6. Once log-transformed, the variable has been shifted to fix the lower end of the distribution to zero to facilitate the interpretation of summary statistics and predictions later on.
- 7. Rules for logarithms imply that a relative change in X (here, toxicity-weighted pollution) implies a constant increase in Y, that is, $\delta Y = \beta * \delta X = \beta * (ln(x_2) - ln(x_1)) = \beta * ln(x_2/x_1)$. Increasing the natural logarithm of X by 1, therefore implies $1 = ln(x_2/x_1)$ and $e^1 = x_2/x_1 \approx 2.7$.
- 8. The average number of households per census grid cell is based on own calculations with 2011 census grid data (Statistische Ämter des Bundes und der Länder, 2014). Grid cells have been restricted to municipalities with at least 100,000 inhabitants to match this paper's focus on cities. The average grid cell in cities contains 1860 inhabitants. To calculate the average number of households within these cells, this number was divided by the average household size (=2.21) in urban grid cells.
- 9. (-0.139*11.80)/10.75.

References

- Akee R, Jones MR and Porter SR (2019) Race matters: Income shares, income inequality, and income mobility for all U.S. races. *Demography* 56(3): 999–1021.
- Alba RD and Logan JR (1993) Minority proximity to whites in suburbs: An individual-level analysis of segregation. *American Journal of Sociology* 98(6): 1388–1427.

- Anselin L and Bera AK (1998) Spatial dependence in linear regression models with an introduction to spatial econometrics. In: Ullah A (ed.) *Handbook of Applied Economic Statistics*. Boca Raton, FL: CRC Press, pp.257–259. Available at: https://www.taylorfrancis.com/ books/9781482269901/chapters/10.1201/97814 82269901-36 (accessed 17 November 2023).
- Ard K (2015) Trends in exposure to industrial air toxins for different racial and socio-economic groups: A spatial and temporal examination of environmental inequality in the U.S. from 1995 to 2004. Social Science Research 53: 375–390.
- Ash M and Boyce JK (2018) Racial disparities in pollution exposure and employment at US industrial facilities. *Proceedings of the National Academy of Sciences* 115(42): 10636–10641.
- Ash M and Fetter TR (2004) Who lives on the wrong side of the environmental tracks? Evidence from the EPA's Risk-Screening Environmental Indicators Model. *Social Science Quarterly* 85(2): 441–462.
- Auspurg K, Hinz T and Schmid L (2017) Contexts and conditions of ethnic discrimination: Evidence from a field experiment in a German housing market. *Journal of Housing Economics* 35: 26–36.
- Banzhaf HS, Ma L and Timmins C (2019) Environmental justice: Establishing causal relationships. Annual Review of Resource Economics 11(1): 377–398.
- Bivand R (2022) R packages for analyzing spatial data: A comparative case study with areal data. *Geographical Analysis* 54(3): 488–518.
- Bivand R, Millo G and Piras G (2021) A review of software for spatial econometrics in R. *Mathematics* 9(11): 1276.
- Bobo L and Zubrinsky CL (1996) Attitudes on residential integration: Perceived status differences, mere in-group preference, or racial prejudice? *Social Forces* 74(3): 883–909.
- Bolitzer B and Netusil NR (2000) The impact of open spaces on property values in Portland, Oregon. *Journal of Environmental Management* 59(3): 185–193.
- Bondy M, Roth S and Sager L (2020) Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the*

Association of Environmental and Resource Economists 7(3): 555–585.

- California Environmental Protection Agency (2022) Consolidated Table of OEHHA /ARB Approved Risk Assessment Health Values. Available at: https://www.epa.gov/rsei/rseitoxicity-data-and-calculations#sources (accessed 18 January 2024).
- Cavailhès J, Brossard T, Foltête J-C, et al. (2009) GIS-based hedonic pricing of landscape. *Environmental and Resource Economics* 44(4): 571–590.
- Chakraborty J, Maantay JA and Brender JD (2011) Disproportionate proximity to environmental health hazards: Methods, models, and measurement. *American Journal of Public Health* 101(S1): S27–S36.
- Chay KY and Greenstone M (2005) Does air quality matter? Evidence from the housing market. *Journal of Political Economy* 113(2): 376–424.
- Cohen-Cline H, Turkheimer E and Duncan GE (2015) Access to green space, physical activity and mental health: A twin study. *Journal of Epidemiology and Community Health* 69(6): 523–529.
- Colmer J and Voorheis J (2020) The grandkids aren't alright: The intergenerational effects of prenatal pollution exposure. Discussion Paper No. 1733. London: Centre for Economic Performance, London School of Economics and Political Science. Available at: https://cep.lse.ac.uk/_new/publications/discussion-papers/ (accessed 3 January 2022).
- Crowder K and Downey L (2010) Interneighborhood migration, race, and environmental hazards: Modeling microlevel processes of environmental inequality. *American Journal of Sociology* 115(4): 1110–1149.
- Currie J (2013) Pollution and infant health. *Child Development Perspectives* 7(4): 237–242.
- Currie J, Davis L, Greenstone M, et al. (2015) Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings. *American Economic Review* 105(2): 678–709.
- Currie J and Walker R (2011) Traffic congestion and infant health: Evidence from E-ZPass.

American Economic Journal: Applied Economics 3(1): 65–90.

- Diekmann A, Bruderer Enzler H, Hartmann J, et al. (2023) Environmental inequality in four European cities: A study combining household survey and geo-referenced data. *European Sociological Review* 39(1): 44–66.
- Dijkstra L, Poelman H and Veneri P (2019) *The EU-OECD definition of a functional urban area.* OECD Regional Development Working Papers 2019/11. Paris: OECD Publishing, 11 December. Available at: https://www.oecd-ili brary.org/urban-rural-and-regional-developme nt/the-eu-oecd-definition-of-a-functional-urban -area_d58cb34d-en (accessed 5 June 2023).
- Engemann K, Pedersen CB, Arge L, et al. (2019) Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. *Proceedings* of the National Academy of Sciences 116(11): 5188–5193.
- European Commission (2006) Regulation (EC) No 166/2006 of the European Parliament and of the Council of 18 January 2006 concerning the establishment of a European Pollutant Release and Transfer Register and amending Council Directives 91/689/EEC and 96/61/EC (Text with EEA relevance). Available at: http://data.europa.eu/eli/reg/2006/166/oj (accessed 16 March 2023).
- European Environment Agency (2020) Urban Atlas Land Cover/Land Use 2018 (vector), Europe, 6-yearly, Jul. 2021. European Environment Agency. Available at: https://doi.org/ 10.2909/FB4DFFA1-6CEB-4CC0-8372-1ED3 54C285E6 (accessed 16 March 2023).
- Eurostat (2022) EU Statistics on Income and Living Conditions microdata2004-2021, version 1, release 3 in 2022. *Eurostat* Available at:https:// doi.org/10.2907/EUSILC2004-2021V.1 (accessed 18 January 2024).
- Flacke J, Schüle SA, Köckler H, et al. (2016) Mapping environmental inequalities relevant for health for informing urban planning interventions—A case study in the City of Dortmund, Germany. *International Journal of Environmental Research and Public Health* 13(7): 711.

- Giesecke J, Kroh M, Tucci I, et al. (2017) Armutsgefährdung bei Personen mit Migrationshintergrund – Vertiefende Analysen auf Basis von SOEP und Mikrozensus: 70. Berlin: Deutsches Institut für Wirtschaftsforschung.
- Heissel JA, Persico C and Simon D (2022) Does pollution drive achievement? The effect of traffic pollution on academic performance. *Journal of Human Resources* 57(3): 747–776.
- Jünger S (2021) Land use disadvantages in Germany: A matter of ethnic income inequalities? Urban Studies 59(9): 1819–1836.
- Kabisch N and Haase D (2011) Diversifying European agglomerations: Evidence of urban population trends for the 21st century. *Population, Space and Place* 17(3): 236–253.
- Kabisch N and Haase D (2014) Green justice or just green? Provision of urban green spaces in Berlin, Germany. *Landscape and Urban Plan*ning 122: 129–139.
- Kohlhuber M, Mielck A, Weiland SK, et al. (2006) Social inequality in perceived environmental exposures in relation to housing conditions in Germany. *Environmental Research* 101(2): 246–255.
- König C and Heisig JP (2023) Environmental inequality and health outcomes over the life course. In: Hoffmann R (ed.) *Handbook of Health Inequalities Across the Life Course*. Cheltenham and Northampton, MA: Edward Elgar Publishing, pp.327–348.
- LeSage J and Pace RK (2009) *Introduction to Spatial Econometrics*. New York, NY: Chapman and Hall/CRC.
- Manduca R and Sampson RJ (2019) Punishing and toxic neighborhood environments independently predict the intergenerational social mobility of black and white children. *Proceedings of the National Academy of Sciences* 116(16): 7772–7777.
- Markevych I, Schoierer J, Hartig T, et al. (2017) Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research* 158: 301–317.
- Massey DS, Condran GA and Denton NA (1987) The effect of residential segregation on black social and economic well-being. *Social Forces* 66(1): 29–56.
- Massey DS and Lundy G (2001) Use of Black English and racial discrimination in urban

housing markets: New methods and findings. *Urban Affairs Review* 36(4): 452–469.

- Mohai P and Saha R (2006) Reassessing racial and socio-economic disparities in environmental justice research. *Demography* 43(2): 383–399.
- Mohai P and Saha R (2007) Racial inequality in the distribution of hazardous waste: A national-level reassessment. *Social Problems* 54(3): 343–370.
- Mohai P and Saha R (2015) Which came first, people or pollution? A review of theory and evidence from longitudinal environmental justice studies. *Environmental Research Letters* 10(12): 125011.
- Moos M (2016) From gentrification to youthification? The increasing importance of young age in delineating high-density living. *Urban Studies* 53(14): 2903–2920.
- Mossaad N, Ferwerda J, Lawrence D, et al. (2020) In search of opportunity and community: Internal migration of refugees in the United States. *Science Advances* 6(32): eabb0295.
- Müller A (2015) Diskriminierung auf dem Wohnungsmarkt: Strategien zum Nachweis rassistischer Benachteiligungen. Berlin: Antidiskriminierungsstelle des Bundes. Available at: https://www.antidiskriminierungsstelle.de/Shar edDocs/downloads/DE/publikationen/Experti sen/expertise_diskriminierung_auf_dem_wohn ungsmarkt.html (accessed 18 January 2024).
- O'Brien RL, Neman T, Rudolph K, et al. (2018) Prenatal exposure to air pollution and intergenerational economic mobility: Evidence from U.S. county birth cohorts. *Social Science & Medicine* 217: 92–96.
- Ondrich J, Stricker A and Yinger J (1999) Do landlords discriminate? The incidence and causes of racial discrimination in rental housing markets. *Journal of Housing Economics* 8(3): 185–204.
- Page M (1995) Racial and ethnic discrimination in urban housing markets: Evidence from a recent audit study. *Journal of Urban Economics* 38(2): 183–206.
- Panduro TE, Jensen CU, Lundhede TH, et al. (2018) Eliciting preferences for urban parks. *Regional Science and Urban Economics* 73: 127–142.
- Pastor M, Sadd JL and Morello-Frosch R (2004) Waiting to inhale: The demographics of toxic

air release facilities in 21st-century California. *Social Science Quarterly* 85(2): 420–440.

- Pebesma E (2018) Simple features for R: Standardized support for spatial vector data. *The R Journal* 10(1): 439–446.
- R Core Team (2021) *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. Available at: https://www.R-project.org/ (accessed 17 November 2023).
- Raddatz L and Mennis J (2013) Environmental justice in Hamburg, Germany. *The Professional Geographer* 65(3): 495–511.
- Roberts S, Arseneault L, Barratt B, et al. (2019) Exploration of NO₂ and PM_{2.5} air pollution and mental health problems using highresolution data in London-based children from a UK longitudinal cohort study. *Psychiatry Research* 272: 8–17.
- Rüttenauer T (2018) Neighbours matter: A nation-wide small-area assessment of environmental inequality in Germany. *Social Science Research* 70: 198–211.
- Rüttenauer T and Best H (2021) Environmental inequality and residential sorting in Germany: A spatial time-series analysis of the demographic consequences of industrial sites. *Demography*: 58(6): 2243–2263.
- Schüle SA, Gabriel KMA and Bolte G (2017) Relationship between neighbourhood socioeconomic position and neighbourhood public green space availability: An environmental inequality analysis in a large German city applying generalized linear models. *International Journal of Hygiene and Environmental Health* 220(4): 711–718.
- Semyonov M, Raijman R and Gorodzeisky A (2006) The rise of anti-foreigner sentiment in European societies, 1988-2000. American Sociological Review 71(3): 426–449.

- Sirmans S, Macpherson D and Zietz E (2005) The composition of hedonic pricing models. *Journal of Real Estate Literature* 13(1): 1–44.
- Statistische Ämter des Bundes und der Länder (2014) Zensus 2011. Available at: https:// www.zensus2022.de/DE/Was-ist-der-Zensus/ gitterzellenbasierte_Ergebnisse_Zensus2011 .html (accessed 16 March 2023).
- Statistisches Bundesamt (2018) Bevölkerung mit Migrationshintergrund - Ergebnisse des Mikrozensus 2017. Fachserie 1 Reihe 2.2, 1 August. Available at: https://www.destatis.de/DE/The men/Gesellschaft-Umwelt/Bevoelkerung/Migra tion-Integration/Publikationen/Downloads-Mig ration/migrationshintergrund-2010220177004 .pdf?_blob=publicationFile&v=4 (accessed 21 November 2023).
- Walker G, Mitchell G, Fairburn J, et al. (2005) Industrial pollution and social deprivation: Evidence and complexity in evaluating and responding to environmental inequality. *Local Environment* 10(4): 361–377.
- Wickham H, Averick M, Bryan J, et al. (2019) Welcome to the Tidyverse. *Journal of Open Source Software* 4(43): 1686.
- Wiedner J, Schaeffer M and Carol S (2022) Ethno-religious neighbourhood infrastructures and the life satisfaction of immigrants and their descendants in Germany. *Urban Studies* 59(14): 2985–3004.
- Will A-K (2019) The German statistical category "migration background": Historical roots, revisions and shortcomings. *Ethnicities* 19(3): 535–557.
- Yinger J (1986) Measuring racial discrimination with fair housing audits: Caught in the act. *The American Economic Review* 76(5): 881–893.
- Yinger J (1995) Closed Doors, Opportunities Lost: The Continuing Costs of Housing Discrimination. New York, NY: Russell Sage Foundation.