Review of Regional Research (2024) 44:337–381
https://doi.org/10.1007/s10037-024-00215-x

ORIGINAL PAPER

Toxic pollution and labour markets: uncovering Europe's left-behind places

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Accepted: 18 July 2024 / Published online: 12 September 2024

Abstract This paper looks at the co-evolution of toxic industrial pollution and economic deprivation by means of spillovers from the plant's production activities. Geolocalised facility-level data from the European Pollutant Release and Transfer Register (E-PRTR) are used to calculate annual chemical-specific pollution, weighted by its toxicity. We combine the latter with regional data on employment, wages, and demographics sourced from Cambridge Econometrics, covering more than 1200 NUTS-3 regions in 15 countries, over the period 2007–2018. We employ quantile regressions to detect the heterogeneity across regions and understand the specificities of the 10th and 25th percentiles. Our first contribution consists in giving a novel and comprehensive account of the geography of toxic pollution in Europe, both at facility and regional level, disaggregated by sectors. Second, we regress toxic pollution (intensity effect) and pollutant concentration (composition effect) on labour market dimensions of left-behind places. Our results point to the existence of economic dependence on noxious industrialisation in left-behind places. In addition, whenever environmental efficiency-enhancing production technologies are adopted we observe associated labour-saving effects in industrial employment, but positive regional spillovers. Through the lens of economic geography, our results call for a new political economy of left-behind places within the realm of sustainable development.

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Keywords Environmental inequality · Left-behind places · Toxic pollution · Labour markets

MSC-Classification JEL classification · Q52 · P18 · R11 · O3

1 Introduction

What do facilities such as ex-ILVA in Italy, ArcelorMittal in France, INEOS Chemicals Grangemouth in the UK, and Lausitz Energie Kraftwerke in Germany have in common? They are tangible illustrations of geographies characterised by the co-evolution of toxic industrial pollution and economic deprivation.

Inspired by those examples, this paper intends to address the geography of left-behind places from an environmental perspective. The existing literature has predominantly characterised left-behind places in terms of their economic and political dimension. We propose a new characterisation of left-behind places as territories in which socio-economic deprivation, measured as negative employment, wage, and demographic prospects, coexist with toxic pollution. To achieve this objective, we empirically examine the relationship between what we ex-ante identify as left-behind places – NUTS-3 geographical units located in the lower percentiles of labour markets, as measured by employment, wages, and demographic outflows – and toxic emissions.

The theoretical rationale behind the link between toxic pollution and left-behind places is that the presence of a highly polluting facility in a given area might adversely affect regional economic development, both in terms of employment segregation in such facility and sector, inducing dependence on noxious industrialisation, but also in terms of the poor economic trajectory and bad specialisation. The latter highlights an economic development path unable to divert from a lock-in, potentially resulting in a decline in employment opportunities over time and a dampening effect on local labour markets (see relatedly Ash and Boyce 2018; Boschma et al. 2017).

The presence of these facilities exerts a significant influence on a given territory, giving rise to both direct and indirect links with its economic development and labour markets. This can be attributed not only to the typically large size of the establishments but also, more fundamentally, to the materialist and historical roles these workplaces play in shaping the socio-economic dynamics of the involved regions. Geographic disparities co-evolve with path-dependent processes, the latter stratifying along different dimensions: advanced production and complex industrial diversification go hand in hand with high-innovative activities and good jobs (Rodrik and Stantcheva 2021), raising employment opportunities for the “winning” regions. On the other side, deindustrialisation, deterioration of productive capacity and locked-in productive activities with low complexity characterise left-behind places, with low-paid jobs and reduced employment opportunities.

So far, only a few case studies have been conducted in such places in order to highlight the role polluting activities play (Greco and Bagnardi 2018; Feltrin et al. 2021). In addition, the literature lacks both a quantitative way to identify such places and a comprehensive mapping of their actual status and evolution. Beyond the economic characterization of social inequality, what happens in terms of environmental inequality? Far from random order, the distribution of highly toxic industrial activity across regions tends to be concentrated as well, and it does so exactly in places experiencing socio-economic deprivation. In this respect, environmental and social inequality tend to stratify. More specifically, is toxic pollution linked to socio-economic inequalities and industrial decay at the regional level?

In order to address such question, we use geolocalised facility-level data from the European Pollutant Release and Transfer Register (E-PRTR) (European Commission 2006) to calculate annual chemical-specific pollution, weighted by CAS-number toxicity using the USEtox 2.12 model (Fantke et al. 2017). The E-PRTR contains environmental data from over 30,000 georeferenced industrial facilities in Europe, with information on quantities of 91 key pollutants released into air, water, and land. Our first contribution is therefore to produce a *geography of toxic pollution*. Accordingly, nowadays many left-behind places are still heavily dependent on fossil and other toxic industries, mainly producing metals, minerals, chemicals, and other raw materials.

Given the geography of toxic pollution, our second contribution is to investigate the nexus between toxic pollution and the socio-economic spillovers on industrial labour markets. Therefore, our dependent variables are defined as left-behind places. Our explanatory variables are two indices of toxic emissions, one accounts for the sheer quantity of toxic emissions, the other accounts for quality improvements in the emissions' mix. To create those indices, we aggregate facility-level pollution by sector at the regional level. Our analysis covers more than 1200 NUTS-3 regions for 15 European countries, over the period 2007–2018, and includes high-polluting traditional industries. Such empirical design allows us to detect potential lock-in dynamics in bad specialisation strategies. Therefore, our second contribution lies in identifying the particularities of left-behind places from a socio-environmental perspective. Third, after mapping toxic pollution to left-behind places, we study channels and sources of spillovers from industrial activities to the whole regional economy by moving from the geography of places to the geography of regions.

We build two indices of pollution: a toxic pollution index, weighting the quantity of pollutants emitted by their toxicity (via CAS number), and a concentration index, capturing the pollutant portfolio at the facility level. The intensity of pollution, i.e., its overall toxicity, and the pollutant concentration are contrasted, by means of quantile regression, against the dynamics of left-behind places in terms of direct sectoral level links with industrial employment and wages, and indirect regional level links at the NUTS-3 level. By the latter, we study the potential spatial spillovers in the regions left behind, in terms of employment, wages, and demographic losses.

We lay out two channels of toxic pollution propagation: a first-order channel according to which intensity of toxic pollution is positively associated with employment and wages at the industrial level. Not surprisingly, this result mainly holds for the lower quantiles of wages and employment distributions, therefore in favour of the *noxious dependence* that left-behind places have developed with industrial decay (Feltrin et al. 2021). A second-order channel according to which the reduction of the pollutant mix at the facility level, a proxy for technical change or inputs recombination in the context of environmental efficiency, is negatively associated with industrial employment and wages, again with higher magnitudes for the lower quantiles of the distributions. In this respect, the abatement of toxic pollution via improved environmental efficiency processes might spur employment reallocation toward other, less noxious sectors of activity, rather than noxious industrialisation. We finally document the existence of spatial inequality feedback loops at the regional level, according to which toxic pollution is robustly negatively associated with net migration from left-behind places. Vice versa, the increasing concentration of the pollutant mix reduces the probability of relocation from a given place.

The rest of the article is structured as follows. The following Sect. 2 embeds the environmental dimension of left-behind places into an economic geography perspective. Sect. 3 describes our data and methods, including how we construct our explanatory variables. The descriptive evidence in Sect. 4 gives a nuanced account of the geography of toxic pollution in Europe, both at facility and regional level, and disaggregated by sector. Sect. 5 explains our estimation strategy and shows the estimation results, for both the direct links focused on industry, as well as the indirect links with the regional economy as a whole. Sect. 6 concludes and lays out several policy considerations.

2 The environmental dimension of left-behind places

The economic geography literature has not yet devoted specific attention to the environmental dimension of left-behind places and neither to the geography of toxic pollution. Left-behind places are conceptually not so far from the South regions in uneven development theory (Prebisch 1950), which builds upon dependence, power structure, and persistent positional asymmetries (Pavlínek 2018; Leyshon 2021). However, uncovering left-behind places involves expanding the more traditional economic literature on North-South gaps and unequal development (Cimoli and Dosi 1995) with a territorial and geographical focus (Boschma et al. 2017). Such places have in common the experience of economic stagnation or even decline, depressed wages, demographic loss, and a general pattern of abandonment. This marginalisation was then compounded by the policy tendency to target urban agglomerations, “smart cities”, and innovative hub-clusters as main engine of economic growth (MacKinnon et al. 2022).

Furthermore, the geography of discontent and left-behind places are closely related concepts. With the recent surge of populist and anti-system tendencies around Europe (Rodríguez-Pose 2018), for instance, the Brexit referendum (Goodwin and Heath 2016; Antonucci et al. 2017), left-behind places conceptually have received increasing attention. The ballot box backlash brought to the forefront socio-economic issues that have grown out of long-term tendencies, but have often been neglected by the economics literature. Hence, while deindustrialised, marginalised, and declining areas have moved out of policy focus, their urgent political relevance has sparked general renewed policy attention. The following subsections explain the intersection between a new conceptualization of left-behind places under the lens of economic geography. We mobilise two broad concepts, namely i) path dependence and regional lock-ins, and ii) the political economy of left-behind places.

Path dependence and regional lock-ins constitute key mechanisms elucidating the materialist dimension of left-behind places. Lock-ins entail place- and history-dependent paths occurring by means of the continuous reproduction of localised knowledge and socio-technological regimes. Specialisation, especially in the production of less dynamic and less complex products, pushes toward low growth trajectories and higher vulnerability to economic crises (Dosi et al. 2022).

The properties of sectoral systems of innovations for economic development were recognised long ago (Malerba and Orsenigo 1996). Traditionally, heavy industries are expected to differ in their technological regimes of innovation and competition compared to others (Breschi and Malerba 1997). In fact, they are not susceptible to either high levels of innovation or intense competition (Tödtling and Trippl 2005). Therefore, ex-ante heterogeneity of between-sectoral pollution patterns is expected to be more relevant than within-sectoral ones. However, research on disproportionality (Freudenburg 2005; Collins et al. 2016) and co-pollutant elasticities (Dedoussi et al. 2019; Zwickl et al. 2021), looking at pollution at the facility-level, finds little evidence for "technological imperatives of a given sector" to pollute, also when controlling for size. In fact, in general, it seems that major polluters are often within-sector outliers characterised by a low rate of efficiency, indicating that environmental damage is often neither economically nor technologically required by the variety of production techniques available. In this respect, pollution, and particularly high-scale toxic pollution, is a proxy for low-technological dynamism and absence of investment in efficient techniques of production, rather than a necessary externality of the sector.

Consider, for instance, the well-known case of the ex ILVA steel plant in Taranto, Italy (Greco and Bagnardi 2018). The latter represents a clear combination of lack of technological upgrading, absence of investment in enhancing techniques of production, and purported employment-health trade-off, revealed by an ownership-managerial orientation historically resistant to promote technical progress in the plant. However, the mono-industrialisation pattern of the area has created a strong economic dependence in terms of job opportunities. Another example is the once-notorious Ruhr region in West Germany, especially the cities of Duisburg and Bochum (Fröhlich et al. 2022). Nowadays, this region is marked by a high incidence of toxic pollution and structural weakness, indicating the importance of equity considerations (Arora and Schroeder 2022). Grabher (1993) gives an in-depth explanation of the lock-in of regional development in the Ruhr area, once a complex industrial growth pole, deeply specialised in coal, iron, and steel. As we shall show, many industrial complexes, especially in the energy and steel industry, are still operating in this area, however, the social contract unraveled, and employment worsened or disappeared. As Grabher (1993) argues, the "weakness of strong ties" emerges as the main cause of such lock-in trajectories.

Are left-behind places a necessary cost to pay for economic development? In the presence of toxic pollution, left-behind places can be considered industrial sacrifice zones (Lerner 2012). In such contexts, socio-economic erosion is a key agent necessary for the reproduction of spatialities of power marking the difference between cores and peripheries (Massey 2009). Exposure to toxic harm coupled with the slow decay of chemical change maintains and reinforces regional divergences. The concept of sacrifice allows to conceptualise toxic pollution as an intended imposition of power over a region and its inhabitants, creating an uneven toxic geography, and implies the “right to pollute” enabled by a naturalised economic power (Freudenburg 2005).

Industries that are dirtier, more dangerous, and more threatening to human health present a special case for the spatiality of power, as conceptualised by Massey (2009). Around those industries, social and labour struggles are actually shaped by their objective relation with capital directed to polluting activities. Given that such places have materialist interests embedded into the production process, place and path dependency mutually reinforce each other, and lead to a lock-in of pollution-dependent growth. Indeed, the geography of toxic pollution might also help to understand the direction in which the political economy of left-behind places might manifest by means of the spatial reproduction of power.

Certainly, toxic pollution is not the sole cause of economic decline. Indeed, there are plenty of places with high levels of exposure to toxicity which are not left behind from a socio-materialist perspective. In fact, in the following, we distinguish two different types of exposure to toxicity: an index of total weighted toxicity, which accounts for a size effect, and an index that measures any type of improvement in the composition of the portfolio of pollutants, in order to track upgrading trends in the pollution mix. Left-behind places are measured in terms of levels of the distribution of employment, wages, and migration flows. They are in the left part of the empirical distributions of these three labour market variables, depending on the quantile regression that will be estimated. We expect, following the lock-in hypothesis, that those areas will be more dependent on toxicity, as a first-order channel. At the same time, we expect that any path of industrial upgrading will incorporate less polluting but also more efficient techniques, or input combinations, and in that require less employment.

3 Data and Methods

Our aim is to give an account of the geography of toxic pollution in Europe, to then study the co-evolution of toxic pollution on economic deprivation, in particular with respect to employment, wages, and net migration flows. This allows us to investigate the environmental dimension of left-behind regions. We combine two datasets in a novel way: facility-pollution data and regional economic data at sectoral level, covering more than 1200 regions in Europe, over the period 2007–2018. Sect. 3.1 describes the dataset of facility-specific industrial pollution sourced from the E-PRTR, from which we calculate two measures at the sector-region-year level. The first index is the facility-level pollution augmented by its toxicity which informs about an intensity effect (Sect. 3.2), while the second is a pollutant concentration index which informs about the mix of the facility pollutant portfolio (Sect. 3.3). Sect. 3.4 presents the industry-level distribution of the constructed indices. Sect. 3.5 describes the set of outcome variables sourced from Cambridge Econometrics (employment and wages) and Eurostat (migration), which illustrate the different dimensions of left-behind places.

3.1 Industrial facilities, sourced from E-PRTR

We get facility-level pollution data from the European Pollutant Release and Transfer Register (E-PRTR) which provides environmental data from industrial facilities in European Union Member States, Iceland, Liechtenstein, Norway, Switzerland, Serbia, and the UK (European Commission 2006). Starting from 2007, the register has been updated every year with annual data reported by some 30,000 industrial facilities covering 65 economic activities. Each active industrial facility is required to provide annual information on the deliberate and accidental quantities of pollutants released to air, water and land. This data covers 91 key pollutants including heavy metals, pesticides, greenhouse gases and dioxins. The E-PRTR defines a pollutant as "a substance or a group of substances that may be harmful to the environment or to human health on account of its properties and of its introduction into the environment" (European Commission 2006, Annex I, Article 2, p.74). Hence, the E-PRTR gives insights into the releases and transfers of regulated substances of the largest industrial complexes in Europe. Annex I of the E-PRTR Regulation lists 65 activities, grouped into 7 activity sectors.[1] The information to which sector a facility belongs allows for an industry-specific analysis.[2]

To build our original data set, we select emissions released by air, taking into consideration both deliberate and accidental emissions, and drop facilities with data entries for five or fewer consecutive years, as we want to focus on polluters that have shown some degree of continuity with regard to their presence in and hence possible impact on the territory.[3] Facilities that did not exceed a threshold of emissions as established by the Commission (2006, pp. 83–86) do not have to report in the E-PRTR in that specific year (even though these facilities were still operating), which leads to missing data within the facility-specific time series. If pollution records are missing in one or more years, but are present before and after, we perform a linear interpolation in order to control for those missing values.[4]

We are focusing on the countries where most facilities are located, i.e., countries with a considerable level of industrial activity. By definition, the nexus industrial pollution-employment dynamics is less interesting in regions with little to no industrial pollution, as suggested by the E-PRTR data. Hence, to sharpen our analysis, we drop the countries that belong to the lowest five percent in terms of the number of

[1] These sector are: agriculture and leather industry, chemical industry, energy, production and processing of metals, mineral industry, paper and wood production and processing, waste and waste water management.

[2] An extensive overview of the E-PRTR classification including a detailed description of all activities covered by our data can be found in the Appendix, Table 8.

[3] The minimum presence in the data set is one year, the maximum 13. On average, a facility has pollution entries for ten years. Eleven percent of facilities are present in the data base for five years or less. Those are the facilities that we exclude from the analysis.

[4] This is motivated by the assumption that missing values, i.e., gaps, arise from the threshold issue. Missing years at the beginning or the end of the time period instead indicate the ceased activity of a facility and therefore are not interpolated. This is analog to the procedure proposed by Rüttenauer and Best (2021b), being confronted with the same E-PRTR data issue. Linear interpolation however only affects a small portion of the entire emission data set (1.78 percent), ruling out the threat of a systematic bias.

polluting facilities. This leaves us with the following 15 countries: Austria, Belgium, Czech Republic, Germany, Spain, Finland, France, UK, Greece, Italy, Netherlands, Poland, Portugal, Romania, and Sweden.

The top ten polluting facilities of the four most toxic sectors (energy, metals, minerals, chemicals), ranked by the sum of emitted pollutants over all years, are presented in Table 1. It lists the names of the facilities as well as the countries and cities that host such facilities, which provides a first glimpse of the detailed information provided by the E-PRTR dataset.

3.2 Measuring toxic pollution

The E-PRTR allows to disentangle pollutants and their underlying toxicity. Indeed, it is well known that pollutants from industrial facilities are dangerous to human health and the environment. The amount of pollution and its pollutant mix is a result of the existing technologies and production processes of the industrial system. Although progress has been made in terms of reduction of the environmental impacts of toxic pollution from industry through regulations and bans, the evidence tells us that there are still innovative search efforts around toxic chemical components (Biggi et al. 2022). Moreover, as we shall see, even banned compounds are still present in the E-PRTR, for example hexachlorobenzene and polychlorinated biphenyls, which are banned globally and universally. They belong to the ten most toxic pollutants present in the data.

In terms of toxicity, the chemical with the highest toxicity in absolute is mercury and its compounds (HG), which clearly emerges as an outlier being twelve times more toxic than the average compound in the data set, and is a highly potent neurotoxin that is closely linked to energy production. For instance, in 2020, the EPA proposed to roll back its Mercury and Air Toxics Standards (MATS) as regulatory limits on hazardous air pollution from coal-burning power plants (EPA 2019).[5] It is hence crucial to account for pollutant's toxicity which differs widely across pollutant groups and single compounds. Given the heterogeneous toxicity of the different pollutants, we weigh pollutants by their toxicity.

We focus on long-term exposure to all pollutants that are known to be dangerous to human health. Out of the original 91 key pollutants we retain 41 distinct pollutants, whose toxicity varies by several magnitudes.[6] The chemical group of heavy metals is the most toxic; at the same time, they are frequent due to wide industrial applications. As said, the data set also shows the presence of several pollutants that have been banned worldwide since the Stockholm convention from 2001.

We account for the variation of toxicity by weighting the quantity (mass in kilogram) of each pollutant by a toxicity weight that we source from the USEtox 2.12 data base (Fantke et al. 2017), as shown in Eq. 1. We match pollutants with their respective toxicity via information on Chemical Abstracts Service numbers (short

[5] This decision is based on cost-benefit analyses, trying to economically justify industrial contamination and disregarding the significant health and environmental benefits by reducing a broad range of hazardous air pollutants, especially mercury, as argued by Aldy et al. (2020), see also Ofrias (2017).

[6] The full list of toxic pollutants retained for this analysis can be found in the Appendix, Table 7.

Table 1 Top-10 polluting facilities that operate in the energy, metals, minerals, and chemicals industries. The column "*Log Poll.*" refers to facility pollution summed over all years, in logs. Source: Own calculation based on E-PRTR

Name of Facility	*Country*	*City*	*Log Poll.*	*Name of Facility*	*Country*	*City*	*Log Poll.*
Energy				Minerals			
PGE Górnictwo i Energetyka Konwencjonalna	PL	Rogowiec	12,61875	CBR sa – Site de Lixhe	BE	Lixhe	10,49804
PPC S.A. SES AGIOY DHMHTRIOY	GR	Agios Dimitrios	12,58762	HOLCIM Belgique sa – Usine d'OBOURG	BE	Obourg	10,31415
Drax Power Station EPR/VP3530LS	GB	Selby	12,24817	CEMEX Polska Cementownia Chelm	PL	Chelm	9,582096
ENEA Wytwarzanie Polsce energii	PL	Swierzach Górnych	12,01695	CCB sa – Site de Gaurain-Ramecroix	BE	Gaurain-Ramecroix	9,302887
LEAG Lausitz Energie Kraftwerk Lippendorf	DE	Neukieritzsch	11,81845	TITAN CEMENT S.A. – KAMARI PLANT	GR	Kamari	9,148636
LEAG, Kraftwerk Jänschwalde	DE	Teichland	11,77331	Whitwell Works	GB	Worksop	9,146606
RWE Power AG Kraftwerk Niederaußem	DE	Bergheim	11,66642	HERACLES G.C.Co, VOLOS PLANT	GR	Portaria	9,055297
RAFFINERIA DI GELA SPA	IT	Gela	11,48725	Górazdze Cement S.A. – Cementownia	PL	Chorula	9,026553
Elektrownia ZE PAK S.A. Patnów	PL	Konin	11,45654	VERALLIA FRANCE	FR	Chalon sur Saone	9,007586
Elektrowni Adamów	PL	Turek	11,44843	Grupa Ozarów S.A.	PL	Karsy	8,876104

Table 1 (Continued)

Name of Facility	*Country*	*City*	*Log Poll.*	*Name of Facility*	*Country*	*City*	*Log Poll.*
Metals				Chemicals			
ArcelorMittal Italia (ILVA)	IT	Taranto	14,15508	Runcorn Halochemicals EPR/BS5428IP	GB	Runcorn	12,17456
Outokumpu Chrome&Stainless Oy, Tornion	FI	Tornio	13,63423	INOVYN FRANCE	FR	Tavaux	11,20224
ACCIAI SPECIALI TERNI – stabilimento di TERNI	IT	Terni	12,89282	KEM ONE LAVERA	FR	Martigues	10,86025
Tata Steel IJmuiden BV	NL	Velsen-Noord	12,60091	NAPHTACHIMIE	FR	Martigues	10,74064
ArcelorMittal Fos Sur Mer	FR	Fos Sur Mer	12,14459	SC CHIM COMPLEX S.A. Borzesti	RO	Ramnicu Valcea	10,52307
ArcelorMittal Dabrowa Górnicza steel plant	PL	Dabrowie Górniczej	12,01051	BASF SE	DE	Ludwigshafen a.R.	10,0455
thyssenkrupp Steel Europe Werk Schwelgern	DE	Duisburg	12,00896	VYNOVA BELGIUM	BE	Tessenderlo	9,865824
ARCELORMITTAL FRANCE	FR	Dunkerque	11,77123	Spolana Neratovice	CZ	Neratovice	9,709022
Port Talbot Steelworks Tata Steel	GB	Port Talbot	11,73189	ORLEN Unipetrol RPA	CZ	Litvínov	9,68126
ARCELORMITTAL LIEGE sa (Coke-Fonte)	BE	Ougree	11,62174	ThermPhos International BV	NL	Ritthem	9,323645

CAS), which are numerical designations for chemicals of the American Chemical Society. The same methodology has been applied, for instance, by Rüttenauer and Best (2021a).[7] USEtox is a scientific consensus model endorsed by the UN's Environment Programme "Life Cycle Initiative" for characterizing human and eco-toxicological impacts of chemicals. By matching each pollutant to a toxicity weight, we enable the comparative assessment of chemicals, i.e., the toxic significance of releases of different pollutants.

Therefore, at facility level, pollution quantity weighted by toxicity, called *Tox Poll* hereinafter, can be defined as:

$$Tox\ Poll_{it} = \sum_{p=1}^{P} Tox\ Weight_p * Quantity_{ipt} \tag{1}$$

for each pollutant p and facility i in year t. In 2007, total weighted toxic pollution amounted to 1.62 billion tons. In comparison, in 2017, facilities released a total of 1.29 billion tons. The facility-level measure $Tox\ Poll_{it}$ will then be aggregated by sector and region later on, which will be our main explanatory variable throughout the analysis.

Table 2 Summary table of industrial facilities in E-PRTR sample, by country. Toxic pollution is expressed in millions of tons and weighted by toxicity. The last column "Percentage total toxic pollution" refers to a country's share of toxic pollution to all pollution in the data set, and sums to 100. The first row in the summary table shows the country with the highest level of aggregate toxic pollution

Country code	Number of facilities	Number of distinct pollutants	Toxic pollution emitted	Percentage total toxic pollution
FR	513	33	24 874	13.97
ES	382	32	23 666	13.30
DE	397	31	23 494	13.20
GB	603	38	20 385	11.45
PL	273	30	19 242	10.81
IT	267	31	13 963	7.84
CZ	93	27	11 361	6.38
BE	169	37	9957	5.59
GR	37	27	6552	3.68
PT	79	22	6050	3.40
SE	77	25	4786	2.69
NL	137	29	4775	2.68
FI	81	20	4712	2.65
RO	39	17	2265	1.27
AT	32	20	1920	1.08

[7] The E-PRTR provides the CAS numbers for a large majority of the present components. We have attributed the missing CAS numbers manually if applicable, collaborating with an organometallic synthetic chemist to ensure accuracy in the matching. In the case of heavy metals the CAS registry number for the most stable metal cation was assigned, which matches the form typically encountered and most relevant in the environment.

The summary Table 2 illustrates the scope of the E-PRTR data set in terms of countries, facilities, and distribution of distinct pollutants and toxic pollution in Europe. Countries are ranked by their number of facilities. While the four larger economies rank in the top positions, the evidence reveals the presence of eastern countries such as Poland and Czech Republic – among highly toxic polluted countries, while Sweden, the Netherlands, and Finland rank in the bottom. Therefore, the index informs about different polluting strategies and ensuing impacts across facilities by countries.[8]

3.3 Concentration index of pollutants

Our analysis covers high-polluting industries (energy, metals, minerals, chemicals, etc.), largely characterised by low-tech, scale-intensive facilities. Such plants, over time, might have however invested in technological upgrading, reducing their environmental impact on the territory, but also employment requirments, as usual in process innovation. Hence, we investigate whether efficiency-enhancing technologies are actually labour-saving, being associated with employment losses in industry. Lacking a direct measure of technological adoption, we proxy environmental technology as the facility-level reduction of the mix of toxic pollutants emitted. Therefore, we intend the ex-post reduction of pollutant mixes as a proxy for recombination of materials, parts, components, and energy processes able to reduce the end pollutant mix. For this purpose, our analysis employs a newly created pollution concentration index that accounts for pollution reduction at the source, i.e., it is an indicator for cleaner production. Departing from facility-level data, we are interested in understanding the potential employment forces of pollutant-mix reduction technologies and processes. In this way, we test for a potential labour-saving effect of environmental technology.

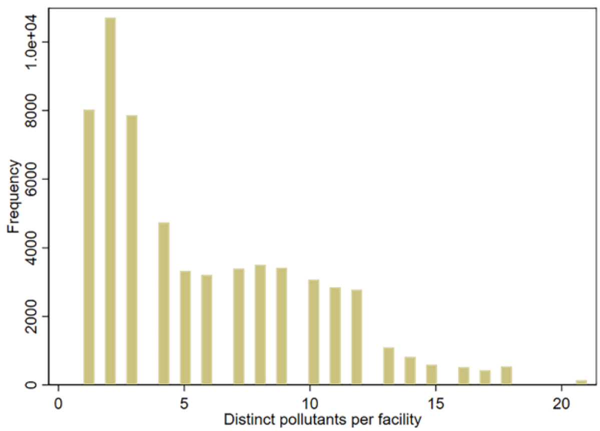


Fig. 1 Histogram of distinct pollutants by facility. Source: Own calculation based on E-PRTR

[8] Note that the data set does not provide any information about the productive output or the profit rates of such facilities.

In other words, other than the level of toxic pollution, we are interested in the pollution portfolio, i.e., in the composition of toxins. In fact, we observe a great deal of heterogeneity with respect to the number of distinct pollutants emitted at the facility-level. Fig. 1 shows the histogram of distinct pollutants by facility, ranging between one and 21, with an average of six pollutants by facility and year.

The literature on co-pollutants with respect to CO_2 confirms this finding (Dedoussi et al. 2019; Zwickl et al. 2021; Boyce 2020), acknowledging very heterogeneous levels of so-called co-pollutant efficiency for fixed amounts of CO_2.[9,10] To capture the heterogeneity of the pollutant portfolio, we construct a Herfindahl-Hirschman Index (HHI) of the pollutant concentration at facility-year level. It is defined as the sum of all squared relative pollution shares and is calculated as:

$$HHI_{it} = \sum_{p=1}^{N} \frac{1}{p_{it}}^{2}, \tag{2}$$

where p is the number of distinct pollutants and $\frac{1}{p}$ is their relative share. The mean of this facility-level HHI is approx. 0.33.[11]

The index accounts for the composition effect and in that proxies for the degree of innovativeness (backwardness) of the production process in use. In line with this, Freudenburg (2005) finds that major polluters are often inefficient producers of low-value commodities. Hence, this measure goes beyond so-called end-of-pipe technologies, which are mostly driven by incremental innovations as they are aimed at mitigating already existing environmental problems. What we aim to capture, instead, is the implementation of technological and production processes that reduce the amount of dangerous, polluting substances introduced into water, land, air, therefore reducing the danger to society and the environment. Such transition and conversion processes then lead to changes in the technological-organizational structure of the plant and can be considered as a form of eco-innovation as described in Cecere et al. (2014). From the point of view of the firm, adopting new production processes for pollution prevention can be motivated by cost reduction, productivity gains, safety issues, waste reduction, and the adaptation to technological change.

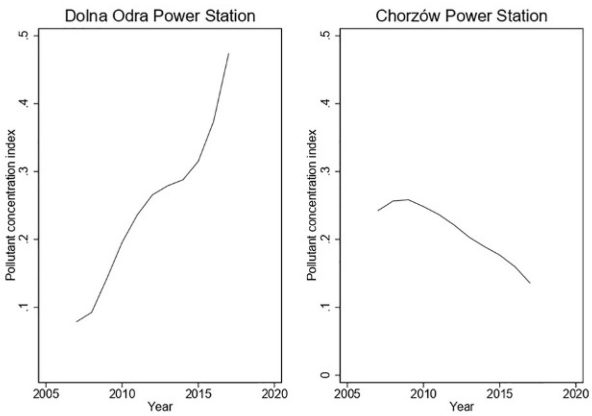
To validate the proposed index, we show anecdotal evidence of its use as a proxy for environmental technology adoption. In Fig. 2, we compare two Polish power stations over the entire time horizon. The left panel depicts the pollutant concentration index (smoothed) for the Dolna Odra Power Station, the right panel for the Chorzów Power Station. Both plants belong to the energy sector, more precisely, they are two power plants that rank among the highest quantiles in terms of pollution.

9 Co-pollutant efficiency measures the ratio of co-pollutant damages to carbon dioxide emissions. From a policy point of view, such co-benefits arise when compliance with a regulation leads to reductions in other pollutants that were not the regulation's intended target.

10 The E-PRTR does not provide data on industrial output or production, hence those contributions to the literature use CO_2 as a proxy for size.

11 The minimum of the index is approx. 0.05, i.e., implying a relatively equal share of pollutants. Energy and metals are the two main industries with such a multi-pollutant portfolio.

Fig. 2 Pollutant concentration index (smoothed) over time for Dolna Odra Power Station, Poland (left panel), and Chorzów Power Station, Poland (right panel). The left panel depicts a case of improved concentration over time (increase in HHI), and the right panel of worsened concentration (decrease in HHI). Source: Own calculation based on E-PRTR



In 2017, the Dolna Odra Power Station recorded toxic pollution equal to 211 tons, and the Chorzów Power Station equal to 175 tons, therefore they both show comparable end-of-period pollution levels. The case in the left panel is an example of improved concentration over time (from 0.1 to 0.5, i.e., an upgrading case), while the right panel shows the opposite (from 0.24 to 0.12, i.e., a downgrading case). The Dolna Odra Power Station is indeed an example of a facility that successfully decreased its number of distinct pollutants, and (consequently) the overall amount of toxic pollution. In 2007, the plant emitted 12 different toxic compounds, among others Arsenic, Cadmium, Chlorine, Chromium, Copper, Lead, Mercury, PCDD, and PAHs. In 2017, this number shrank to two different compounds, which are Chlorine and Mercury. Notice, however, that Mercury is the most toxic single toxin within coal-fired power plants, considered one of the major emission sources. A 2009 newspaper article announces more 'clean' energy from Dolna Odra thanks to new flue gas desulphurization plants, i.e., a technological upgrade leading to cleaner gas, with a contract value of approximately 25 million euro (PGE Group 2007). In line with EU standards, it provides technological solutions for thermal and waste treatment. Generally, flue-gas cleaning describes a set of technologies that remove $S0$, $S0_2$ and other toxic pollutants (e.g., Arsenic, Selenium, and Mercury), often needed to comply with emissions' regulations (Al-Abed et al. 2008).

3.4 Why industries matter

We move toward aggregating facilities at the industry level. In fact, we are interested in the industry composition with respect to toxic pollution and pollutant groups. Given that our data set is industry- and pollutant-specific, we are able to disaggregate and visualise toxicity-weighted emissions by industry by pollutant groups.[12] Fig. 3

[12] We distinguish between the following pollutant groups: Greenhouse gases, halogens, heavy metals, (polycyclic) aromatic hydrocarbons ((P)AHs), persistent organic pollutants (POPs), and volatile organic compounds (VOCs). Note that even though the E-PRTR collects information on CO_2, it has no toxicity information for local exposure and hence is not part of our data sample, which focuses on industrial pollutants known to be dangerous for human health.

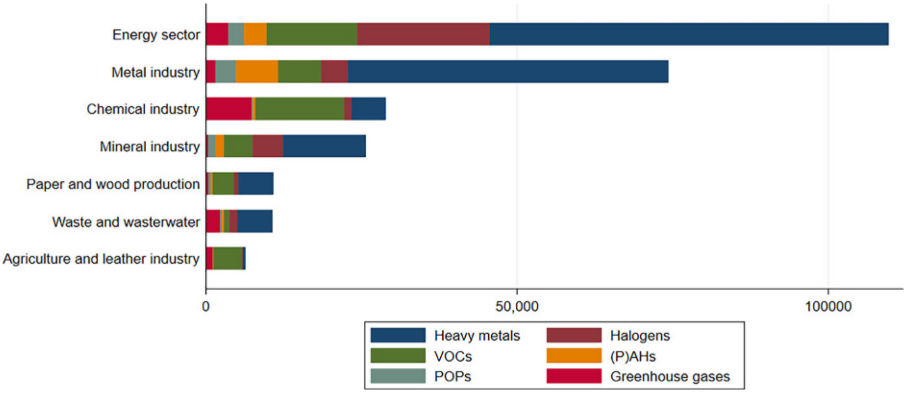


Fig. 3 Total toxic pollution by industry, disaggregated by pollutant groups, and ranked from industry from highest toxic pollution to lowest, over 2007–2018. Source: Own calculation based on E-PRTR

shows the disaggregation of such pollutant groups by industry. The pollutant group of heavy metals account for the largest share of toxic pollution across all industries, except for the chemical, agriculture, and leather industries, whose pollutant portfolios vary significantly. The energy and metal industries are the heaviest polluters, and their sectoral characteristics show high percentages of heavy metals compared to other pollutant groups: approximately 50 percent of toxic pollution coming from energy is associated with the release of heavy metals, while this share increases to approximately 70 percent for the metal industry (see blue segment of bars).

Within the energy sector, the release of mercury and other highly noxious heavy metals is mostly associated with coal combustion but also oil-fired power plants (EPA 2019). This makes the alarming case for the biggest industrial emitters of globally-harming CO_2, often situated in proximity to urban zones, being also a highly dangerous local polluter.

Next, we explore the inter-industry variability of our measures of toxic pollution and how they evolve over time. For doing so, we depict mean toxic pollution, in logs, and mean pollutant concentration, as by the index HHI, by industry over time (see Fig. 4). The overall time trend of toxic pollution is slightly decreasing, meaning that most industries were able to moderately curb their toxic emissions down. The metal, waste and wastewater, and paper and wood production industries, however, show a stagnating trend over the period 2007–2018.

The pollutant concentration index is a proxy for technological efficiency at the sectoral level, e.g., the end effect of the adoption of pollution-abatement technologies, potentially induced by environmental regulations, that reduce the number of co-pollutants emitted. As shown below, the index increases over time, i.e., the average number of pollutants by region and sector decreases as facilities on average reduce their number of pollutants by approximately 20%: from 0.41 in 2007 to 0.49 in 2018. The HHI measures the production of co-pollutants especially in the energy sector, where CO_2 is the main pollutant. However, for the remaining industries, it is mainly a proxy for environmental and technological efficiency.

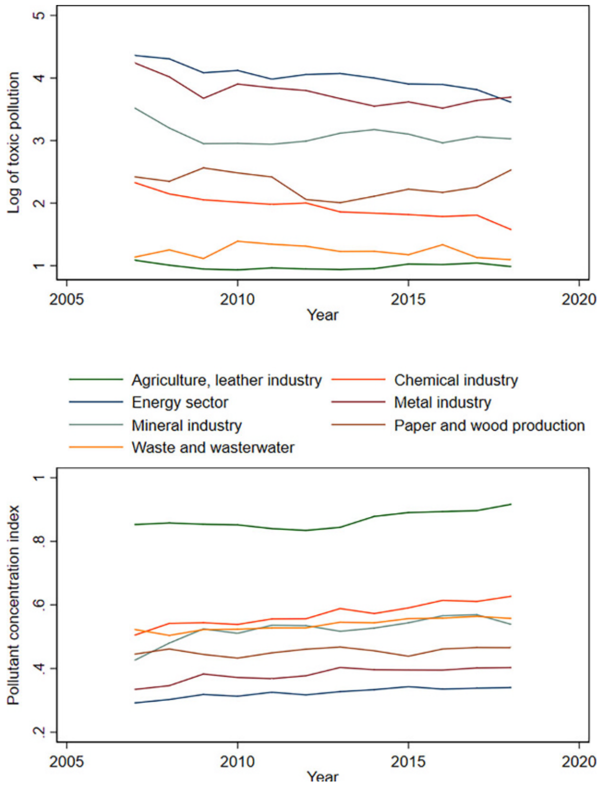


Fig. 4 Mean toxic pollution by industry from 2007 to 2018 (upper panel) and mean concentration index of pollutants by industry from 2007 to 2018 (bottom panel). Source: Own calculation based on E-PRTR

Across-industry variability of both measures is very high. The energy and the metal industries clearly emerge as the two most pollution-intense and toxic industries (see blue and dark red line in upper panel), while other sectors contribute very little to overall levels of toxic pollution, for instance, waste and wastewater (orange line), and agriculture and leather industry (green line). Average pollution concentration is more clustered than toxic pollution. With regard to the former, the agriculture and leather industry emerges as an outlier, with an index close to one, indicating mono pollution.

The energy industry has the lowest pollutant concentration index, i.e., on average is the industry that emits the highest number of different toxic pollutants (blue line in bottom panel), followed by the metal industry (red line in bottom panel).

Higher levels of toxic pollution are on average associated with lower levels of pollutant concentration, i.e., tend to have multi-pollutant portfolios as they emit a great variety of different chemicals. A scatterplot confirms such an inverse relationship. Fig. 5 plots unweighted pollutant concentration against toxic pollution. Every dot of the same color represents one country in our sample. The clear negative relationship indicates that on average facilities with a multi-pollutant portfolio also are bigger emitters.

The within-industry clustering, especially evident for industries such as minerals (see grey cross symbols) or metals (see blue cross symbols), reflects industry-spe-

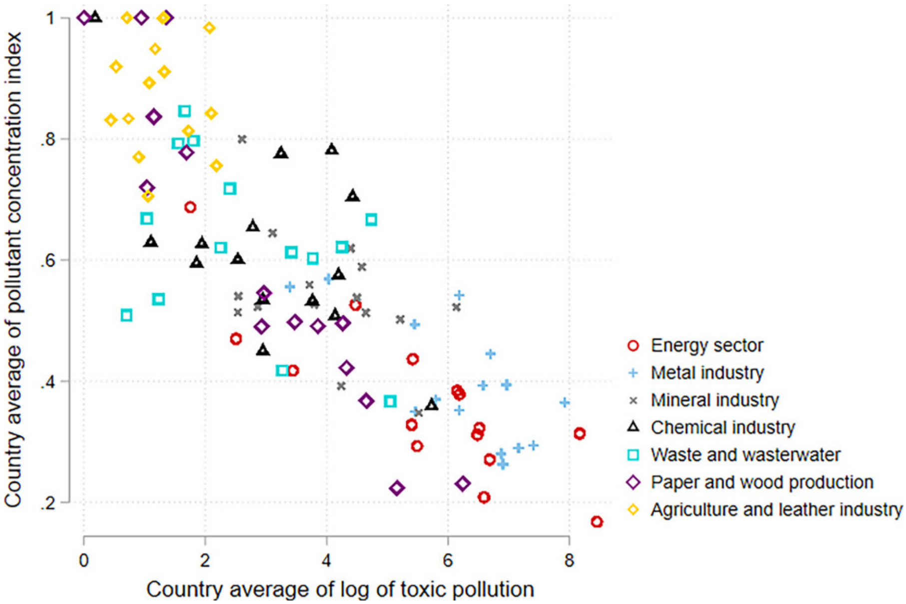


Fig. 5 Scatterplot of country averages of pollutant concentration (y-axis) and toxic pollution (x-axis) across 2007–2018. Source: Own calculation based on E-PRTR

cific pollution patterns and production processes. However, we highlight significant within-industry variation across countries. For instance, there are countries in the chemical industry that have comparable levels of toxic pollution but different types of pollutant mix, i.e., pollutant concentration indices (see, for instance, the vertical variations of the black triangle symbols).

3.5 Regional Economic Variables: Cambridge Econometrics

Next, we turn to the regional economic variables. With these variables, we aim to depict the local labour market in left-behind regions, often characterised by precarious employment, underemployment, and demographic changes. The labour market data come from Cambridge Econometrics, which combines regional and sectoral data from both Eurostat's REGIO database and AMECO, which is provided by the European Commission's Directorate General Economic and Financial Affairs. The disaggregated data is available for 27 EU countries (all EU member states except Malta) at NUTS-3 level and six sectors from 1990 to 2018.[13] From this data base, we use employment (both industry and total) which "covers all persons engaged in some productive activity" and wages (both industry and total) for the countries

[13] These are: A (agriculture, forestry and fishing), B-E (industry), F (construction), G-J (wholesale, retail, transport, accommodation and food services, information and communication), K-N (financial and business services), and O-U (non-market services).

and years as in the E-PRTR data. All variables are expressed in logs, to handle the skewness of the distributions.

In addition, we source population changes from Eurostat's "demographic balance and crude rates at regional level". In specific, we look at crude rate of net migration, which represents total population changes cleaned for natural changes (births and deaths). It is expressed as the change of the population in region r over the past four years.[14]

4 Geography of Toxic Pollution

Our first contribution consists in giving a novel account of the geography of toxic pollution in Europe. Below is shown the spatial distribution of the industrial facilities in our data set. Emission quantity is expressed in kilograms, weighted by human toxicity of each pollutant, and summed by facility and across all years in the sample, 2007–2018. The size of the dots is proportional to the amount of toxic pollution released per facility, aggregated into four clusters. The color indicates to which broad activity the facility is associated, as described in the legend of Fig. 6.

Most industrial facilities are located in France, Spain, Germany, and the UK. Furthermore, industries are clustered within countries and regions. We thus carry out our analysis at the sectoral level, not least because sectors are very heterogeneous with respect to toxicity levels and emission quantities.

Zooming in, the example of Germany (Fig. 6.b) shows that the facilities that emit the largest amount of toxic pollution are from the energy sector (green large dots). They mostly belong to coal-fired power stations, located in the Rhine area (state of North Rhine-Westphalia, Western Germany) and in Lusatia (state of Saxony, Eastern Germany). However, also other industries are home to major polluting facilities, for example "Werk Schwelgern", one of Europe's biggest steelworks, also located in the Rhine area (city of Duisburg). Indeed, a recent study on structurally weak regions in Germany points to the cities of Duisburg and Dortmund – both in the Rhine area heavily impacted by deindustrialisation –, as well as several areas in Eastern Germany (Bitterfeld-Wolfen and Vorpommern-Greifswald) (Das Progressive Zentrum 2022). This anecdotal evidence points to a potential link between the presence of highly toxic industrial complexes and regional economic deprivation.

The E-PRTR provides geospatial information, i.e., longitude and latitude, for every facility. We use the latest Administrative Level data from Eurostat (2021) and use the same NUTS-3 borders for all years. We attribute a NUTS-3 level code to every point, i.e., a facility's geolocation, that falls within a polygon from the shapefile.[15] This matching strategy results in a data set of approximately 69.000 industry-region-year pairs nested within 1.215 NUTS-3 regions (this methodology is explained, for

[14] Sect. 2 of the Appendix shows a map of employment at NUTS-3 level in Europe and the descriptive statistics of the regional economic variables using violin plots, see Figs. 8 and 10, respectively.

[15] In this way, offshore facilities get dropped from the data set, for instance oil and gas platforms.

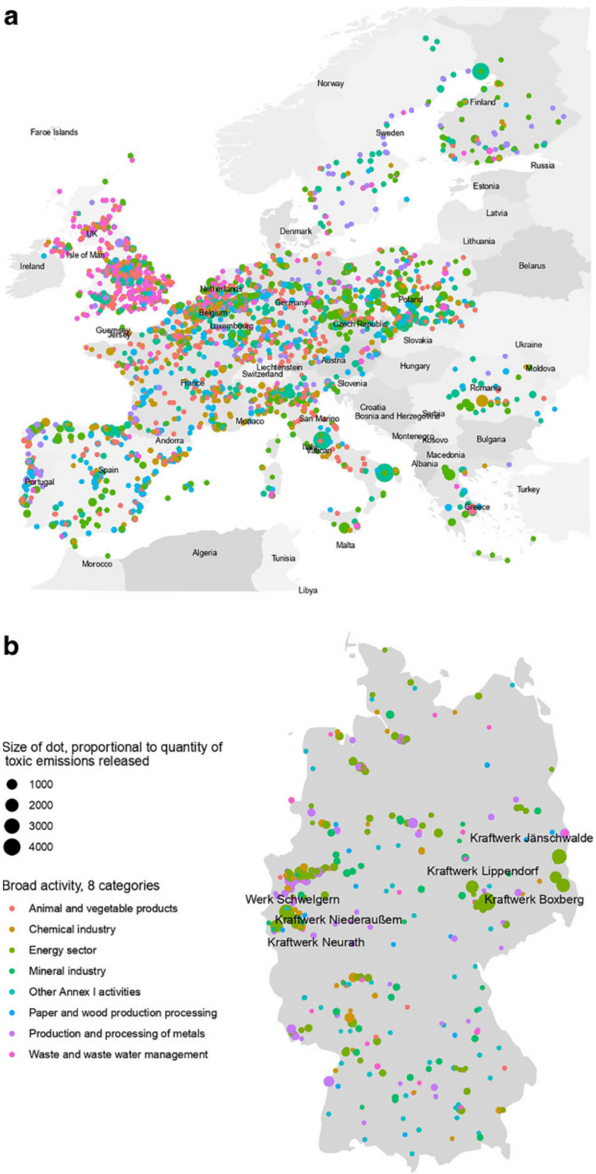


Fig. 6 Spatial distribution of industrial facilities in 15 European countries **(a)** and of Germany **(b)** over 2007–2018. Colour of the dots indicates industry, size of the dot indicates quantity of toxic pollution. Source: Own calculation based on E-PRTR

instance, in Mohai and Saha 2006). Next, departing from Eq. 1, we aggregate toxic pollution at industry-region-year level according to the following specification:

$$Tox\ Poll_{srt} = \sum_{i=1}^{N} Tox\ Poll_{isrt}, \tag{3}$$

where i refers to facilities, s to sectors, r to NUTS-3 regions, and t to years.

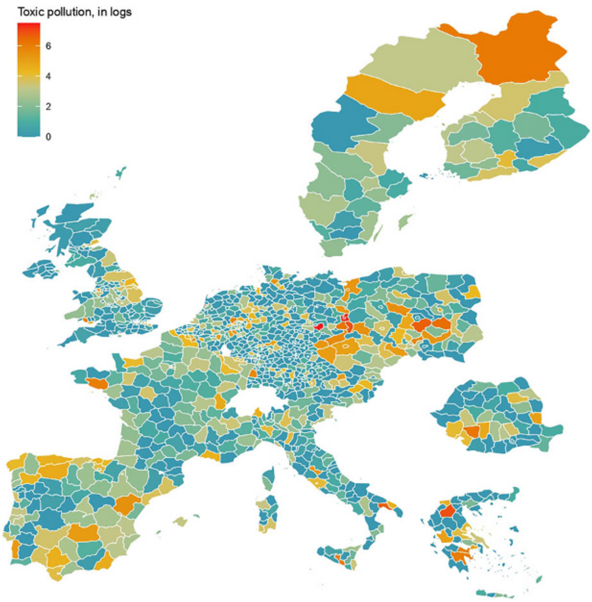


Fig. 7 Regional map of toxic pollution in Europe, in logs, averaged over 2007–2018. Source: Own calculation based on E-PRTR

Fig. 7 displays the distribution of toxic pollution in logs and averaged over the years 2007–2018 across European NUTS-3 regions in the data set. This map shows patterns of clustering of toxic pollution: a highly polluted region is likely to be in geographical proximity to another polluted region. Such clusters are visible in particular in Spain, the UK, Germany, Poland, the Czech Republic, and Romania. Moreover, we notice that the polluted regions encompass both urban-deindustrialised (i.e., Ruhr Valley) as well as rural types of territories (i.e., North Finland).

We proceed in a similar way to regionally aggregate the concentration index of pollutants (HHI). We aggregate the HHI at sector-region-year level, and weight it by the contribution of each sector to the overall regional toxic pollution, expressed as a percentage (see right part of the equation). The weighted sectoral HHI is then written as:

$$HHI_{srt} = \frac{\sum_{i=1}^{N} HHI_{it}}{N_{srt}} * \frac{Tox\ Poll_{srt}}{Tox\ Poll_{rt}}. \tag{4}$$

This regional concentration index has a mean of 0.22 and a standard deviation of 0.25. Once aggregated, the heterogeneity of the HHI becomes especially visible across industries, with facilities belonging to the energy, metals, and paper industries having the highest number of distinct pollutants (so-called multi-polluters), and therefore lower values of the concentration index.

5 Toxic pollution and labour markets in left-behind places

In the following, we present our econometric specification, divided into direct links, estimated for the industrial labour market, and indirect links, estimated at the regional level, including therefore also non-industrial labour markets. In both cases, we are interested in detecting the links between toxic pollution and employment, wages, and migration (in the regional estimation), in order to characterise the labour market associations in left-behind places.

5.1 Econometric Specification

We use quantile regressions as in Koenker and Hallock (2001) to estimate our dependent variables. Quantile regressions are advantageous because they allow us to analyse the different roles of toxic pollution for left-behind places, located in the left tail of the distributions, vis-à-vis the rest. In this way, we take into account the heterogeneity across regions regarding employment and wage levels, as well as demographic changes. Furthermore, this estimation method is more robust to outliers than OLS models and does not require assumptions about the parametric distribution of the error term (see Koenker and Hallock 2001). We estimate percentile equations for the 10th, 25th, 50th, 75th, and 90th percentiles. Quantile Regression methods allow flexibility in the estimation of the coefficients, enabling us to obtain a range of conditional quantile functions (CQF), which in our case will be given by the employment, wages, and migration CQF.

Furthermore, we take into account that there are regions in the dataset for which toxic pollution is zero due to the absence of a large industrial facility in that area. This implies recoding region-year pairs for which we do not have data on toxic pollution as zero.[16] Hence, our predictor is left-censored, meaning that we can observe toxic pollution only above a certain threshold, as established by the E-PRTR regulation (European Commission 2006) and our own methodology that drops non-continuous polluters. We also find that the average employment and wage difference between polluted and censored regions is positive. To correct for the censoring, we introduce a binary indicator variable at region-year level, $Indicator_{rt}$, as specified in Eq. 5.[17] Following this approach, we estimate baseline specifications of the following general form:

$$LB_{rt} = \alpha_s + \alpha_c + \alpha_t + \beta_1 \log(Tox\ Poll)_{srt} + Indicator_{rt} + \gamma \mathbf{X}_{rt} + \varepsilon_{rt}, \tag{5}$$

where the dependent variable LB, "Left-Behind", is a vector that takes into consideration three different dimensions of being left behind of a given NUTS-3 region r in year t: log of employment, log of wages, and net migration. This is regressed on sectoral toxic pollution, in logs, computed at the regional level. The nested nature

[16] For 23.7 percent of the data set, we observe the economic variables, but do not observe the level of toxic pollution.

[17] Note that the indicator takes the value 1 for a censored region, i.e., when there is no observed pollution, and 0 otherwise.

of the empirical specification allows for taking into account sectoral heterogeneity, which emerges as a key facet of the emission data.[18] Sectoral toxic pollution is the amount of pollution weighted by toxicity and emitted at the regional level in sector s at time t. $Indicator_{rt}$ is the dummy for the censored regions, for which we do not observe any toxic pollution. α_s, α_c, and α_t are sector, country and year fixed effects, respectively. $\mathbf{X}_{rt}$ represents the set of control variables, which are (four-years) lagged gross value added (gva) per capita and lagged employment.[19] Both variables control for regional economic activity. Gva is a proxy of the sectoral production/demand, while lagged employment accounts for feedback effects from past levels of employment.[20] Moreover, by including gva, we account for the potential contracting force that the financial crisis has had, e.g., depressing industrial production, being asymmetrical across European countries and regions, as laid out in Dijkstra et al. (2015); Davies (2011); Groot et al. (2011), all pointing to spatial heterogeneity regarding crisis sensitivity. Finally, standard errors are bootstrapped.

While toxic pollution is a measure of intensity and dangerousness, the concentration index adds the notion of pollutant mix, or negative quality, to the analysis. On average, sectors with multi-pollutant profiles also have higher levels of toxic pollution as shown in Figs. 4 and 5. We hence augment the baseline specification by introducing the pollutant concentration index HHI_{srt} at sector-region-year level:[21]

$$LB_{rt} = \alpha_s + \alpha_c + \alpha_t + \beta_1 \log(Tox\ Poll)_{srt} + \beta_2 HHI_{srt} + Indicator_{rt} + \gamma \mathbf{X}_{rt} + \varepsilon_{rt}. \quad (6)$$

5.2 Direct links: Industrial labour market

We consider as direct the first-order associations at the industry level. We look at the links between toxic pollution and pollutant concentration, and industrial labour markets in terms of employment and wages. Table 3 departs from the baseline specification as written in Eq. 5. The estimation of different percentiles provides a nuanced picture of left-behind places (defined as the 10th and 25th percentiles) vis-à-vis the rest. For employment in industry,[22] which we refer to as industry employment, we find a positive and significant relationship, particularly for the lower

[18] We perform a robustness check where we aggregate sectoral toxic pollution by region on the right-hand side of the equation, hence abstracting from the industrial dimension and focusing solely on the regional level. This leads to a regional-level empirical specification where the level of analysis is identical on both sides of the equation. This reduces the sample size approximately by half. The qualitative results with this alternative setup remain the same compared to the baseline specification, stressing the robustness of our findings.

[19] We carry out a robustness check on the control variables by using different lags, from two to five years. However, this does not change the qualitative results of the analysis.

[20] The inclusion of the lagged employment variable is standard in the estimation of labour demand equations.

[21] A Wald test between the baseline and the augmented specification confirms the statistical significance between those models.

[22] “Industry” refers to industry as a whole and is consistent with the NACE Rev. 2 sectoral definition. It is the lowest level of aggregation for which NUTS-3 level data is available.

Table 3 Direct links with industrial labour market, baseline specification (Eq. 5)

	Direct Effects on Employment and Wages									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var:	Industry Employment					Industry Wages				
Quantile (%):	10	25	50	75	90	10	25	50	75	90
Log(Sectoral toxic pollution)	0.014***	0.008***	0.004**	0.001	–0.001	0.008***	0.005***	–0.009***	–0.007***	–0.007***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
Indicator censored regions	–0.474***	–0.344***	–0.267***	–0.186***	–0.099***	–0.301***	–0.135***	–0.096***	–0.026*	0.008
	[0.013]	[0.014]	[0.012]	[0.009]	[0.009]	[0.036]	[0.018]	[0.014]	[0.015]	[0.035]
Log(gva per capita) lagged	–0.335***	–0.160***	–0.013	0.173***	0.340***	0.126***	0.239***	0.409***	0.368***	0.398***
	[0.027]	[0.021]	[0.014]	[0.024]	[0.013]	[0.041]	[0.023]	[0.013]	[0.015]	[0.020]
Log(employment) lagged	0.974***	0.918***	0.909***	0.881***	0.852***	0.253***	0.290***	0.232***	0.218***	0.205***
	[0.007]	[0.005]	[0.006]	[0.004]	[0.003]	[0.016]	[0.007]	[0.007]	[0.005]	[0.014]
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	30,074	30,074	30,074	30,074	30,074	28,314	28,314	28,314	28,314	28,314
Pseudo R2	0.5931	0.5902	0.601	0.615	0.6387	0.3133	0.2996	0.2832	0.3218	0.3725

Notes: Standard errors are bootstrapped. *** $p < \mathbf{0.01}$, ** $p < \mathbf{0.05}$, * $p < \mathbf{0.1}$

end of the distribution, i.e., the 10th and 25th percentiles (columns 1 and 2). The link decreases along the quantiles, becoming even negative in the 90th percentile, even though not significant. Hence, we find the association to be mostly limited to what we identify as left-behind places, which are characterised by weak labour markets. For instance, for the 10th percentile, a 1 percent increase in toxic pollution is associated with a 0.014 percent increase in industry employment. The result highlights the economic dependence, above outlined, that left-behind places manifest with noxious industrialisation. In addition, it points to poor economic trajectories and bad specialisation in those places whereby industry employment, even though potentially of poor quality, is directly linked to the presence of noxious facilities. For the regions characterised instead by higher levels of employment, the lack of significance points to a decoupling between industry employment and toxic pollution. Indeed, the higher the employment level of a given region, the higher the economic performance therein, and the lower will be the burden exerted by bad specialisation, here proxied by pollution at the sectoral level. Therefore, employment dependence on toxic pollution overall decreases along the conditional distribution of employment.

For industry wages, a comparable picture emerges. While the coefficient of industry wages is positive for left-behind places (columns 6 and 7), the association becomes negative for the higher quantiles. Hence, within regions with low industry wages, toxic pollution is positively associated with wages, again signaling dependence on the sector, while in regions with already high industry wages, the association gets negative. The association for the 10th percentile is comparable in magnitude with the median, however of opposite sign. The opposing association for left-behind places vis-à-vis the rest is in line with the notion of spatial inequality feedback loops as pointed out by Pinheiro et al. (2022). The declining co-evolution of toxic pollution along the wage distribution, similar to the employment dynamics, suggests that in high-wage regions, take the example of Bavaria, highly toxic facilities have a penalizing effect on wages. These results therefore highlight the relationship being heterogeneous along the conditional distribution of both industry employment and wages. At the same time, they suggest that OLS estimation clouds such heterogeneity, undermining the specialty of left-behind places. Such heterogeneity therefore strengthens the case for our choice of applying quantile regression to the data.

Furthermore, the indicator for the censored regions is always negative and significant and increases monotonically along the employment and wage quantiles. Hence, in left-behind regions (first two quantiles), the difference in labour market variables between polluted and non-polluted areas is greater. The negative relationship is mainly due to the degree of industrialisation and industrial activity, which has a direct effect in terms of both economic development of the area and higher pollution levels, when compared with e.g., rural areas where industrial activities are not present. Overall, we document that toxic pollution impacts especially the left-behind places. Lagged gva per capita is negative in the lower quantiles, indicating a regional employment change towards sectors other than industry, possibly activated by noxious deindustrialisation. Lagged employment is always positive, with high persistent magnitudes which decrease along the distribution.

Generally, left-behind places are considered to be both low-industry employment and low-industry wages areas (as per our definition, see above), in line with the fact that such places often face industrial decline. Indeed, low industry employment is associated with both areas of deindustrialisation and areas which never industrialised. The fact that our indicator of pollution intensity is positively associated with employment and wages only until the median of the distribution does signal that these territories do experience economic dependence on toxic industrialisation, although the overall share of industry employment is low. In fact, the intensity of pollution is not significant in affecting the higher quantiles since they are not dependent on industrial activity. Furthermore, the association of gva per capita signals that the first two quantiles are dependent on industry gva, as the sign for employment becomes negative. This means that when industry increases production, the number of people employed in industry decreases, as per productivity gains that are employment-shedding or as a mark of deindustrialisation paths, while it is positive for areas with higher industrial employment. This is due to the fact that industrial territories with complex industries that emit less pollution are generally concentrated in areas with high employment in the service sector. Take three exemplary cases, North Rhine-Westphalia in Germany, Auvergne-Rhône-Alpes in France and Emilia Romagna in Italy. All three regions are in the higher quantiles of industry employment but all of them are very much service-based areas.[23] In order to better understand the correlation between industry and service employment, we construct some additional descriptive evidence in the Appendix. Fig. 9 shows a map of correlation coefficients between industry and service employment by NUTS-2 regions. Indeed, the two variables show high correlation coefficients with an average of 0.7 at the NUTS-2 level. Countries such as Germany, Poland, the UK, and Sweden show relatively high inter-country heterogeneity. Especially East Germany, the Czech Republic and Western Poland show relatively lower levels of correlation. The strong correlation coefficient indicates that left-behind places are not low industry employment areas because they are specialised in services (substitute positive specialisation) but rather because they are generally low employment areas, both in industry and in services (complementary bad specialisation).

Next, we include the pollutant concentration index, as per Eq. 6. Table 4 shows the augmented specification. The introduction of the additional explanatory variable does not change the qualitative results with respect to the baseline specification. Again, we find that sectoral toxic pollution co-evolves with industry employment, especially in left-behind regions. Looking at the newly introduced variable, sectoral pollutant concentration, we see that the coefficients are negative along all quantiles. For instance, looking at the 10th percentile, a 1 percent increase in pollutant concentration is associated with a 0.255 per cent decrease in industry employment. This confirms that the concentration index is a proxy for efficiency-enhancing processes inasmuch its increase over time signals the elimination of some specific pollutants.

Therefore, technological efficiency gains, proxied by the HHI increase over time, have a labour-saving trait: if environmental technology increases, that is process innovations to reduce and abate pollutant emissions, employment in industry decreases. As expected, such linkages steadily reduce in magnitude along the quantiles, meaning that left-behind places, being more dependent on noxious industrialisation,

[23] See Table 9 in the Appendix for examples of the correlation between industry and service employment.

Table 4 Direct links with industrial labour market, augmented specification (Eq. 6)

	Direct Effects on Employment and Wages									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var:	Industry Employment					Industry Wages				
Quantile (%):	10	25	50	75	90	10	25	50	75	90
Log(Sectoral toxic pollution)	0.010***	0.009***	0.005***	0.001	–0.001	0.008**	0.005***	–0.009***	–0.007***	–0.006***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
Sectoral pollutant concentr.	–0.255***	–0.149***	–0.098***	–0.051***	–0.022**	–0.103***	–0.072***	0.025**	–0.024*	–0.022
	[0.013]	[0.013]	[0.013]	[0.009]	[0.009]	[0.027]	[0.015]	[0.012]	[0.012]	[0.016]
Indicator censored regions	–0.567***	–0.420***	–0.309***	–0.213***	–0.108***	–0.345***	–0.162***	–0.087***	–0.036**	–0.006
	[0.016]	[0.016]	[0.010]	[0.011]	[0.014]	[0.043]	[0.020]	[0.021]	[0.014]	[0.027]
Log(gva per capita) lagged	–0.312***	–0.161***	–0.005	0.172***	0.330***	0.137***	0.240***	0.409***	0.363***	0.399***
	[0.017]	[0.013]	[0.012]	[0.013]	[0.013]	[0.043]	[0.018]	[0.023]	[0.019]	[0.030]
Log(employment) lagged	0.951***	0.910***	0.896***	0.877***	0.853***	0.257***	0.290***	0.234***	0.218***	0.208***
	[0.007]	[0.004]	[0.007]	[0.005]	[0.005]	[0.017]	[0.005]	[0.010]	[0.007]	[0.014]
Energy sector	–0.304***	–0.209***	–0.161***	–0.128***	–0.102***	–0.290***	–0.209***	–0.097***	–0.002	0.023
	[0.015]	[0.011]	[0.010]	[0.010]	[0.009]	[0.031]	[0.019]	[0.016]	[0.012]	[0.014]
Metal industry	–0.020	–0.029**	–0.034***	–0.036***	–0.008	–0.110***	–0.058***	–0.039**	0.033**	–0.001
	[0.017]	[0.014]	[0.012]	[0.010]	[0.010]	[0.025]	[0.012]	[0.017]	[0.016]	[0.018]
Mineral industry	–0.148***	–0.083***	–0.015	0.006	–0.003	–0.121***	–0.054***	–0.036***	0.015	0.040**
	[0.033]	[0.014]	[0.011]	[0.010]	[0.010]	[0.027]	[0.014]	[0.013]	[0.019]	[0.016]
Chemical industry	–0.093***	–0.097***	–0.063***	–0.064***	–0.053***	–0.014	–0.023	–0.008	0.043***	0.016
	[0.014]	[0.014]	[0.010]	[0.011]	[0.009]	[0.019]	[0.015]	[0.015]	[0.011]	[0.010]
Waste and wastewater	–0.171***	–0.123***	–0.123***	–0.080***	–0.036***	–0.206***	–0.112***	–0.041**	0.005	0.001
	[0.018]	[0.011]	[0.013]	[0.009]	[0.011]	[0.035]	[0.021]	[0.018]	[0.012]	[0.015]
Paper and wood production	0.071***	0.015	–0.042***	–0.065***	–0.040***	–0.097**	–0.024	–0.030	–0.033**	–0.025
	[0.016]	[0.011]	[0.011]	[0.010]	[0.010]	[0.038]	[0.018]	[0.024]	[0.016]	[0.022]
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	30,116	30,116	30,116	30,116	30,116	28,339	28,339	28,339	28,339	28,339
Pseudo R2	0.5984	0.5928	0.6022	0.6154	0.6388	0.3138	0.3001	0.2832	0.3219	0.3726

Notes: Standard errors are bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

are also exposed to higher labour expelling forces whenever process innovation is undertaken. The negative employment associations might be the consequence of a reorganization of productive systems, processes, input recomposition, and new techniques of production employing a higher capital/labour ratio, mantaining the control for industry gva. Therefore, the type of technical change we measure, given the neat negative link with employment, goes well beyond the effect that the introduction of an end-of-pipe technology could have and hence validates our assumptions. The associations with wages are coherent, with negative and statistically significant coefficients in left-behind places.

Given the importance of industry heterogeneity, we now want to focus on industry-specific pollution to pin down whether the origin of pollution plays a role in affecting industrial labour markets. Therefore we show in the bottom part of Table 4 a series of dummy variables capturing the sectoral origin of pollution. Considering that our dependent variables are industrial employment and wages, the associations are negative, whenever significant, as expected, signaling substitution dynamics in terms of industrial specialisation and composition across industries. Granted the overall positive co-evolution with toxic pollution, seen as a sign of economic dependence on noxious industrial specialisation, higher negative signs as in energy and in waste and wastewater mean that if the area is specialised in those industries, overall industrial employment eventually declines for transition to non-industrial employment. In fact, both industries have facilities normally more embedded into and located closely to urban areas. Their proximity to urban territories prompts indeed higher possibility of tertiarization of the region.

5.3 Indirect links: regional spillovers

We now move on to present the analysis in terms of indirect links, i.e., the potential propagation forces of industrial pollution beyond the industrial labour market to the regional labour market as a whole. In this set-up we also add as a dependent variable the regional net migration, a proxy for labour force outflows/inflows. In doing so, we look at the entire bulk of employment and wages in other sectors of the economy, beyond the industrial one. Associations are therefore expected to be of lower magnitude, when compared to the previous specification, considering that our measure of pollution is only related to industrial activities and does not take into consideration pollution from, e.g., logistics, among the most responsible for greenhouse gas emissions in the service sector. Therefore, the question we want to address is the extent to which propagation phenomena from the industrial-polluter complex exist, and affect other places in the region, beyond left-behind ones.

This time, we directly show in Table 5 the augmented specification including toxic pollution and the concentration index. The regression table of the baseline configuration can be found in the Appendix (Table 12). The coefficients for sectoral toxic pollution are identical for both specifications (employment and wages), negative and significant across the board, but with a very low magnitude. In contrast to the industrial labour market, in the regional specification, the negative coefficients become relevant for the upper part of the conditional employment and, particularly, wage distributions, in line also with the result of the indicator variable for censored

Table 5 Indirect links with toxic pollution on regional labour market, augmented specification (Eq. 6) for total employment and wages

	Indirect Effects on Employment and Wages									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var:	Total Employment					Total Wages				
Quantile (%):	10	25	50	75	90	10	25	50	75	90
Log(Sectoral toxic pollution)	–0.000	–0.000***	–0.001***	–0.001***	–0.001***	–0.001	–0.005*	–0.008***	–0.010***	–0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.003]	[0.002]	[0.003]	[0.002]
Sectoral pollutant concentr.	0.001	0.002*	0.001	0.001	0.003	0.059*	0.034**	0.060***	0.037**	–0.006
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.035]	[0.016]	[0.015]	[0.015]	[0.009]
Indicator censored regions	–0.002	–0.002*	0.000	0.003***	0.006**	0.155***	0.042**	0.135***	0.118***	0.092***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.022]	[0.020]	[0.014]	[0.015]	[0.013]
Log(gva per capita) lagged	0.009***	0.011***	0.015***	0.018***	0.019***	0.143***	0.236***	0.378***	0.447***	0.512***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.003]	[0.022]	[0.020]	[0.022]	[0.020]	[0.033]
Log(employment) lagged	1.010***	1.008***	1.007***	1.003***	0.999***	0.417***	0.384***	0.301***	0.260***	0.134***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.016]	[0.011]	[0.012]	[0.009]	[0.012]
Energy sector	–0.001	0.000	0.002***	0.004**	0.006***	–0.025	–0.026	0.021	0.047***	0.094***
	[0.002]	[0.002]	[0.001]	[0.001]	[0.003]	[0.044]	[0.025]	[0.019]	[0.017]	[0.016]
Metal industry	–0.002	–0.001	–0.002*	0.000	0.001	0.010	0.017	0.019	0.034**	0.034**
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.027]	[0.020]	[0.014]	[0.017]	[0.015]
Mineral industry	–0.002	–0.003**	–0.002**	–0.000	0.000	0.067**	0.030	0.058***	0.062***	0.064***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.032]	[0.020]	[0.019]	[0.016]	[0.014]
Chemical industry	0.000	–0.001	–0.001**	–0.001	–0.001	0.121***	0.033	0.063***	0.066***	0.074***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.029]	[0.026]	[0.018]	[0.018]	[0.017]
Waste and wastewater	–0.004*	–0.002	–0.000	0.001	–0.000	0.021	0.019	0.075***	0.086***	0.090***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.035]	[0.024]	[0.017]	[0.019]	[0.017]
Paper and wood production	–0.000	–0.001	–0.001	–0.001	0.000	0.047	–0.009	–0.026	–0.009	0.032
	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.037]	[0.022]	[0.032]	[0.024]	[0.025]
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,087	23,087	23,087	23,087	23,087	21,718	21,718	21,718	21,718	21,718
Pseudo R2	0.9473	0.949	0.9484	0.9489	0.95	0.4022	0.3738	0.3328	0.3227	0.3578

Notes: Standard errors are bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 Indirect links with toxic pollution on regional demographic change, augmented specification (Eq. 6) for regional net migration, expressed changes

	Indirect Effects on Demography				
	(1)	(2)	(3)	(4)	(5)
Dep. Var:	Net Migration, Changes				
Quantile (%):	10	25	50	75	90
Log(Sectoral toxic pollution)	–0.056***	–0.076***	–0.100***	–0.098***	–0.118***
	[0.020]	[0.015]	[0.012]	[0.011]	[0.026]
Sectoral pollutant concentr.	–0.141	0.310***	0.754***	0.767***	1.085***
	[0.125]	[0.078]	[0.079]	[0.111]	[0.207]
Indicator censored regions	–1.150***	–0.449***	0.519***	1.002***	1.640***
	[0.180]	[0.113]	[0.122]	[0.118]	[0.214]
Log(gva per capita) lagged	1.506***	2.609***	3.456***	3.617***	4.114***
	[0.264]	[0.171]	[0.138]	[0.063]	[0.251]
Log(employment) lagged	0.451***	0.255***	0.164**	0.082*	–0.170**
	[0.092]	[0.048]	[0.064]	[0.048]	[0.084]
Energy sector	–0.367**	0.025	0.218*	0.265*	0.633***
	[0.144]	[0.106]	[0.111]	[0.139]	[0.230]
Metal industry	–0.491***	–0.301***	–0.317**	–0.173	0.022
	[0.165]	[0.090]	[0.137]	[0.144]	[0.194]
Mineral industry	–0.354**	–0.131	–0.139	–0.191	–0.183
	[0.157]	[0.101]	[0.109]	[0.135]	[0.186]
Chemical industry	–0.228	0.050	–0.046	–0.147*	0.060
	[0.179]	[0.081]	[0.084]	[0.077]	[0.200]
Waste and wastewater	–0.523***	–0.165	–0.214*	–0.057	0.078
	[0.136]	[0.104]	[0.126]	[0.147]	[0.182]
Paper and wood production	0.164	–0.045	0.017	–0.020	0.005
	[0.119]	[0.076]	[0.118]	[0.122]	[0.202]
Country Effects	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Obs.	23,087	23,087	23,087	23,087	23,087
Pseudo R2	0.1383	0.1609	0.17	0.1507	0.1321

Notes: Standard errors are bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

regions. This means that, across more advanced regions in terms of economic performance, the presence of toxic pollution from the industrial sector is negatively associated with employment and wages when compared to similar high-productive regions non-exposed (or less exposed considering the E-PRTR construction) to toxic pollution. In this respect, toxic pollution does represent a clear signal of low-innovative strategies, rather than a necessary burden that a community must bear.

As expected, the HHI shows positive but weakly significant associations with employment and wages. The result confirms that the HHI index is essentially a proxy for industry-level technological improvements, therefore regions experiencing technological advancement, hereby in terms of abatement of some toxic pollutants, also benefit from positive, although quite weak, co-evolvements with the labour market.

Table 6 shows the results for demographic change, again employing the augmented specification in Eq. 6. The results for the baseline specification can be found in the Appendix (Table 13). Demographic changes are measured as the changes in net migration, hence overall changes in the population cleaned for its natural changes, births and deaths, measured across one year. The quantile approach is an attempt to distinguish between regions of inflows (above median quantiles) versus regions of outflows (below median quantiles), i.e., representing a stylised dynamic.[24]

Interestingly enough and in line with results on employment, the coefficient for sectoral toxic pollution is negative and significant at the 1 per cent level for all quantiles. The magnitude of the association however increases along the quantiles. Higher quantiles are associated with regions that have experienced an influx of inhabitants, i.e., a positive change. Therefore, the higher the influx of migrants (higher quantiles) the higher the negative co-evolution with pollution. The flip side is that toxic pollution is associated with a reduction in migration toward a given region as destination. Lower quantiles, experiencing instead below-median changes, and therefore being regions of abandonment, also record a negative and significant co-evolution with toxic pollution, after controlling for the lagged employment and the value added of the region, as in the other specifications.

The concentration index is instead positive whenever significant, meaning that higher levels of concentration, i.e., less distinct pollutants, are associated with less people leaving the region (below the median) or positively affect migration inflows (above the median). This result is again inline with high levels of HHI as a proxy for a less polluting, dangerous mix when compared to low levels of HHI representing a more dangerous mix.

In line with our previous results and interpretation on the industry mix of pollution, especially the concentration of pollution from the energy sector is negatively associated with migration outflow (below the median) or alternatively is positively associated with migration inflow (above the median), as shown by the sector dummy variable.

The result indicates that the energy sector, being the most proximate to urban, diversified, and dynamic areas, is a signal of labour market attraction. The opposite holds for traditionally low-innovative sectors such as the metal and mineral industries, whose toxic emission encourages abandonment of the region, with associations particularly strong in the lowest quantile of the conditional demographic change distribution. Therefore, bad specialisation in low-innovative, high-toxic industries favours economic deprivation of an area.

Overall, the study of the indirect associations of toxic pollution has confirmed the presence of spatial spillovers ranging from the site of the industrial facilities toward the entire region. Indeed, our place-based analysis helps to overcome the productivist fictitious dichotomy between labour market dependence and exposure to toxic pollution.

[24] The distribution of the population change variable has a mean of 2.9, and hence is not centered around 0, otherwise the distribution behaves normally. Hence, for quantiles above the median, the regions can always be characterised as regions of inflows. The majority, however not all, regions below the median can be characterised as regions of outflows.

Related to the question of why or how toxic pollution aligns with economic deprivation, the first index holds significance. It relies on the weighted amount of toxic emission by region, functioning as an indicator of regional-level specialisation. This concentration manifests in specific industrial sectors, captured by their level of toxicity. Indeed, pollutants are highly sector-specific, as Fig. 1 highlights (also see various reports by the International Energy Agency, e.g., OECD et al. 2016).

In that way, the first index allows studying the extent to which toxic pollution – emerging from sectoral specialisation of a given territory – affects the local labour market. In this context, the theory of territorial lock-in and path dependency upon high-toxic industrial sectors becomes pertinent: left-behind regions exhibit a stable and positive relationship with toxicity in terms of employment and wages (compare Sect. 2). This phenomenon is attributed to the pronounced economic dependence of the territory on highly-toxic industrial sectors.

Apart from industrial lock-in, it is essential to consider potential paths for upgrading or downgrading in terms of toxic emissions to comprehend the trajectory of the territory. In this respect, the second index we propose captures the extent to which the composition of the pollutant portfolio has changed over time: less toxic portfolios are a proxy of an upgrading path, vice-versa, more toxic portfolios are a proxy of a downgrading path. Therefore, the HHI index captures the channels not of pollution as such, but rather as a proxy of the evolution of the lock-in trajectory. Indeed, the index presents a stable and negative relationship with employment and wages at the industry levels only in left-behind places, while it is not significant in non-left-behind places. The rationale behind this is that it represents a proxy for technological upgrading of the region, incorporating less emitting but also less labour-intensive technologies.

6 Conclusions and policy implications

Arguably, the contemporary crises overlapping across social, economic, and ecological spheres are creating systemic inequalities across space. We conceptualise left-behind regions through economic deprivation and explore their environmental dimension. We explore the co-evolution of toxic industrial pollution and socio-economic deprivation through channels of path dependence, regional lock-ins, and the labour-saving effects of technology, therefore adopting the lens of economic geography and its scope of interpretation as a useful toolbox to address environmental inequality. Using data for 15 European countries at NUTS-3 level, after providing one of the first comprehensive attempts to map toxic pollution in Europe, we employ quantile regression to study how toxic pollution and pollutant concentration impact disproportionally the left-behind regions.

All in all, our findings trace histories of industrial decay, providing evidence that persistent exposure to pollution works as a compounding factor aggravating already existing socio-economic deprivation. This has compelling implications for sustainable development. We find opposing results for left-behind places vis-à-vis the rest, pointing to spatial inequality feedback loops. Due to path dependence in industry, such left-behind places, often materially dependent on toxic industries and with a heavily impaired environment, find themselves locked in their poor economic trajectories, and bad specialisation path they have evolved into. Therefore, for such left-behind places, the trade-off between health and employment kept being perpetuated. In fact, Lerner (2012) uses the term "sacrifice zones" which jointly conceive environmental toxicity and economic disinvestment. This concept has recently been developed further by Feltrin et al. (2021) to coin the term "noxious deindustrialisation" as left-behind places where ongoing pollution and underemployment coexist.

Hence, while the sustained release of industrial toxic pollutants disrupts human, environmental, and economic health, it maintains the status quo of reproductive and social disparities. The political economy of left-behind places would suggest that a transition of technological systems towards a zero-toxic world requires the co-evolution not only of productive forces and technological domains but also of political structures currently too much favouring inertia. Taken at large, the relationship between labour, capital, and the environment laid bare in the analysis raises questions about the environmental and societal sustainability of capitalism (Faber 2008).

The empirical analysis strongly supports the need for a place-sensitive regional policy, with an urgent focus on left-behind places, which can guide the new Just Transition Fund (2021–2027) and EU cohesion policy. In order for environmental and climate policies to even out territorial inequalities, policy-makers have to take into account local contexts in terms of industrial specialisation, technological lock-ins, employment segregation as well as the materialist and economic dependence on highly toxic industries. Moreover, the results of our place-based analysis help to partially overcome the productivist opposition between labour and environment, as we show that whenever processes of environmental-technological upgrading are undertaken, they tend to crowd out workers from the industrial labour market but are associated with positive regional spillovers, improving labour market variables overall. Thus, regions where fewer toxic pollutants are emitted are regions with in-migration flows, while the opposite is true for regions characterised by a highly diversified, highly polluting mix of pollutants.

Furthermore, it is crucial to understand the policy implications of a labour-saving effect of environmental technology in polluting industries. A very recent publication by the International Monetary Fund (IMF) lays out the high geographical concentration of high-polluting jobs (Bluedorn et al. 2022). However, the report stresses the issue of labour reallocation, given that individual workers are less likely to successfully reallocate to greener jobs, hence compounding the disadvantages of already left-behind people and places. Behind the impediment of a labour transition away from toxic and fossil-dependent occupations towards greener ones is the lack of an industrial policy able to create coordinated policy actions to govern the twin (technological and ecological) transition (Bianchini et al. 2023). Although growing, "green jobs" do not represent a sector per se but are rather occupations related to the production of potentially "greener goods". However, they hardly might represent the solution for entire sectors and related supply chains under deep organizational and productive restructuring, such as automotive. In this respect, place-based policy initiatives must coexist with coordinated European industrial policies (Cimoli et al. 2009) aiming to build productive but sustainable capacity in the near future. Left-behind, peripheral regions ought to be the starting point for this type of policy action, with guided reconversion and socio-economic upgrading.

Finally, our paper also connects to the broader concept of the geography of discontent. If toxic pollution contributes to a place being left behind, then the environmental dimension might matter for politics, i.e., populist stances, which however are mostly anti-environmentalist. Instead, left-behind places would have reason to become subjects in environmental struggles in general and the Green New Deal in particular, due to their materialist dependencies on toxic economic growth. In this regard, economists are advised to apply environmental justice approaches to contemporary environmental challenges. This points to the general need to bring deindustrialised and marginalised places back into policy focus, apart from their political relevance.

Future lines of research include, firstly, the use of spatial econometric techniques to detect spatial correlation processes across left-behind places. Second, a study of growth patterns at the facility level could be useful to distinguish between "growth by pollution" and "growth by decontamination" strategies. Thirdly, research could delve into the materialist histories of left-behind places by looking at micro-level data on workers, examining labour market outcomes, and intersecting class and gender dimensions of environmental justice (Faber et al. 2021).

7 Appendix

7.1 Details on E-PRTR data sample: pollutants and sectors

Table 7 Summary table of 41 distinct toxic pollutants and CAS numbers as in our E-PRTR sample, listed by pollutant groups and ranked according to their USEtox 2.12 toxicity score

Pollutant name	Pollutant CAS	Pollutant group name	Toxicity score (USEtox 2.12)
Tetrachloromethane	56-23-5	Greenhouse gases	0.0000974
Hydrochlorofluorocarbons	593-70-4	Greenhouse gases	0.0000301
Halons	1897-45-6	Greenhouse gases	4.71E-03
Chlorofluorocarbons	75-69-4	Greenhouse gases	1.75E-04
Hydro-fluorocarbons	811-97-2	Greenhouse gases	1.52E-04
Fluorine and inorganic compounds (as HF)	75-02-5	Halogens	0.0000756
Chlorine and inorganic compounds (as HCl)	136-40-3	Halogens	0.0000281
1,1,2,2-tetrachloroethane	79-34-5	Halogens	0.0000205
Mercury and compounds (as Hg)	14302-87-5	Heavy metals	3.49
Cadmium and compounds (as Cd)	22537-48-0	Heavy metals	0.195
Arsenic and compounds (as As)	17428-41-0	Heavy metals	0.0538
Chromium and compounds (as Cr)	18540-29-9	Heavy metals	0.0465
Lead and compounds (as Pb)	14280-50-3	Heavy metals	0.0428
Zinc and compounds (as Zn)	23713-49-7	Heavy metals	0.0155

Table 7 (Continued)

Pollutant name	Pollutant CAS	Pollutant group name	Toxicity score (USEtox 2.12)
Nickel and compounds (as Ni)	14701-22-5	Heavy metals	0.00136
Copper and compounds (as Cu)	15158-11-9	Heavy metals	0.0000892
Benzo(g,h,i)perylene	191-24-2	(Polycyclic) Aromatic Hydrocarbons	0.000412
Anthracene	120-12-7	(Polycyclic) Aromatic Hydrocarbons	0.000288
Di-(2-ethyl hexyl) phthalate	117-81-7	(Polycyclic) Aromatic Hydrocarbons	0.0000228
Xylenes	1330-20-7	(Polycyclic) Aromatic Hydrocarbons	6.66E-04
Toluene	108-88-3	(Polycyclic) Aromatic Hydrocarbons	2.55E-04
Phenols (as total C)	108-95-2	(Polycyclic) Aromatic Hydrocarbons	2.35E-04
Nonylphenol and Nonylphenol ethoxylates	25154-52-3	(Polycyclic) Aromatic Hydrocarbons	2.33E-04
Hexachlorobenzene	118-74-1	Persistent Organic Pollutants	0.000934
Polychlorinated biphenyls	1336-36-3	Persistent Organic Pollutants	0.000519
Pentachlorophenol	87-86-5	Persistent Organic Pollutants	0.000128
Pentachlorobenzene	608-93-5	Persistent Organic Pollutants	0.0000732
Ethyl benzene	100-41-4	Persistent Organic Pollutants	6.98E-03
Polycyclic aromatic hydrocarbons	2243-62-1	Persistent Organic Pollutants	5.03E-03
Vinyl chloride	75-01-4	Volatile Organic Compounds	0.0000617
Naphthalene	91-20-3	Volatile Organic Compounds	0.0000243
Ethylene oxide	75-21-8	Volatile Organic Compounds	0.0000119
Tetrachloroethylene	127-18-4	Volatile Organic Compounds	8.34E-03
Trichloromethane	67-66-3	Volatile Organic Compounds	7.13E-03
Non-methane volatile organic compounds	100-41-4	Volatile Organic Compounds	6.98E-03
1,2-dichloroethane	107-06-2	Volatile Organic Compounds	5.91E-03
Benzene	71-43-2	Volatile Organic Compounds	5.34E-03
Dichloromethane	75-09-2	Volatile Organic Compounds	3.38E-03
Trichloroethylene	79-01-6	Volatile Organic Compounds	5.54E-04
1,1,1-trichloroethane	71-55-6	Volatile Organic Compounds	4.73E-05

Table 8 Summary table of sectors and description of activity as in Annex I of the E-PRTR

Sector	Detailed description of activity as in Annex I of the E-PRTR
Energy sector	Coal rolling mills with a capacity of 1 tonne per hour
Energy sector	Installations for gasification and liquefaction
Energy sector	Thermal power stations and other combustion installations
Energy sector	Installations for the manufacture of coal products and solid smokeless fuel
Energy sector	Mineral oil and gas refineries
Energy sector	Coke ovens
Metal industry	Metal ore (including sulphide ore) roasting or sintering installations

Table 8 (Continued)

Sector	Detailed description of activity as in Annex I of the E-PRTR
Metal industry	Installations for the processing of ferrous metals, Application of protective fused metal coats
Metal industry	Installation for the production of non-ferrous crude metals from ore, concentrates or secondary raw materials by metallurgical, chemical or electrolytic processes
Metal industry	Ferrous metal foundries with a production capacity of 20 tonnes per day
Metal industry	Installations for the production of pig iron or steel (primary or secondary melting) including continuous casting
Metal industry	Installation for the smelting, including the alloying, of non-ferrous metals, including recovered products (refining, foundry casting, etc.)
Metal industry	Installations for the processing of ferrous metals.
Metal industry	Installations for the production and/or smelting of non-ferrous metals.
Metal industry	Installations for the processing of ferrous metals, Hot-rolling mills
Metal industry	Installations for surface treatment of metals and plastic materials using an electrolytic or chemical process
Mineral industry	Installations for the production of cement clinker in rotary kilns, lime in rotary kilns, cement or lime in other furnaces
Mineral industry	Opencast mining and quarrying
Mineral industry	Installations for the production of lime in rotary kilns
Mineral industry	Installations for the production of cement clinker or lime in other furnaces
Mineral industry	Installations for the production of cement clinker in rotary kilns
Mineral industry	Installations for the manufacture of ceramic products by firing, in particular roofing tiles, bricks, refractory bricks, tiles, stoneware or porcelain
Mineral industry	Installations for the manufacture of glass, including glass fibre
Mineral industry	Underground mining and related operations
Mineral industry	Installations for melting mineral substances, including the production of mineral fibres
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Nitrogenous hydrocarbon.
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals: Acids.
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Synthetic rubbers
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Sulphurous hydrocarbons
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals.
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals: Bases.
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Surface-active agents and surfactants
Chemical industry	Chemical installations for the production on an industrial scale of basic plant health products and of biocides
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Dyes and pigments
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals: Salts
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals

Table 8 (Continued)

Sector	Detailed description of activity as in Annex I of the E-PRTR
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Organometallic compounds
Chemical industry	Installations for the production on an industrial scale of explosives and pyrotechnic products
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Simple hydrocarbons
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Phosphorus-containing hydrocarbons
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals: Non-metals, metal oxides or other inorganic compounds
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Basic plastic materials
Chemical industry	Chemical installations for the production on an industrial scale of phosphorous, nitrogen or potassium based fertilisers (simple or compound fertilisers)
Chemical industry	Chemical installations for the production on an industrial scale of basic inorganic chemicals: Gases
Chemical industry	Installations using a chemical or biological process for the production on an industrial scale of basic pharmaceutical products
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Halogenic hydrocarbons
Chemical industry	Chemical installations for the production on an industrial scale of basic organic chemicals: Oxygen-containing hydrocarbons
Waste and waster-water	Installations for the disposal or recycling of animal carcasses and animal waste
Waste and waster-water	Urban waste-water treatment plants
Waste and waster-water	Installations for the recovery or disposal of hazardous waste
Waste and waster-water	Independently operated industrial waste-water treatment plants
Waste and waster-water	Installations for the incineration of non-hazardous waste
Waste and waster-water	Installations for the disposal of non-hazardous waste
Waste and waster-water	Landfills
Paper and wood production	Industrial plants for the preservation of wood and wood products with chemicals
Paper and wood production	Industrial plants for the production of pulp from timber or similar fibrous materials
Paper and wood production	Industrial plants for the production of paper and board and other primary wood products
Agriculture and leather industry	Installations for the building of, and painting or removal of paint from ships with a capacity for ships 100 m long
Agriculture and leather industry	Treatment and processing intended for the production of food and beverage products from vegetable raw materials
Agriculture and leather industry	Treatment and processing intended for the production of food and beverage products from animal raw materials (other than milk)

Table 8 (Continued)

Sector	Detailed description of activity as in Annex I of the E-PRTR
Agriculture and leather industry	Treatment and processing of milk
Agriculture and leather industry	Installations for the production of carbon (hard-burnt coal) or electro-graphite by means of incineration or graphitisation
Agriculture and leather industry	Slaughterhouses
Agriculture and leather industry	Plants for the tanning of hides and skins
Agriculture and leather industry	Intensive aquaculture
Agriculture and leather industry	Treatment and processing intended for the production of food and beverage products
Agriculture and leather industry	Plants for the pre-treatment or dyeing of fibres or textiles
Agriculture and leather industry	Installations for the surface treatment of substances, objects or products using organic solvents

7.2 Details on regional variables

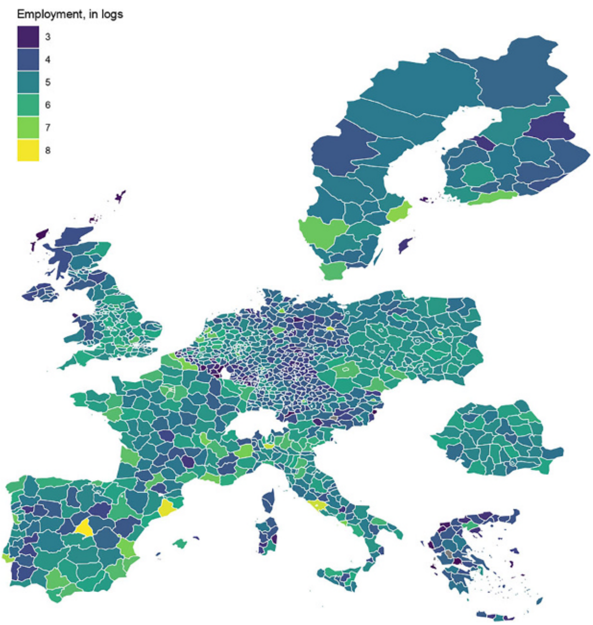


Fig. 8 Regional map of employment in 15 European countries, in logs, at NUTS-3 level, averaged across 2007–2018, showing the 15 countries in our sample. Source: Own calculation based on Cambridge Econometrics

Table 9 Examples for the correlation between industry and service employment. The depicted percentages indicate how many of the region-year pairs are within the 50th percentile of the distribution

Percentage of region-year pairs above the median of the distribution for		
	Industry employment	Service employment
Auvergne-Rhone-Alpes (FR)	72	75
Emilia Romagna (IT)	91	86
North Rhine-Westphalia (DE)	76	72
Stuttgart Area (DE)	93	56

Table 10 Descriptive statistics showing the quantiles of industry employment and wages stratified by urban-rural classification at NUTS-3 level and sourced from Eurostat

	Industry Employment and Wages stratified by Urban-Rural Classification									
	Industry Employment					Industry Wages				
Quantiles:	10	25	50	75	90	10	25	50	75	90
Share:										
% predominantly urban	14.91	21.67	30.67	35.69	52.84	10.28	29.18	25.57	42.7	42.21
% intermediate	29.23	37.8	38.67	46.83	38.97	42.28	34.28	42.44	34.18	40.63
% predominantly rural	55.86	40.53	30.67	17.48	8.19	47.43	36.54	31.99	23.12	17.17
Sum %	100	100	100	100	100	100	100	100	100	100

Table 11 Descriptive statistics showing the quantiles of total employment and wages stratified by urban-rural classification at NUTS-3 level and sourced from Eurostat

	Total Employment and Wages stratified by Urban-Rural Classification									
	Total Employment					Total Wages				
Quantiles:	10	25	50	75	90	10	25	50	75	90
Share:										
% predominantly urban	10.26	22.31	29.23	28.03	65.96	8.44	32.08	21.27	35.92	52.2
% intermediate	33.27	33.39	36.98	54.53	33.31	44.72	33.79	42.65	39.94	32.72
% predominantly rural	56.47	44.31	33.79	17.44	0.73	46.84	34.13	36.08	24.14	15.08
Sum %	100	100	100	100	100	100	100	100	100	100

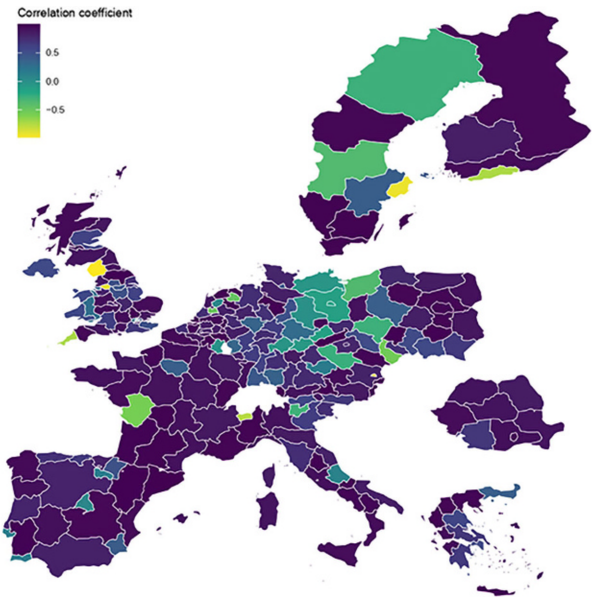


Fig. 9 Map of correlation coefficients between industry and service employment by NUTS-2 regions depicting within-region correlations, pooled across all years, based on Cambridge Econometrics

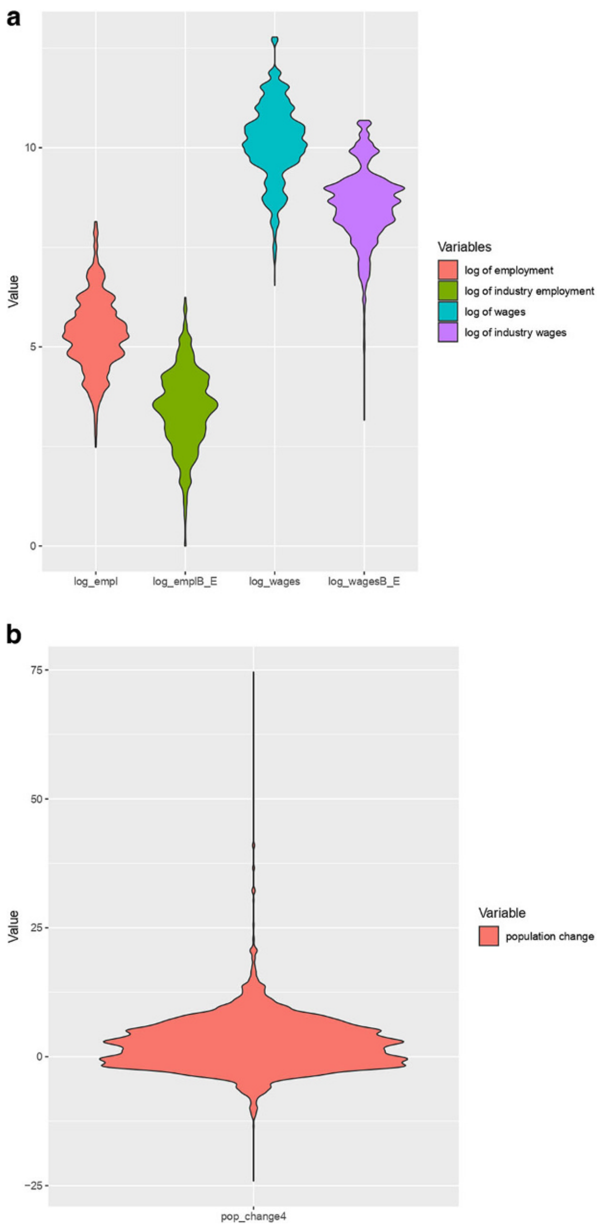


Fig. 10 Violin plots for **a** employment, industry employment, wages, industry wages, in logs; and **b** population changes evaluated over the last four years. The descriptives refer to the average across 2007–2018. **a** Variables expressed in logs from Cambridge Econometrics, **b** Variable expressed in changes from Eurostat

7.3 Details on estimation results

Table 12 Indirect links with toxic pollution and total regional labour markets, baseline regression for total employment and wages

	Indirect Effects on Employment and Wages									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var:	Total Employment					Total Wages				
Quantile (%):	10	25	50	75	90	10	25	50	75	90
Log(Sectoral toxic pollution)	–0.000**	–0.000***	–0.001***	–0.001***	–0.001***	0.000	–0.005*	–0.008***	–0.010***	–0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.002]	[0.002]	[0.003]	[0.002]
Indicator censored regions	–0.002	–0.002***	–0.000	0.003**	0.004**	0.132***	0.025	0.100***	0.103***	0.096***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.022]	[0.024]	[0.018]	[0.020]	[0.018]
Log(gva per capita) lagged	0.009***	0.011***	0.015***	0.018***	0.020***	0.143***	0.237***	0.382***	0.450***	0.509***
	[0.002]	[0.001]	[0.001]	[0.002]	[0.003]	[0.031]	[0.026]	[0.018]	[0.022]	[0.030]
Log(employment) lagged	1.010***	1.008***	1.007***	1.003***	0.999***	0.418***	0.381***	0.294***	0.258***	0.135***
	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.015]	[0.011]	[0.012]	[0.011]	[0.009]
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,087	23,087	23,087	23,087	23,087	21,718	21,718	21,718	21,718	21,718
Pseudo R2	0.9473	0.949	0.949	0.9489	0.95	0.4021	0.3737	0.3324	0.3225	0.3578

Notes: Standard errors are bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13 Indirect links with toxic pollution and regional demographic change, baseline regression for regional net migration, expressed changes

	Indirect Effects on Demography				
	(1)	(2)	(3)	(4)	(5)
Dep. Var:	Net Migration, Changes				
Quantile (%):	10	25	50	75	90
Log(Sectoral toxic pollution)	–0.057***	–0.074***	–0.106***	–0.094***	–0.098***
	[0.019]	[0.011]	[0.012]	[0.016]	[0.024]
Indicator censored regions	–1.093***	–0.564***	0.120	0.683***	1.217***
	[0.178]	[0.111]	[0.156]	[0.094]	[0.196]
Log(gva per capita) lagged	1.502***	2.578***	3.478***	3.559***	4.236***
	[0.204]	[0.155]	[0.160]	[0.133]	[0.235]
Log(employment) lagged	0.457***	0.230***	0.100	0.017	–0.277***
	[0.072]	[0.055]	[0.062]	[0.075]	[0.102]
Industry Effects	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Obs.	23,087	23,087	23,087	23,087	23,087
Pseudo R2	0.1383	0.1605	0.1683	0.1492	0.1304

Notes: Standard errors are bootstrapped. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Acknowledgements The authors wish to acknowledge the work of the editor and of the two anonymous reviewers, who have helped to significantly strengthen the manuscript. We also acknowledge comments and suggestions from participants to the CJRES – Re-Imagining Evolutionary Economic Geography Workshop, Dublin, UK; the 30th Gerpisa International Colloquium, Detroit, USA; the PERI Seminar on the Political Economy of the Environment in May 2022, Amherst, USA; and the 2021 Annual CERCIS Workshop, Ferrara, Italy. We also want to thank Laura Magazzini, Stefania Barca, Tobias Rüttenauer, Lorenzo Feltrin, Michael Ash, and James K. Boyce for their helpful comments and open dialogue. Lastly, we thank Lorenz Steiner for the expert validation concerning toxic chemical compounds.

M.E.V. acknowledges the financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 1409 published on 14.9.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU– Project Title "Triple T – Tackling a just Twin Transition: a complexity approach to the geography of capabilities, labour markets and inequalities" – CUP F53D23010800001 by the Italian Ministry of Ministry of University and Research (MUR).

Funding Open Access funding enabled and organized by Projekt DEAL.

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