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Decoupling trends of emissions across EU regions and the role of environmental policies☆

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A R T I C L E   I N F O

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A B S T R A C T

The paper combines grid-level data of eight emission types – CO2, N20, CH4, NH3, NOX, PM10, PM2.5, and SO2 – with sub-national economic data to create a 1995–2015 balanced panel for NUTS 2 regions in EU countries. Regions on average show decoupling of emissions from output but most of the emission reductions are achieved before the 2008 financial crisis. Post 2008, very weak decoupling and even coupling can be observed. Using OECD's Environmental Policy Stringency (EPS) Index as an intervention variable, an event study analysis shows that strong policies significantly reduce emissions, but there is considerable heterogeneity in the response by emission types and regional income levels.

1. Introduction

The scale of economic activity of the past decades has caused serious environmental concerns and has threatened the "safe operating space for humanity" (Rockström et al., 2009; Steffen et al., 2015). This is not surprising as exponential economic and population growth (Krausmann et al., 2009), rising living standards (Stiglitz et al., 2018), and globalized markets have resulted in a manifold increase in emissions, material extraction, and energy use (Krausmann et al., 2017; UNEP, 2019; IPCC, 2021). To deal with these issues, several multi-lateral treaties such as the Paris Climate Agreement, the Convention on Biological Diversity, and the Sustainable Development Goals (SDGs) have been introduced with the aim of understanding, measuring, and regulating various environmental pressures that include, among others, emissions, rising temperatures, biodiversity loss, warming of oceans, and land-use change (Steffen et al., 2015; Raworth, 2017; IPCC, 2018).

Due to growing environmental concerns and better data availability, the fields of ecological, environmental, and climate economics have contributed significantly to help better understand the environment-economy interactions (IPCC, 2018; Hickel and Kallis, 2020). In recent years, debates on green growth, de-growth, and post-growth theories have gained traction (Victor, 2012; van den Bergh and Kallis, 2012; Jackson, 2018; Hickel and Kallis, 2020), and several high-income countries, have started incorporating stronger environmental regulations within their policy frameworks (IPCC, 2018; UNEP, 2019; EEA, 2020a). At the heart of the above points is the premise that economic activity needs to decouple from environmental pressures in order to avoid crossing some irreversible thresholds that can negatively impact socioeconomic systems (Peters et al., 2020; IPCC, 2021).

The topic of decoupling was initially brought to the forefront in the seminal OECD (2002) report, that showcased trends of several environmental indicators like emissions, material consumption, and energy use in relation to economic growth. This report, together with its numerous follow-ups (Peters et al., 2011; Haberl et al., 2020; Wiedenhofer et al., 2020) show that many high-income countries have achieved relative decoupling especially in direct emissions. Relative decoupling occurs when the environmental indicators grow at a slower pace than economic growth. Absolute decoupling, by contrast, occurs when the environmental variables have a zero or negative growth while the economic variable has a positive growth, and coupling implies that environmental indicators are growing faster than output. From an environmental standpoint, absolute decoupling would be necessary to achieve climate targets especially under continued economic growth (IPCC, 2021). The question whether wide-scale and consistent absolute decoupling is even technologically possible and politically feasible remains an on-going debate (IPCC, 2018; OECD, 2018; UNEP, 2019).

The decoupling literature, while providing an invaluable contribution, currently lacks two aspects. First, decoupling studies focus on

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countries, or a group of countries, as the unit of analysis. Regions within countries are very heterogeneous with respect to both economic and environmental indicators especially emissions. As a result, national level studies are likely to average out the underlying distributions resulting in an “aggregation bias” (Kojima and Bacon, 2009; de Koning et al., 2015). For example, investigating countries, sectors, and emissions types in Europe, Naqvi and Zwickl (2017) find considerable variation in decoupling across different dimensions with no clear trend towards or away from more environmentally desirable decoupling outcomes. In order to overcome this issue, data at the finest spatial resolution available should be utilized. Second, CO2 remains the main environmental indicator used for analysis (Wiedenhofer et al., 2020) although other harmful emissions are also generated from economic activity, but are not given sufficient attention (OECD, 2018; EEA, 2020a). These emissions have their own negative impacts and might not necessarily exhibit the same development trends as CO2 emissions.

In order to explore changes in emission and economic output at the sub-national level, this paper constructs a unique dataset for European Union (EU) countries for the NUTS 2 regions.[1] The economic data is taken from ARDECO (2020), a homogenized NUTS 2-level database for Europe that provides various indicators like output, income levels, and economic sector shares. The emissions data is taken from the EU Joint Research Commission’s (JRC) EDGAR v5 database (Crippa et al., 2020a,b). EDGAR v5 provides information on different emission types at a 0.1×0.1 degree grid-cell resolution. The grids are mapped on to NUTS 2 boundaries and data for eight emission types – CO2, N20, CH4, NH3, NOX, PM10, PM2.5, and SO2 – is extracted. The two datasets are combined to form a NUTS 2-level panel for the years 1995–2015.

Descriptive results show evidence of relative decoupling of emissions from output but there are large variations across NUTS 2 regions and by emission types. Furthermore, if the data is split into two subsample periods, 1995–2008 and 2008–2015, then one observes that most of the decoupling took place before the 2008 financial crisis while post-2008 several NUTS 2 regions exhibit very weak decoupling or even coupling trends. In the next part, the OECD’s Environmental Policy Stringency (EPS) Index (Botta and Koźluk, 2014; OECD, 2018) is used as a treatment variable to explore the role it plays in reducing emissions. This is analyzed using an event study design based on recent methodological advances in difference-in-difference methods (Callaway and Sant’Anna, 2020; Goodman-Bacon, 2021; Borusyak et al., 2021). After controlling for GDP output, industry and agriculture sector shares, and time fixed-effects, regression results shows that, on average, strong EPS policies reduce all emission types. There is also considerable heterogeneity across emission types where NH3, CO2, CH4, and N2O decline significantly in response to policies while NOX, PM10, PM2.5, and SO2 show a weak response. Furthermore, if the regions are differentiated by the top one-third and the bottom two-third percentiles based on real output per capita, then the bottom regions show a much stronger policy response across all emissions types. In contrast, top regions show a strong policy response in N2O and NH3 only, while CO2 and NOX respond weakly to policies. This paper contributes to the decoupling literature by (a), highlighting the significance of regional spatial–temporal variations in economic and emission indicators across EU regions, and (b), showing variations in causal response to emission policies by emission types and income levels across these regions.

The remainder of the paper is organized as follows. Section 2 provides a literature review of recent decoupling studies with a focus on Europe. Section 3 describes the data and Section 4 shows descriptive spatial–temporal decoupling trends. Section 5 conducts event study analysis on the impact of policies on emissions while Section 6 presents conclusions and discusses directions for future research.

[1] NUTS stand for Nomenclature of Territorial Units for Statistics. Based on 2016 definitions, the EU consists of 283 NUTS 2 regions nested within country boundaries.

2. Literature review

The empirical literature that analyzes the development of economic indicators in relation to environmental indicators has grown significantly in the past years, and several papers provide a comprehensive overview (Lenzen, 2016; Zhang et al., 2018; Wiedenhofer et al., 2020). While the term “environment” encompasses various topics like raw material extraction, energy use, land use change, and biodiversity loss, the dominant focus of this literature remains on air emissions, especially CO2, greenhouse gasses (GHGs) and pollutants. Since this paper also focuses on emissions, the literature discussed below covers only relevant studies.

The emissions-economy literature can be divided in two broad topics; decoupling studies (Zhang et al., 2018; Lenzen, 2016; Haberl et al., 2020), and estimations of the Environmental Kuznets Curve (EKC) (Stern, 2004; Carson, 2010; Özokcu and Özdemir, 2017; Torras and Boyce, 1998). The decoupling literature aims to empirically assess the relative change in emissions in relation to economic output usually measured by gross domestic product (GDP) or gross value added (GVA). Here, emissions growing at a slower rate than output is relative decoupling, if emissions growth is zero or negative, while economic growth is positive, it is absolute decoupling, and emissions growth faster than output is coupling (OECD, 2002). Extensions of these broad definitions have been explored elsewhere in the literature as well (Tapio, 2005; Jackson, 2009; Naqvi and Zwickl, 2017). The EKC hypothesis states that emissions initially grow with output, slow down, reach a turning point, and eventually decline. In short, there is an inverted U-shape relationship between emissions and growth that can be categorized as going from coupling, relative decoupling, to absolute decoupling.

A recent review by Wiedenhofer et al. (2020) highlights some interesting patterns in this literature. First, the topics of decoupling and EKC have increasingly gained traction with journal publications growing at 20% per anum in the past decade. Second, the geographical focus of the studies remains mostly on the USA, Europe, OECD, Japan and China, where there is both an interest in this topic, and there is availability of longitudinal data. And third, papers predominantly focus on direct or production-based emissions, which are easier to capture and analyze. In contrast, analysis of indirect or consumption-based emissions (Davis and Caldeira, 2010; Malik et al., 2019; Krausmann et al., 2017; Zhang et al., 2018; Peters et al., 2020) require detailed input–output or supply-use tables, which either have limited spatial–temporal coverage, or the level of granularity is not sufficiently high enough for a comprehensive analysis. Despite these limitations, studies that deal with indirect emissions are also slowly growing (Peters, 2008; Peters et al., 2011; Wiedmann and Lenzen, 2018; Haberl et al., 2019).

2.1. Evidence on decoupling trends in europe

Several papers estimate the EKC for emissions for European countries and find weak evidence of a turning point while flattening of the EKC curve is observed in most cases (Stern, 2004; Bacon and Bhattacharya, 2007; Li et al., 2007; Shuai et al., 2017; Le Quéré et al., 2019). López-Menéndez et al. (2014) shows evidence of an EKC turning point for Cyprus, Greece, Slovenia, and Spain. Similarly, Shuai et al. (2017), Simas et al. (2017), Fanning and O’Neill (2019) find evidence of relative decoupling for production-based emissions in most European countries, but also show that indirect emissions continue to rise. Large country sample studies, which also include EU, come to the same conclusions as well (Knight and Schor, 2014; Gupta, 2015; Sanchez and Stern, 2016; Fernández-Amador et al., 2017; Simas et al., 2017; Bampatsou and Halkos, 2019; Hickel and Kallis, 2020).

In terms of country-specific papers, Baiocchi and Minx (2010) for the UK, Faehn and Bruvoll (2009) for Norway, Palm et al. (2019) for Sweden, find improvements in direct emissions but also find evidence that consumption-based emissions have gone up. Other studies show that in the former Soviet countries, emissions fell dramatically after the end of communism (Liobikiene et al., 2016), but recovery has resulted in strong emissions growth (Štreimikienė and Balezentis, 2016). Naqvi and Zwickl (2017) conduct a sectoral analysis of decoupling trends across EU countries and find evidence of relative decoupling, but also highlight that there are strong variations across sectors both within and across countries. Some studies provide additional insights about the drivers of decoupling trends in the EU. For example, Robaina-Alves et al. (2015), Cruz and Dias (2016), Gazheli et al. (2016), Valadkhani et al. (2016), Beltrán-Esteve and Picazo-Tadeo (2017) link emissions decoupling with technology innovations, productivity gains, limited access to natural resources, and research and development (R&D) spending.

2.2. Gaps in the literature

In the decoupling literature, two gaps persist. First, most of the studies tend to focus on countries, or group of countries, continents, or the globe as a whole. With the exception of USA and China (Boyce et al., 2016; Cohen et al., 2019), which account for most of the sub-national studies, hardly any regional analysis exists at the European level (Haberl et al., 2020). The only exception that was found at the time of writing this was Borozan (2018) which explored the relationship between energy use and output at the NUTS 2 level. Sub-national analysis can yield interesting insights since regions vary significantly in their socioeconomic composition and the level and type of emissions (Tapio, 2005; Akizu-Gardoki et al., 2018). Second, CO2 is usually taken as the key indicator for analysis. Besides CO2, various other harmful emissions, which could be either greenhouse gases (GHGs) or pollutants, also need to be considered. Furthermore, while the development of some emissions might be highly correlated with CO2 and can be co-regulated (Zwickl et al., 2014), others might develop completely different trends. A better understanding of these two gaps can also help with emissions-related policy response.

3. Data

The data for analysis is compiled at the NUTS 2 level for European Union (EU) countries. NUTS regions are homogenized administrative units defined by the European Commission's Statistical Agency, or Eurostat. There are four NUTS levels. NUTS 0 represent countries, NUTS 1 represent major provinces, NUTS 2 are districts, and NUTS 3 are further subdivisions representing municipalities or counties.[2] According to the 2016 NUTS definitions used in this paper, there are 283 NUTS 2 regions in the EU.

3.1. Economics data

The economic data comes from the Annual Regional Database of the European Commission or ARDECO, a dataset that was initially released in 2019 and is periodically updated (ARDECO, 2020).[3] The ARDECO database provides a unique and consistent NUTS 2 level information on various economic indicators including real Gross Value Added (rGVA), income levels, and industry sector shares.

ARDECO ranges from 1970–2019 and has two advantages over similar data available from the Eurostat, the official statistical agency for the EU. First, it standardizes the data to 2016 NUTS classifications, while Eurostat provides information using the latest NUTS classification. NUTS regions have been reclassified in 1995, 1999, 2003, 2006, 2010, 2013, 2016, and more recently, in 2021. At each reclassification, new regions are created, split, merged, or have their boundaries shifted. This makes it very challenging to create a homogeneous panel dataset at the regional level. Second, the ARDECO database provides sectoral breakdown of economic indicators. The sectors are also homogenized to NACE revision 2 classifications. NACE stands for "Statistical classification of economic activities in the European community" and is used for mapping economic activity in Europe.[4] NACE codes have been reclassified three times (NACE revision 1 in 1996, revision 1.1 in 2002, and revision 2 in 2007), where the correspondence across finer NACE classifications remains a major challenge.[5] ARDECO provides information for six NACE rev2 sectors — Agriculture (A), Industry (B-E), Construction (F), Wholesale Retail and Trade (G-J), Finance and Business (K-N), and Non-market Services (O-U). For this paper, the sectors are collapsed into two groups that cause direct emissions; the primary Agriculture (A) sector and the secondary Industrial (B-E, F) sector. The residual tertiary or the Service sector is excluded from this analysis since it is more relevant for studies dealing with indirect or consumption-based emissions.

Fig. 3.1 shows the distribution of real GVA, and shares of agriculture and industry in real GVA for 2015. Here one can observe the disparity between central European and periphery regions, and rural and urban NUTS regions. Periphery regions are more dependent on agriculture and have lower output. Similarly, one can also observe industrial clusters that tend to be on the eastern side.

3.2. Emissions data

Emissions data comes from the Emissions Database for Global Atmospheric Research, or EDGAR v5, hosted at the European Commission's Joint Research Center (JRC) (Crippa et al., 2020a,b). The dataset provides 0.1×0.1 degree grid-level emissions from 1970–2015. Emissions are categorized into Greenhouse Gasses (GHGs) and pollutants which are individually discussed below.

3.2.1. Greenhouse gasses (ghgs)

GHGs are emissions that enter the upper atmosphere and prevent radiation from escaping back into space, and as a result, cause global warming. In 1994, the United Nations Framework Convention on Climate Change (UNFCCC) came into force with the aim of stabilizing GHG concentrations in the atmosphere to prevent potential serious future consequences for example global warming (IPCC, 2018). Updates to the regulations and targets takes place through the Conference of Parties or COPs. The COP in 1997 resulted in the Kyoto Protocol which provided binding agreements to reduce emissions for two obligation periods, 2008–2012 and 2012–2020 (Delbeke and Vis, 2016). Policies after 2020 are determined by the Paris Agreement (COP 2015) that also deals with the two-degree global warming target. For Europe, the emission targets are monitored by the European Environmental Agency (EEA) and the emission inventories are maintained by the JRC (EEA, 2020).

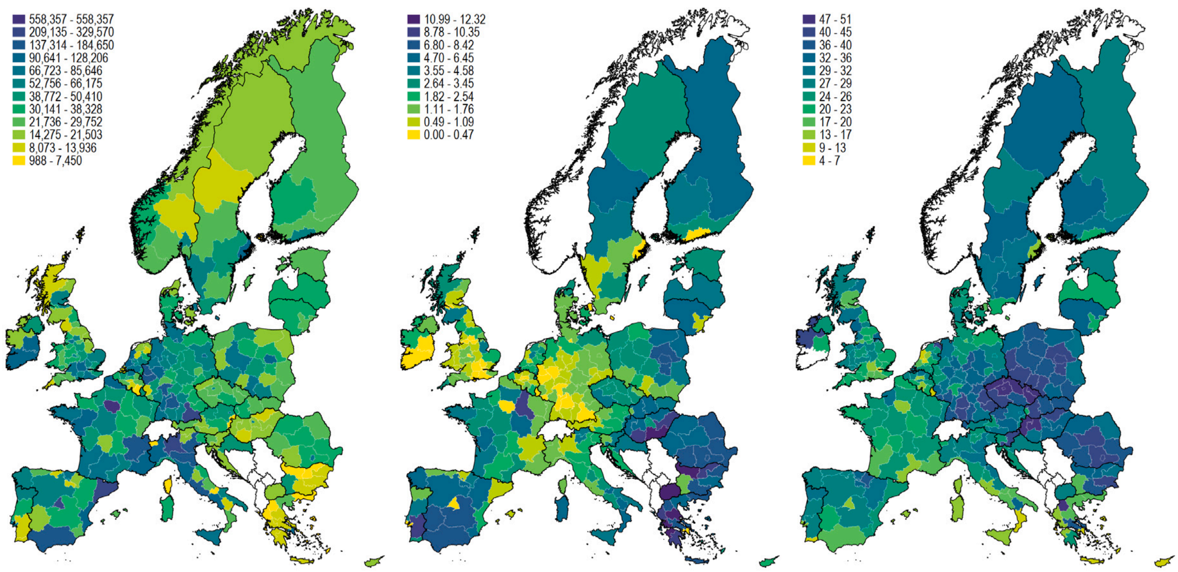
Three GHGs are selected for analysis for this paper, Carbon Dioxide (CO2), Methane (CH4), and Nitrogen Dioxide (N2O). CO2 is produced as a result of burning of fossil fuels and from chemical reactions like manufacturing of construction material especially cement. It also naturally emits from trees, biological materials, and waste. Methane (CH4) is emitted during the production and transportation of fossil fuels. It is also produced heavily in the agriculture sector, for example, directly by livestock, through fertilization, and decay of organic waste in landfills. N2O is produced through agriculture and industrial activities, combustion of fossil fuels and solid waste, and treatment of waste water.

[2] Definitions of administrative boundaries vary across countries. For more information, see https://ec.europa.eu/eurostat/web/nuts/background.

[3] This database is part of recent efforts by the European Commission to homogenize regional indicators (https://ec.europa.eu/knowledge4policy/territorial/ardeco-online_en) and was formerly hosted by Cambridge Econometrics as the European Regional Database (ERD).

[4] For details, see https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Statistical_classification_of_economic_activities_in_the_European_Community_(NACE).

[5] See the correspondence mapping from Rev. 1.1 to Rev. 2 here https://ec.europa.eu/eurostat/web/nace-rev2/correspondence_tables.



(a) Real GVA (Eur PPS) (b) Share of Agriculture (%) (c) Share of Industry (%)

Fig. 3.1. Spatial distribution of economic indicators for 2015.
Source: ARDECO (2020). K-mean clusters used for cut-offs.

3.2.2. Pollutants

The second type of emissions are pollutants that stay suspended low in the air and can also travel via wind currents. They cause direct harm to humans and animals (through inhalation), and plants (through eutrophication). In 1979 the United Nations Economic Commission for Europe (UNECE) established the Geneva Convention on Long-Range Trans-boundary Air Pollution or LRTAP. The LRTAP was implemented as the European Monitoring and Evaluation Program (EMEP) under the UNECE. Since 1979, the EMEP program has been extended by eight different protocols. The last one, known as the Gothenburg Protocol, came into effect in 2005 and introduced extensive monitoring of LRTAP. The Gothenburg protocol also provided EU countries pollution reduction targets and ceilings for emissions relative to 1990 levels (UNECE, 2020).

For this paper, five pollutants are selected. Sulfur Oxide (SOX), which is produced through extraction of minerals and burning or sulfur-rich fossil fuels (for example, during wine production). Nitrous Oxide (NOX) which is emitted through internal combustion of car engines. Ammonia (NH3), a key ingredient in the agriculture sector where almost 90% of NH3 is used in fertilizers, pesticides, dyes, and cleaning products. Particulate Matter (PM10 and PM2.5) are micro-particles that stay suspended in air. Most of industrial economic activity causes PM emissions. The number represents the size of PM measured in micrometers (μm). PM below 10 μm can be easily inhaled and enter the bloodstream and is highly detrimental to human health (WHO, 2014).

Fig. 3.2 shows grid-level maps for the European region for four different emission types (CO2, PM10, N20, and NH3) extracted from the EDGAR v5. The figure highlights the spatial variations both within and across countries. The emission grids are mapped on to NUTS 2 administrative boundaries and aggregated using a spatial overlay (see Appendix A for details). Fig. 3.3 shows the distribution of four emissions at the NUTS 2 level for the year 2015. The maps of the remaining emissions are given in Fig. B.1 in the Appendix.

The economic and emission datasets are merged to form a balanced panel from 1995–2015. 1995 is selected as the starting year since it maximizes the number of NUTS 2 regions in the EU as most of the EU enlargement took place before 1995. Additionally, mechanisms to monitor the emissions and the implementation of environmental policies mostly took place around 1990–1995. Therefore, the quality of the data is also of higher for both the datasets after 1995.

3.3. Oecd's environmental policy stringency (eps) indicator

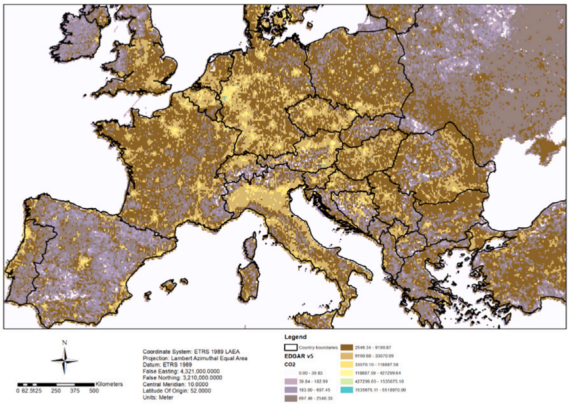
Climate policies in the EU are formulated at the highest EU-level with national member states adapting these regulations based on their own circumstances. As Delbeke and Vis (2016) neatly summarize, the EU's climate policies are one of the most comprehensive in the world, that have slowly evolved based on climate targets, impact on key economics sectors, in relation to other key regulations, and in consultation with member countries. Emissions specifically need a pan-EU response since they cannot be restricted within national borders. As a result, EU as a whole, commits to emission reduction targets. Member countries can develop further strategies on top of baseline EU regulations. This also aligns with various other EU-wide policy areas like decarbonization, reducing dependence on imported fossil fuels, and scaling-up green technologies, within the Single Market framework (Delbeke and Vis, 2016). Even though policies can be attributed to EU and country-level decisions, the aim of this paper is to explore their impact on heterogeneous regions within countries.

In order to evaluate the impact of environmental policies on emissions, the OECD Environmental Policy Stringency (EPS) Index (Brunel and Levinson, 2013; Botta and Koźluk, 2014; OECD, 2018) is used. EPS is a homogenized composite index comprising of market and non-market based policies covering 27 OECD countries and six non-OECD countries for the time period 1990 till 2015.

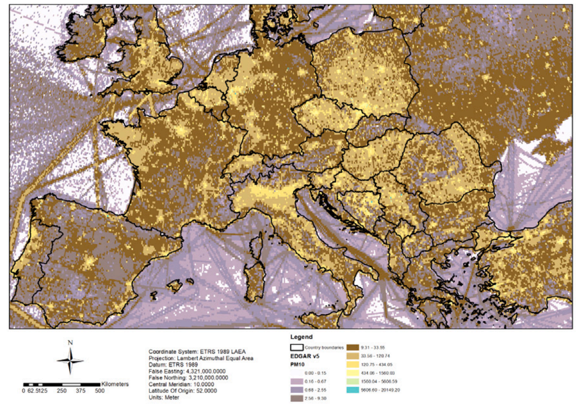
As shown in Fig. 3.4, market-based policies include taxes on various emissions, trading schemes, and feed-in-tariffs (FITs) for wind and solar energy. Non-market based policies include policy-determined standards and limits for emissions and public R&D subsidies. The overall EPS index is a weighted average of each category. The index is normalized to the 0–6 range where higher values indicate higher stringency.[6]

This index has been selected for two reasons. First, it is the only homogenized indicator available that allows one to compare climate policies across the sample EU countries over time. Second, even though, the index is labeled as "environmental" policy stringency, which implies a broad spectrum of climate topics, the index itself mostly focuses on emissions, as can be observed in Fig. 3.4. All of the individual

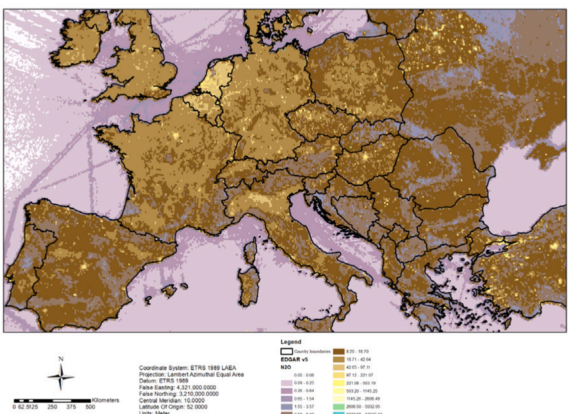
[6] The OECD EPS data is available at https://stats.oecd.org/Index.aspx?DataSetCode=EPS and the documentation is available here.



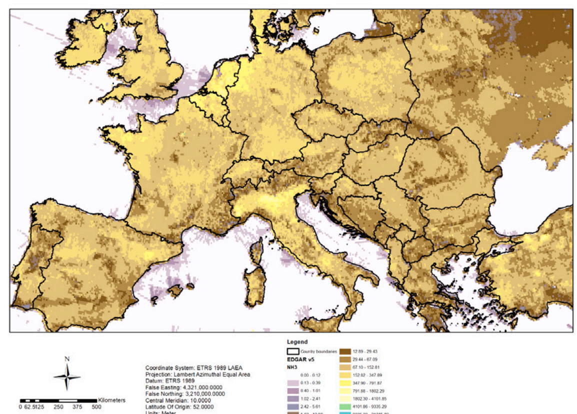
(a) CO2



(b) PM10



(c) N2O



(d) NH3

Fig. 3.2. Sample EDGAR v5 emission grids.
Source: EDGAR v5 (Crippa et al., 2020a).
Emissions given in tons.

components either have a direct impact on emissions reduction or indirectly target emission reductions via scaling-up of green technologies. As Botta and Koźluk (2014) explain in the documentation, emissions-related policies are one of the few environmental indicators that can be homogenized and compared across countries due to data availability.

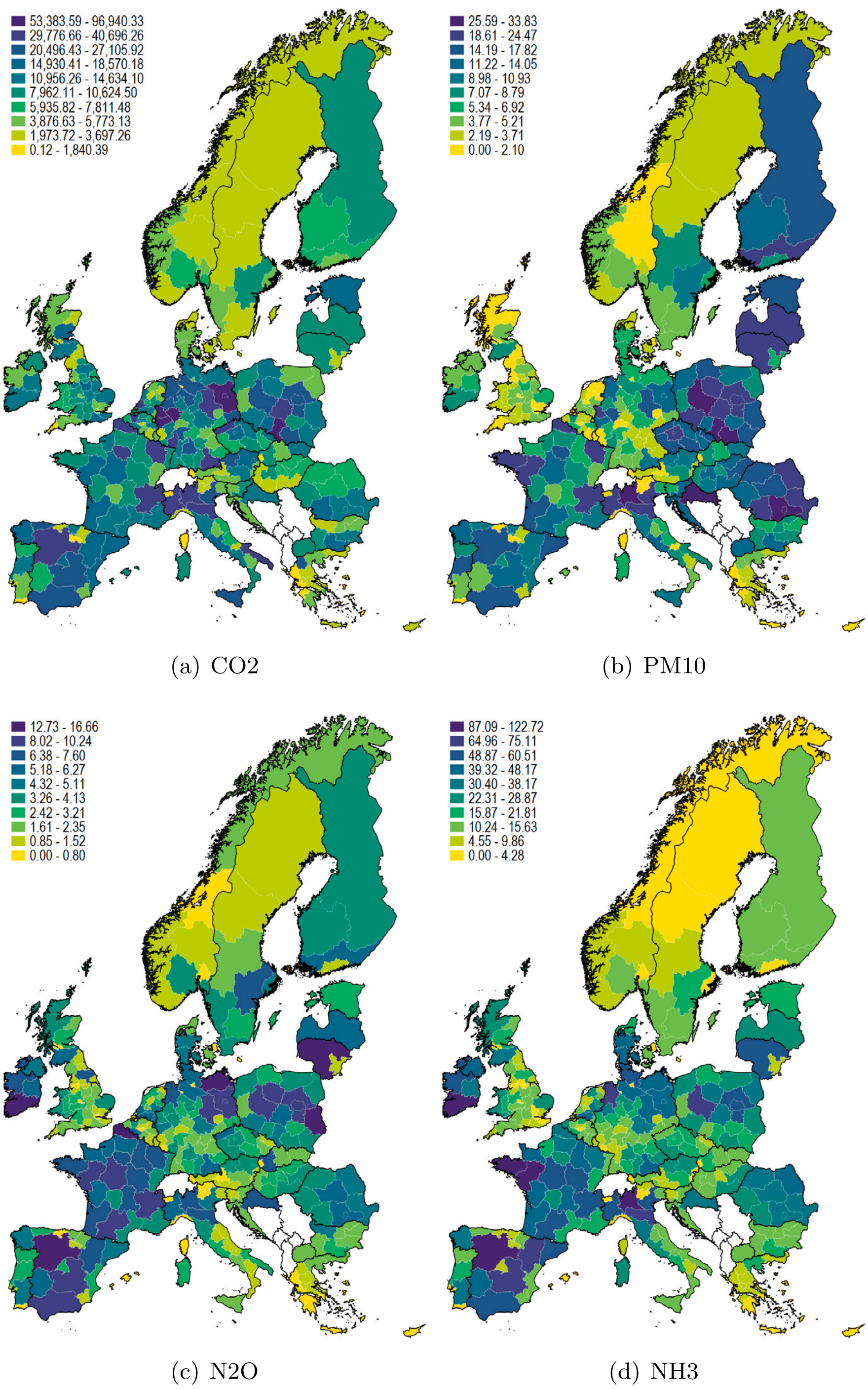
Even though the data for individual index components is available, the aggregate EPS is utilized as the policy intervention variable. A main reason for this is that it is not clear to which extent individual index component directly or indirectly impact various emissions. For example standards for limiting sulfur in diesel indirectly reduces other emissions especially CO2. Or R&D subsidies, a large component of the index, are probably very important in developing green technologies. Additionally, the combination of market and non-market policies, work in tandem to induce private firms to shift to new technologies (Acemoglu et al., 2012). Therefore, the overall EPS index, allows us to jointly test the impact of several policies on emissions.

Fig. 3.5 plots the trends of the overall EPS index of the EU countries. The figure shows how the policy stringency increased after 1995 but after the 2008 financial crisis, declined slightly before increasing again. Variations in policies stringency are also visible. For most of the EU countries, the EPS data only exists till 2012, which marks the end of the first commitment period of the Kyoto Protocol (EEA, 2020a). In order to make this indicator useful for the data time range, a cut-off of $EPS \geq 2.5$ is taken as strong policy measure or the treatment variable. The value of 2.5 is also used in Botta and Koźluk (2014) to differentiate strong versus weak policy countries. For the paper, we assume that once a country crosses the strong policy threshold, it stays in the treatment group. This is also based on the assumption that policies, especially in European countries, once implemented, are not easily reversed, and generally tend to stay in place. This assumption also allows us to extrapolate the policy-related treatment status for countries that do not have data after 2012.

4. Descriptive statistics

The final dataset is a perfectly balanced panel for NUTS 2 regions for the time period 1995–2015. The variables used in the paper are summarized in Table 4.1. The first entry in the table, real Gross Value Added (rGVA), shows the variation in the output of regions after accounting for purchasing power standards (PPS). In terms of per capita rGVA, the average income is around EUR 23,000 for all the data points. But on the extreme ends, regions can have a GDP per capita as low as EUR 4,387 (PL72: Swietokrzyskie, Poland in 1995) to as high as Eur 181,173 (UKI3: Inner London West, UK in 2015). Other indicators highlight the trends as well. For example agriculture share in rGVA ranges from 0–21%s while industry ranges from 4%–59%. Similar variations can also be observed in the emissions across the NUTS regions. Fig. B.2 in the Appendix shows the correlation across various variables in a matrix plot.

Fig. 4.1 highlights aggregate EU-wide trends of economic and emission variables. All indicators are indexed to their respective 1995 levels. The main economic indicator, real Gross Value Added (rGVA) shows a constant increase relative to 1995 index with the dip in 2008, at the time of the financial crisis, followed by the recovery period. The



(a) CO2 (b) PM10

(c) N2O (d) NH3

Fig. 3.3. Spatial distribution of emissions for 2015. *Source:* EDGAR v5 (Crippa et al., 2020a). Emissions are given in thousand tons. K-mean clusters used to determine groups.

industry sector follows a similar trend but exhibits a widening gap from total rGVA. Agriculture shows significant fluctuations in output across the years with some stability after the 2008 crisis. Emissions decline relative to 1995 but there are huge variations. CO2 and NH3 stay relatively close to their 1995 level with CO2 showing a decline mostly after 2010. PM10, PM2.5 and N2O start declining immediately after 1995 but their levels stay relatively stable after 2003. The last two emissions, NOX and SO2, show a constant decline relative to 1995.

While the trends in Fig. 4.1 are averages for the sample regions, Fig. 4.2 plots the trends for real GVA and CO2 emissions for individual NUTS 2 regions. The average trends, shown as solid lines, are exactly the same as in Fig. 4.1. The bands show the range of values of all the NUTS 2 regions which are indexed to their own 1995 values. As seen in the figure, even though average real GVA has increased over time, the spread indicates that some regions are performing worse than their 1995 level while some have grown significantly. Similarly, the band for CO2 shows that emissions have increased in several regions relative to 1995. These variations highlight how average trends can result in an aggregation bias.

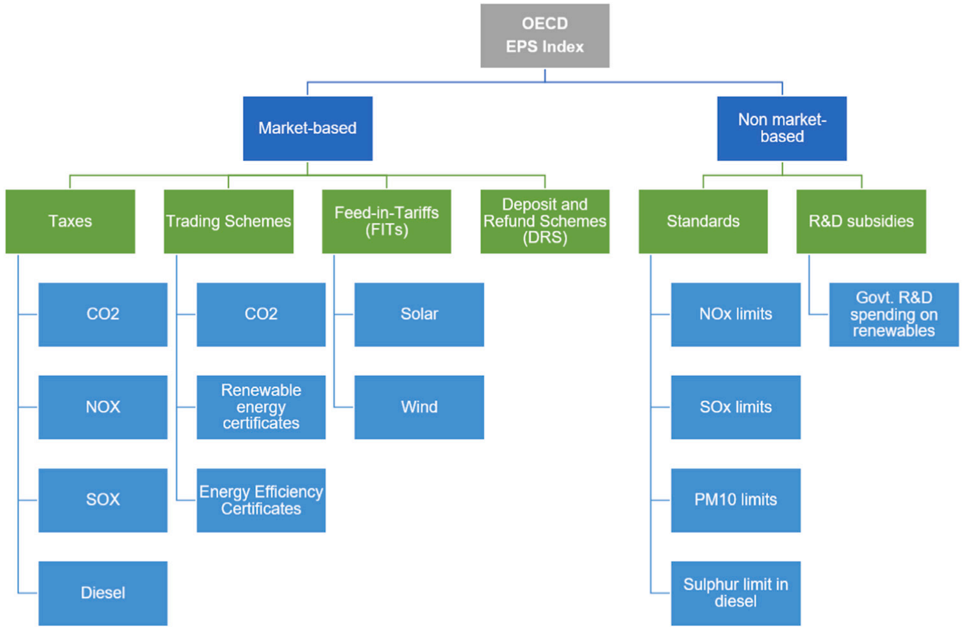


Fig. 3.4. Overview of the OECD's Environmental Policy Stringency (EPS) Index.
Source: Reproduced from Botta and Koźluk (2014) and OECD (2018).

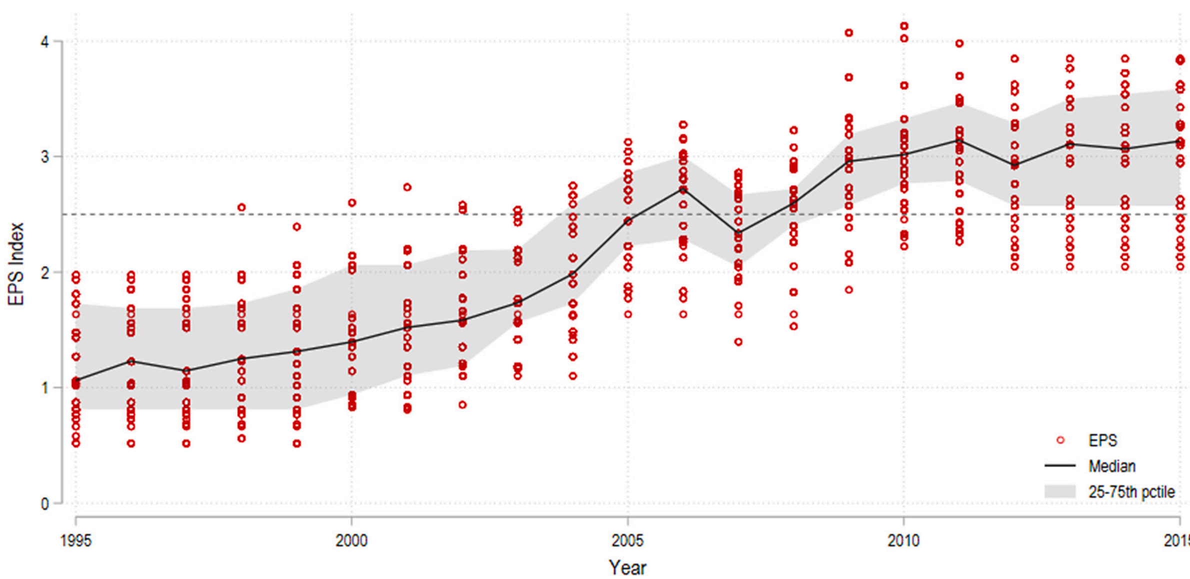


Fig. 3.5. OECD's Environmental Policy Stringency (EPS) Index trends.
Source: Botta and Koźluk (2014) and OECD (2018). The horizontal line marks the strong policy threshold of EPS $\geq$ 2.5.

In order to explore the relationship between environmental and economics variables, the OECD's Decoupling Factor (DF) (OECD, 2002) is introduced here:

$$DF_t = 1 - \left(\frac{\mathtt{Emm}_t / \mathtt{rGVA}_t}{\mathtt{Emm}_0 / \mathtt{rGVA}_0} \right) \tag{1}$$

where $\mathtt{Emm}$ represents emission type. The economic indicator is represented by $\mathtt{rGVA}$. Time is indexed by t and the baseline reference period is sub-scripted with 0. The ratio $\mathtt{Emm}_t/\mathtt{rGVA}_t$ is the emissions intensity at the time $t \geq 0$ relative to emissions intensity at the baseline $\mathtt{Emm}_0/\mathtt{rGVA}_0$. The DF is bounded above at one where one is absolute decoupling. The range $0 < DF \leq 1$ shows the intensity of relative decoupling. The indicator is not bound in the negative range and values less than zero indicate the extent of coupling, where emissions grow at a higher rate than rGVA.

According to the OECD formula, the baseline reference period determines whether a region is decoupling or not. Just by changing the baseline, different DF values can be obtained. This is important to highlight because most studies show decoupling of emissions from output over a long time horizon. Such analyses are very likely to show relative decoupling since longer time spans are also likely to include technological improvements and introduction of new policies that reduce emissions (Peters et al., 2011) and therefore, are likely to have a "temporal bias".

In order to elaborate the above point, the time range of 1995–2015 is broken down into two sub-periods; 1995–2008, and 2008–2015. The first sub-period 1995–2008 reflects the initial phases of implementing

Table 4.1
Summary Statistics (1995–2015).
Source: Economic variables: ARDECO (2020). Environmental variables Crippa et al. (2020a). Environmental Policy Stringency (EPS) (OECD, 2018).

	Mean	SD	Min	Max	Obs.
Economic variables					
GVA (Mil. Eur PPS)	37,664.37	42,932.32	435.61	558,356.88	5,439
GVA - Agriculture (Mil. Eur PPS)	735.59	812.95	0.97	10,142.94	5,292
GVA - Industry (Mil. Eur PPS)	10,041.81	10,249.10	60.96	94,607.54	5,291
Agriculture share in GVA (%)	3.00	2.90	0.00	21.39	5,292
Industry share in GVA (%)	28.11	8.60	3.72	59.20	5,291
Environmental variables					
CH4 ('000 tons)	91.03	81.90	0.00	1,354.62	5,943
CO2 ('000,000 tons)	12.46	12.79	0.00	105.56	5,439
N2O ('000 tons)	3.40	3.63	0.00	64.86	5,943
NH3 ('000 tons)	19.16	18.77	0.00	126.53	5,943
NOX ('000 tons)	36.55	27.43	0.02	178.99	5,943
PM25 ('000 tons)	5.01	4.49	0.00	42.10	5,943
PM10 ('000 tons)	7.82	7.16	0.00	61.84	5,943
SO2 ('000 tons)	24.39	39.12	0.01	628.30	5,943
EPS Index (0–6)	2.20	0.86	0.52	4.13	5,439

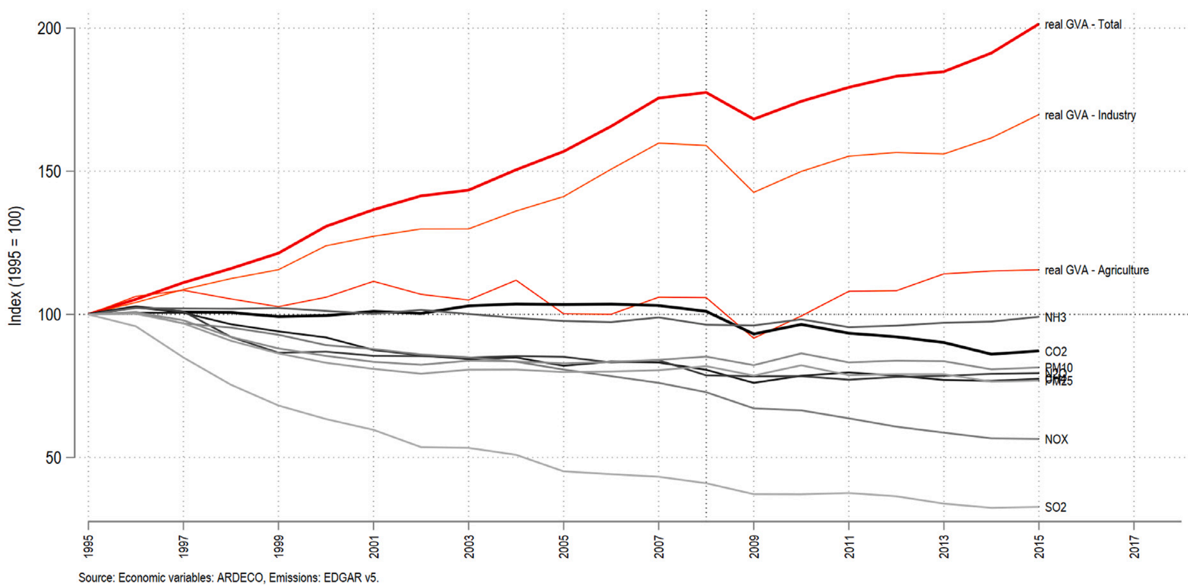


Fig. 4.1. EU-wide trends in economic and environmental variables, 1995–2015.
Source: Own calculations from Crippa et al. (2020a) and ARDECO (2020).

climate policies in the EU (Delbeke and Vis, 2016). The second period, 2008–2015 represents the post-2008 global financial crisis phase which saw a decline in the global economy where most of the policies focused on getting growth back on track (Burns et al., 2020). Fig. 4.3 shows the boxplots of DF across NUTS 2 regions for the eight emission types relative to rGVA by different time periods.

The DF for the full 1995–2015 data range is shown in red in Fig. 4.3. Here the DF is calculated for 2015 values relative to 1995 as the baseline. Over this time period, one can observe high decoupling where the median values for all the emissions are above 0.5. SO2 shows the strongest decoupling while N2O and NH3 have the lowest median decline in emissions. CO2, NH3, and N2O have a large set of outliers with some NUTS regions even in the negative range indicating coupling.

The two sub-periods show how the intensity of decoupling changes across different time periods. For the first sub-period from 1995–2008, where emission intensity in 2008 is given relative to 1995 (blue box), one can observe that the median decoupling across all emissions is slightly below the full sample. Furthermore, the number of outliers for this time range also go up indicating higher decoupling variation. For the second sub-period 2008–2015 (gray box), where 2015 is relative to 2008, several NUTS 2 regions show coupling, and the median DF values are also closer to zero. PM10, PM2.5, N20, CH4, and NH3, exhibit a large gap between the first and the second sub-period implying that most of the decoupling was achieved before 2008. This is contrast to CO2, which shows that decoupling gains were relatively evenly split between the two time periods. This figure underscores the temporal bias where long time periods hide the underlying developments in decoupling trends. For policy purposes, shorter time spans might be more relevant since they provide a more accurate picture of recent developments.

Fig. 4.4 shows the spatial distribution of the DF for three emissions, CO2, NH3, and PM10, for the whole sample period, and the two sub-periods. The maps for the remaining emissions are provided in Figs. B.3 and B.4. The intensity of blue shows the extent of decoupling (positive values), while the intensity of red shows the extent of coupling (negative values). Gray areas show almost no or very little change in emissions relative to growth. All the maps have some general patterns. Most of the decoupling has taken place in central and northern European countries while the southern and eastern countries tend to show lower levels of relative decoupling or even coupling. Coupling is also clearly visible after 2008.

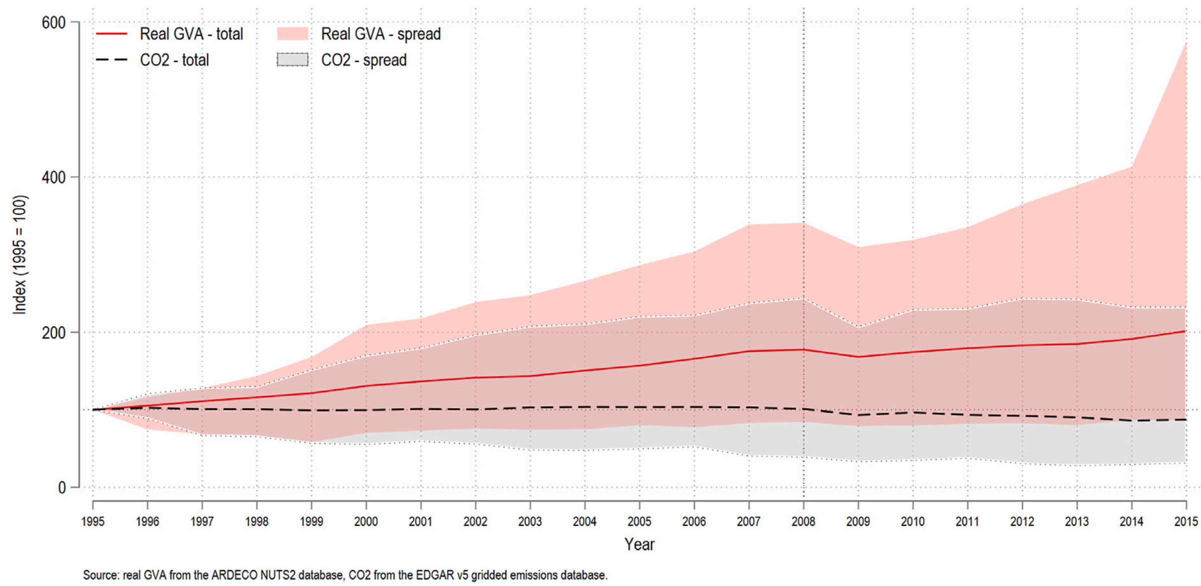


Fig. 4.2. NUTS 2 level variation in rGVA and CO2, 1995–2015.
Source: EDGAR v5 Crippa et al. (2020a) and ARDECO (2020), own calculations

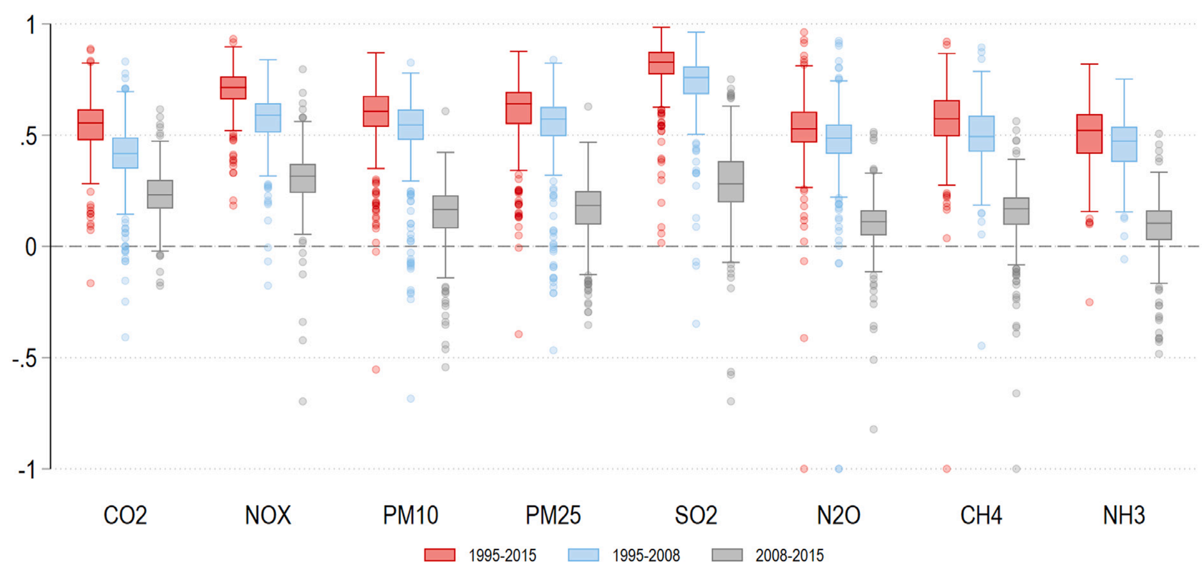


Fig. 4.3. Distribution of the Decoupling Factor (DF) by emissions and real GVA. The figure shows the DF for the three time periods. A value of one indicates decoupling while values below zero implies coupling. The box plots represent the 50th percentile bounded by the 25–75th percentiles, while the whiskers represent the 1–99th percentiles and the dots are the outliers. Few values that are below -1 have been re-coded to -1 for this figure.

5. Regressions

Fig. 5.1 shows a local polynomial fit of the log of emissions versus the log of rGVA for all the data points. This represents estimates of the EKC where the inverted U-shape is clearly visible for NH3, CH4, and N2O. Individual data points for each emission type together with quadratic fits are provided in Fig. B.5. Since lower rGVA regions have higher shares of agriculture and industry sectors (see Fig. 3.1), they also emit more, and are also likely to be more targeted with policies to reduce direct emissions. This potentially explains the decline in the change in emissions in the mid rGVA ranges. As regions continue to become richer, emission levels flatten out or even decline. Potential reasons for this include emission peaking in the mid rGVA range, better enforcement of emissions-related policies, or regions transition to the services sector resulting in a decline in direct emissions.

In order to explain the EKC curves in Fig. 5.1, the role of emission-related policies are explored below. Here the EPS index of greater than 2.5 is defined as a strong policy “treatment” variable. Since EPS is a composite index of several policies, where some policies might be stronger than other in some countries, the argument here is that an overall increase in stringency sends a strong signal to sectors as a whole, and collectively reduces various emissions. Therefore, here we test the joint impact of a set of policies on emission reductions without having to worry about isolating the actual impact of individual policies on individual emissions.

The regression strategy used in this paper to explore the impact of EPS is an event-study design. Event studies are a quasi-experimental method that split the average impact of a treatment on the treated (ATT) across different time periods. This allows us to see how policy interventions evolve over time in a dynamic setting. Recent advancements in event studies stem from newer estimation techniques in

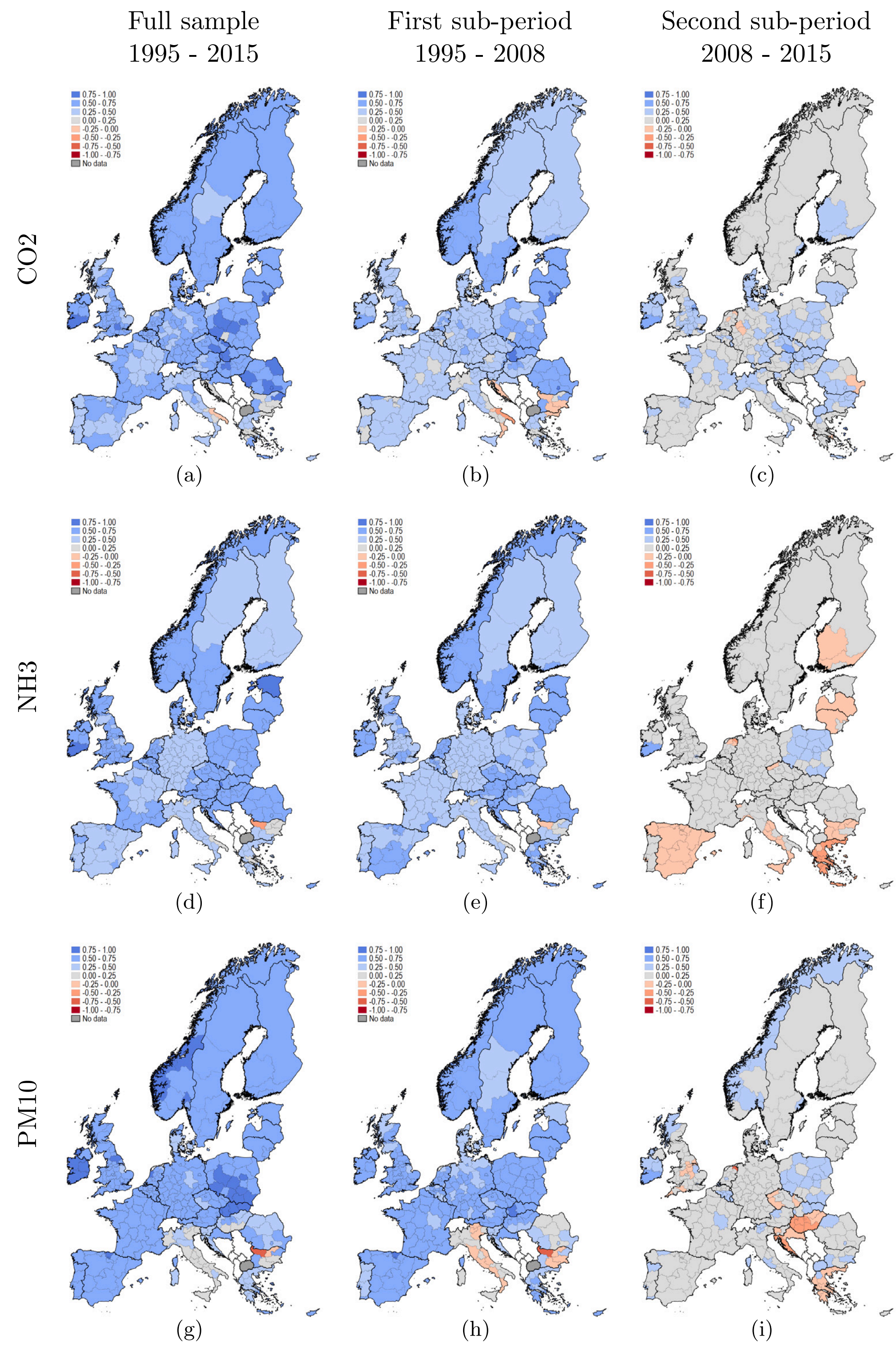


Fig. 4.4. Decoupling of emissions and real GVA by time periods.

difference-in-difference (DiD) methods, that have seen a methodological resurgence in the past year (Schmidheiny and Siegloch, 2019; de Chaisemartin and D'Haultfœuille, 2020; Sant'Anna and Zhao, 2020; Callaway and Sant'Anna, 2020; Abraham and Sun, 2020; Borusyak et al., 2021; Cunningham, 2021; Roth and Sant'Anna, 2021). This new literature starts of by criticizing the canonical DiD model which has two time periods (pre and post), two groups (one control and one treatment), and the outcome is the change in treatment group over time compared less the change in the control group over time. Due to time and unit controls, the classical DiD is also referred to as a Two-way Fixed Effects (TWFE) model. The 2 × 2 TWFE model can also be extended to multiple time periods and units where some units get a treatment. Two key assumptions for the TWFE model to work is that, (a) in the baseline pre-treatment period, the treatment and control groups should exhibits parallel trends to make them comparable, and (b), the intervention across all the units should takes place at the same point in time. Both of these assumptions are unlikely to hold in real world applications. Different unit-specific covariates can also impact trends and real-world interventions are rarely simultaneously rolled out across the treatment units. While there has been innovations in

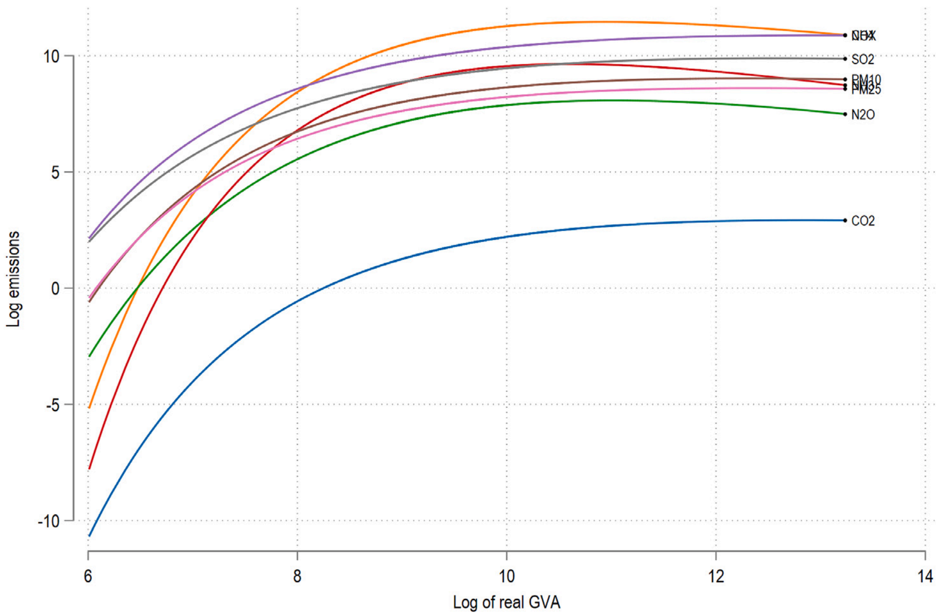


Fig. 5.1. Trend of emissions versus real GVA.

literature on correcting for the parallel trends, for example by using inverse probability weights and imputation methods (Abadie, 2005), methodological innovations dealing with differential timings are very recent and are still evolving.

Several papers, most of which came out in the late 2020 and early 2021, have shown that TWFE estimators in the case of differential treatment timings are biased often resulting in negative weights that can influence the magnitude and even the direction of the coefficients of interest (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sant'Anna and Zhao, 2020; Gardner, 2021). To understand these biases, Goodman-Bacon (2021) proposes a Bacon Decomposition method that derives weights of different treatment "timing cohorts". The timing cohorts are determined by the time of the first intervention across different units. Since treatment across different units roll out over time, the treated unit in a time cohort are compared to combinations of "never-treated" and "already-treated" units. Therefore, for each time cohort, a 2×2 DiD estimator is calculated and the coefficients are recovered together with the weight of each cohort based on the cohort's size and duration. These weights determine the influence of each time cohort on the overall TWFE estimates and can be used to recover the "correct" average treatment effect on the treated (ATT).

Since the early version of the Goodman-Bacon (2021) paper, several innovations have been proposed to correct for the biases arising from negative weights. These include stacking treatments by re-centering the panel on the year of the first treatment (Dube, 2019; Cengiz et al., 2019), generating influence functions and utilizing probability weights (Sant'Anna and Zhao, 2020; Callaway and Sant'Anna, 2020), estimating bootstrapped confidence intervals after correcting for time cohort weights (de Chaisemartin and D'HaultfŒuille, 2018; de Chaisemartin and D'Haultfœuille, 2020), and utilizing synthetic controls and multiple imputations (Liu et al., 2020; Borusyak et al., 2021). Since these methods are very recent, applications are also extremely limited especially in the environmental economics literature. The only exceptions found were Hsiang and Jina (2014), Hsiang (2016) and Berlemann and Wenzel (2018) that analyze climate shocks but rely on the classic TWFE model.

For this paper, the method developed in Borusyak et al. (2021), and applied in von Bismarck-Osten et al. (2021) is utilized. Two main reasons to use this estimator is that it specially focuses on event study design and allows for time varying controls. Furthermore, it also corrects for parallel trends in the pre-treatment groups using imputation methods, a novel innovation that makes DiD estimates highly robust.

To estimate the impact of environmental policies, the following DiD specification is used:

$$Ln(Emm)_{it} = \alpha_i + \theta_{it} + Year_t + \gamma_{it} EPS_{it} + \theta_{it} + \epsilon_{it} \tag{2}$$

where $Ln(Emm)_{it}$ are the log of emissions for a NUTS 2 region i at time t. The intercept α_i represents NUTS 2-specific trends. Unit specific controls are represented by θ_{it} which include log of rGVA ($Ln(rGVA)_{it}$), share of industry (s^{ind}_{it}) and share of agriculture (s^{agr}_{it}) sectors in rGVA. The broad controls are selected for two reasons. First, emissions are driven by real output as also shown in Fig. 5.1. Second, higher shares of agriculture and industry are primarily responsible for direct emissions and as Fig. B.2 shows, these shares are not highly correlated with output levels. Year fixed effects, $Year_t$, control for time-varying trends including changes in emissions caused by the 2008 financial crisis. The third coefficient γ_{it} is the coefficient of interest on the intervention variable EPS_{it}. This treatment variable equals one if $EPS \geq 2.5$ and 0 otherwise. Here we assume that once a unit cross the threshold of $EPS \geq 2.5$, it is labeled as treated and stays treated.[7] Here a key assumption of DiD models is that once the treatment takes place, it is not rolled back. We indeed see this from Fig. 3.5 as well. Furthermore, since EPS policies are at the country level, the standard errors are also clustered at the country level.

The above DiD model recovers ATT in the γ_{it} parameter, which is essentially a weighed sum of treated versus not-yet-treated and already-treated groups for different time cohorts. Therefore, an event study design, or a dynamic specification of Eq. (2), of the following form can be recovered:

$$Ln(Emm)_{it} = \alpha_i + \theta_{it} + Year_t + \sum_{t=-4}^{-1} \gamma_{it} EPS_{it} + \sum_{t=0}^{6} \gamma_{it} EPS_{it} + \epsilon_{it} \tag{3}$$

Due to the limited data range, four leads and six lags are estimated. Here the parameter γ_{i0} is the year when the treatment was

[7] Variations of DiD models where units can move in and out of treatments and are subjected to varying degrees of treatment levels are currently being developed to correctly capture the ATT. The only exception is de Chaisemartin and D'Haultfœuille (2020).

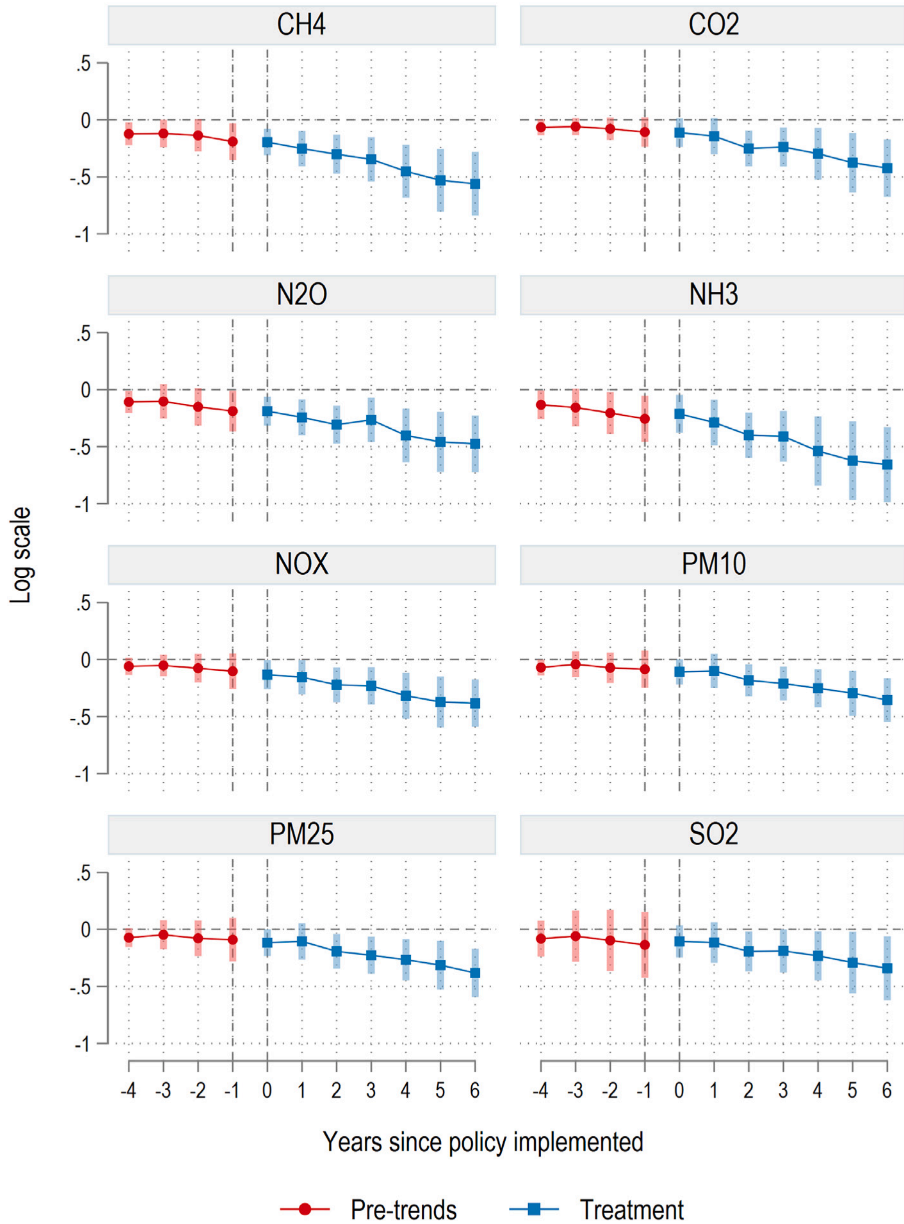


Fig. 5.2. Event study of the impact of environmental policies on emissions. Note: The event study figures isolate the cumulative impact of policies on emissions. Significance of policies is determined by deviation away from no-impact zero line on the *y*-axis. If the standard error bands are fully below zero, then the impact is highly significant.

first introduced, and is used as a reference period for pre and post treatment impacts. The pre-treatment years, or leads, should ideally be insignificant or clustered around zero, and the post-treatment years, or lags, should ideally be significant and negative to show that the policies work. If the leads are significantly different from zero, then they violate the parallel trend assumption implying that other factors, not captured by the specification in Eq. (2), might be influencing the changes in emissions. Regardless, it is still interesting to observe significant changes in the slopes among the leads and lags.

Fig. 5.2 presents the event study results where the *y*-axis show the change in the log of emissions and therefore capture reduction in levels resulting from policies after controlling for unit and time fixed effects and other covariates. The leads are mostly clustered around zero with some emissions like CH4 and NH3 exhibiting some evidence of pre-existing trends. Post intervention ($t \geq 0$), all emission levels go down implying that strong policies work. According to Fig. 5.2, NOX, PM10 and PM2.5 show the strongest decline. CO2 and N2O decline three to four years after strong policies are implemented. The weakest decline is in SO2 with policy impacts only visible after five to six years. Since SO2 has already seen a large decline since 1995 (Fig. 4.1), environmental policies probably have little direct impact.

Fig. 5.2 can also be summarized in terms of cumulative impacts where the coefficients from the regressions are recovered as follows:

$$\Gamma_T = \sum_{t=1}^{T} \gamma_t \tag{4}$$

Eq. (4) represents a linear combination of the γ coefficients and standard errors. Cumulative impacts are shown in Table 5.1. CH4, N20, and NH3 respond strongly to policies and decline continuously across the regions. In contrast, CO2, NOX, PM10, PM2.5 show a decline two years after policies are implemented while SO2 shows the weakest response.

As discussed earlier, regions vary significantly by rGVA and agriculture and industrial shares. In order to explore these variations, the data is split into high and low income regions using rGVA per capita. Regions

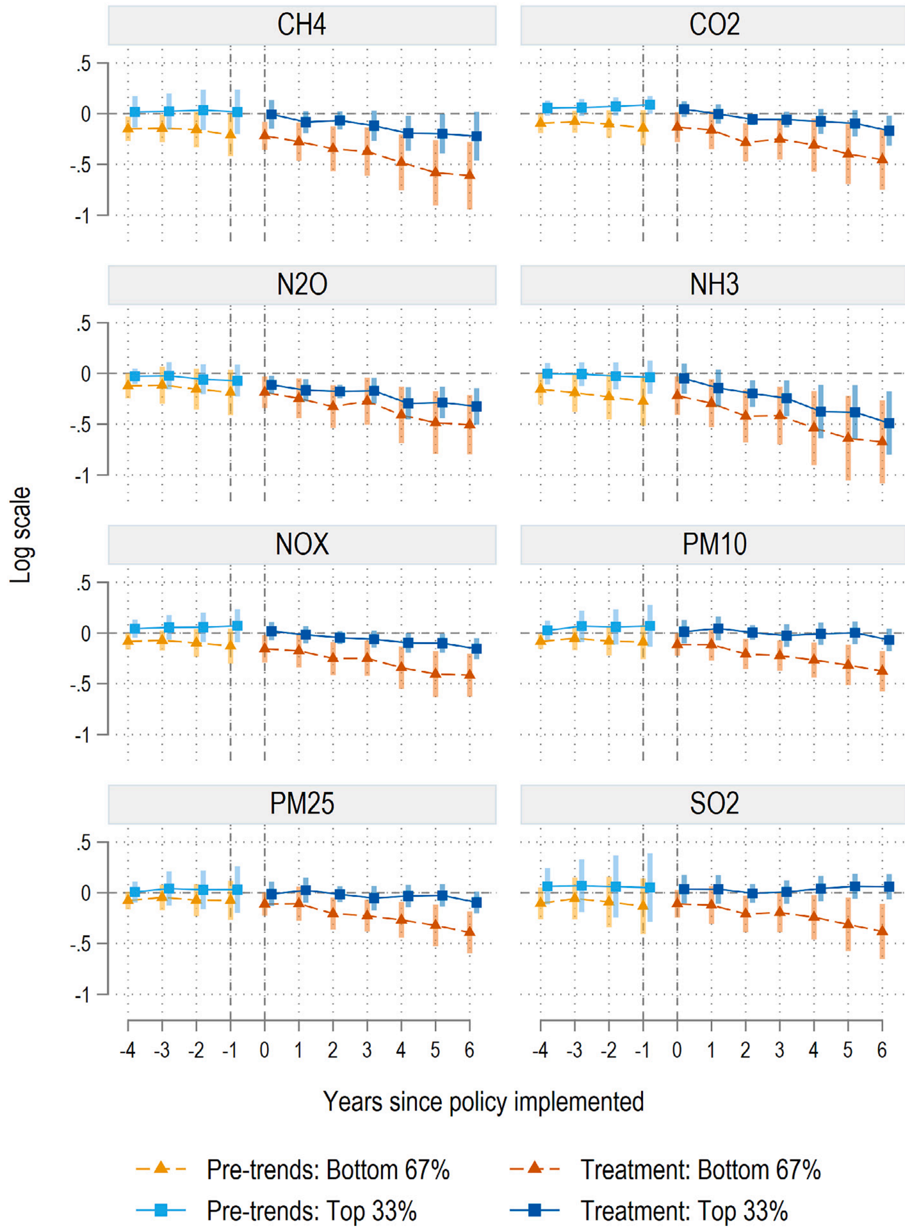


Fig. 5.3. Event study by income groups. Note: The event study figures isolate the cumulative impact of policies on emissions. Significance of policies is determined by deviation away from no-impact zero line. If the error bars or bands are fully below or above zero, then the impact is highly significant. Significance levels for overall policy-related emission reductions are given in Table 5.1.

Table 5.1
Cumulative impact of EPS on emissions.

	(1) CH4	(2) CO2	(3) N2O	(4) NH3	(5) NOX	(6) PM25	(7) PM10	(8) SO2
1 year after	-0.240^{**}	-0.133	-0.231^{**}	-0.278^{**}	-0.132	-0.082	-0.083	-0.077
	(0.077)	(0.082)	(0.081)	(0.108)	(0.073)	(0.078)	(0.075)	(0.082)
2 years after	-0.289^{***}	-0.240^{**}	-0.294^{***}	-0.389^{***}	-0.195^{*}	-0.167^{*}	-0.164^{*}	-0.150
	(0.085)	(0.079)	(0.086)	(0.107)	(0.076)	(0.073)	(0.069)	(0.081)
4 years after	-0.432^{***}	-0.281^{*}	-0.383^{**}	-0.526^{**}	-0.277^{**}	-0.228^{**}	-0.225^{**}	-0.169
	(0.116)	(0.118)	(0.122)	(0.165)	(0.100)	(0.087)	(0.084)	(0.099)
6 years after	-0.537^{***}	-0.403^{**}	-0.453^{***}	-0.642^{***}	-0.335^{**}	-0.336^{***}	-0.324^{***}	-0.268^{*}
	(0.139)	(0.128)	(0.127)	(0.176)	(0.103)	(0.099)	(0.093)	(0.131)

Note: Cumulative impact of EPS on emissions after controlling for region and year fixed effects, rGVA, and agriculture and industry shares. Standard errors are clustered at the country level. *** $p<0.001$, ** $p<0.01$, * $p<0.1$.

are distinguished between the NUTS 2 in the top one-third percentile versus the bottom two-third using 2015 observations.

Fig. 5.3 shows the results of the event study by top and bottom income groups. There is a clear split across the two income categories. For the top one-third regions by income, strong declines are visible

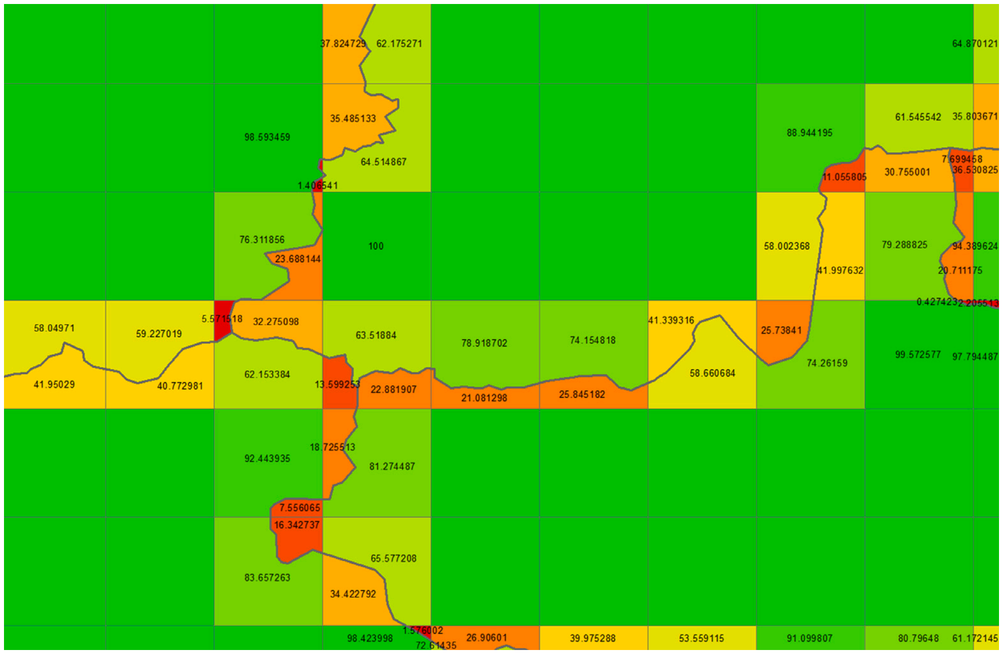


Fig. A.1. Splitting grids across boundaries. Note: Overlap of emission grids and NUTS 2 boundaries. The numbers reflect the percentage share of the area that is split by the administrative boundaries.

for N20 and NH3, while CO2 and NOX show a weak policy response. This could be driven by the fact that these regions have low levels of direct emissions to begin with, or they have achieved some stability in emission reductions where further reductions are most likely not easily achievable. Further exploration is needed to better understand these patterns. For the bottom two-third income regions, policies play a major role, resulting in strong a decline across all emissions within one to two years of policy implementation. The large standard error bars also indicate significant variations in regional response.

In order to conduct robustness checks, Fig. C.1 conducts a Bacon Decomposition on the impact of EPS on emissions using the basic TWFE model. The figure clearly show that different treatment cohorts result in negative weights that can result in biased estimates. To see these biases, Fig. C.2 compares the DiD events study plots from Borusyak et al. (2021) with the standard TWFE results. Here we can see that the TWFE grossly underestimate the impact of the policies, showing that they have no effect at all on emissions reduction.

6. Discussion, gaps, and steps for future research

Economic activity results in increased environmental pressures including generating various types of emissions. In recent years, a growing body of literature has explored whether there is evidence of decoupling of emissions from economic output. The consensus in literature is that direct production or territorial-based emissions usually show relative decoupling while absolute decoupling has been an elusive target so far. Two broad gaps exist in this literature. First, the focus on assessing outcomes is usually at a country or a multi-country level where sub-national regional variations are not discussed. Second, on the emissions side, the focus remains on CO2 even though other harmful emissions also need a careful evaluation. In order to address these points, this paper constructs a unique dataset at the sub-national NUTS 2 level for countries in the EU. The economic data is taken from ARDECO (2020) that provides a host of homogenized economic indicators at the NUTS 2 level. Data for eight emission types; CO2, N20, CH4, NH3, NOX, PM10, PM2.5, and SO2, is extracted from EDGAR v5 grid-level database (Crippa et al., 2020a). Both datasets are combined to form a fully balanced panel from 1995–2015.

Descriptive results show that there are significant variations in decoupling trends both within and across NUTS 2 regions. Furthermore, trends show that most of the decline in emissions occurred before the 2008 financial crisis. Post-2008, there is a significant slow down in emission reductions where some regions show very weak decoupling or even coupling. Therefore, if economic recovery is given precedence over emission reductions, then events like COVID-19 could also potentially undermine emission targets.

The next part of the analysis looks at how the Environmental Policy Stringency (EPS) (OECD, 2018), a composite index of emissions-related market and non-market policies, impacts the development of various emissions after controlling for real output, agriculture and industry sector shares, and time fixed effects. By using an event study design, the analysis shows that most of the emissions react to strong policies although the speed of response and the extent of the decline varies by emission type. For example, CH4 and N2O decline sharply while CO2, PM10 and PM2.5 are slower to respond. If the NUTS 2 are split between top one-third and bottom two-third income per capita regions, then one can also observe that the bottom regions react strongly and immediately to policies across all emission types. The high-income regions only show a small decline in NH3, N2O with a weak response from CH4 and CO2. This outcome is also corroborated from the regional Environmental Kuznets Curves (EKCs) which show that emission levels are positively correlated with lower income regions but flatten out at higher income levels, and only a few emissions show a turning point. A potential reason is higher dependence on agriculture and industry activity in lower income regions resulting in an increase in emissions. Thus these regions are also likely to respond strongly to stringent emission policies. At higher income levels, regions are likely to transition towards service sectors and therefore environmental policies might have little impact. These explanations need further investigation.

While the results show that emission policies in European regions work, additional analysis can be easily conducted using the ARDECO and EDGAR datasets. For example, the analysis can be extended to a

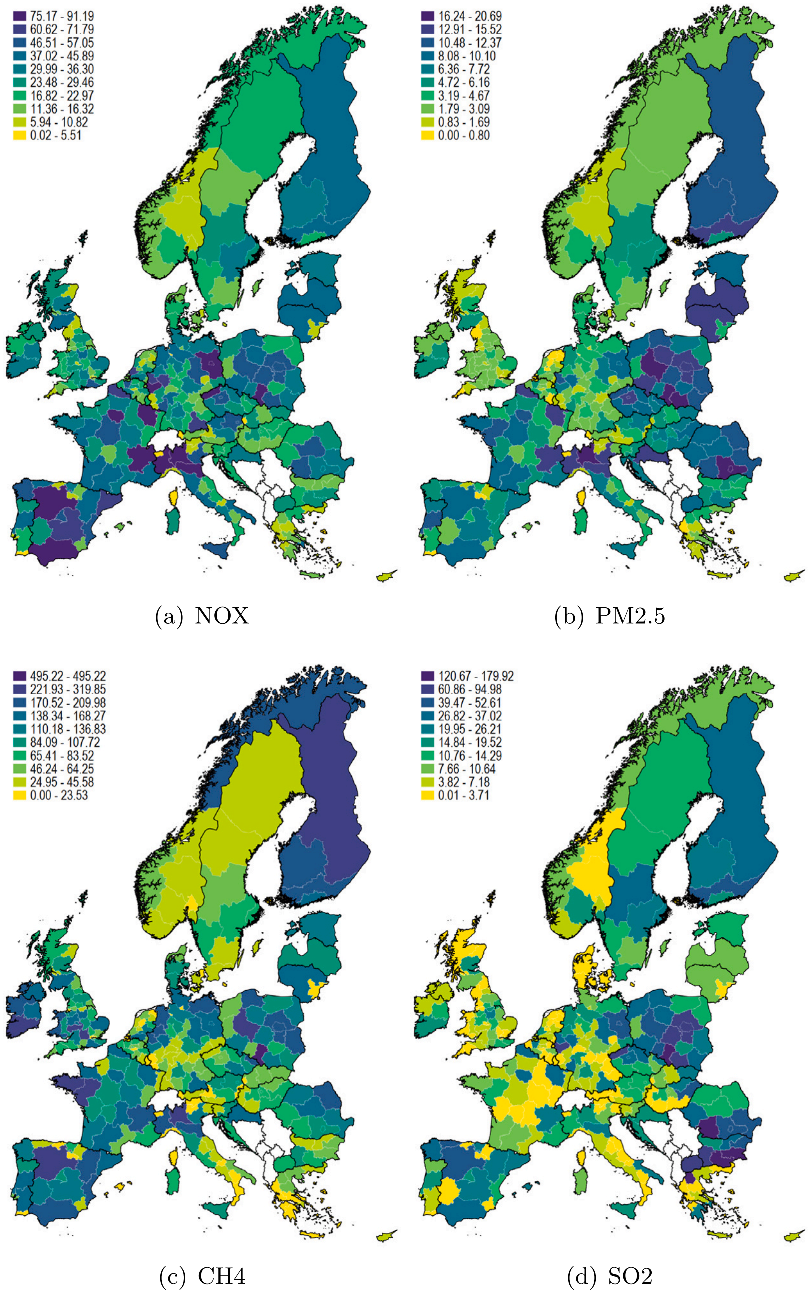


Fig. B.1. Emission trends for 2015. *Source:* EDGAR v5 (Crippa et al., 2020a). Emissions are given in thousand tons. K-mean clusters used to determine groups.

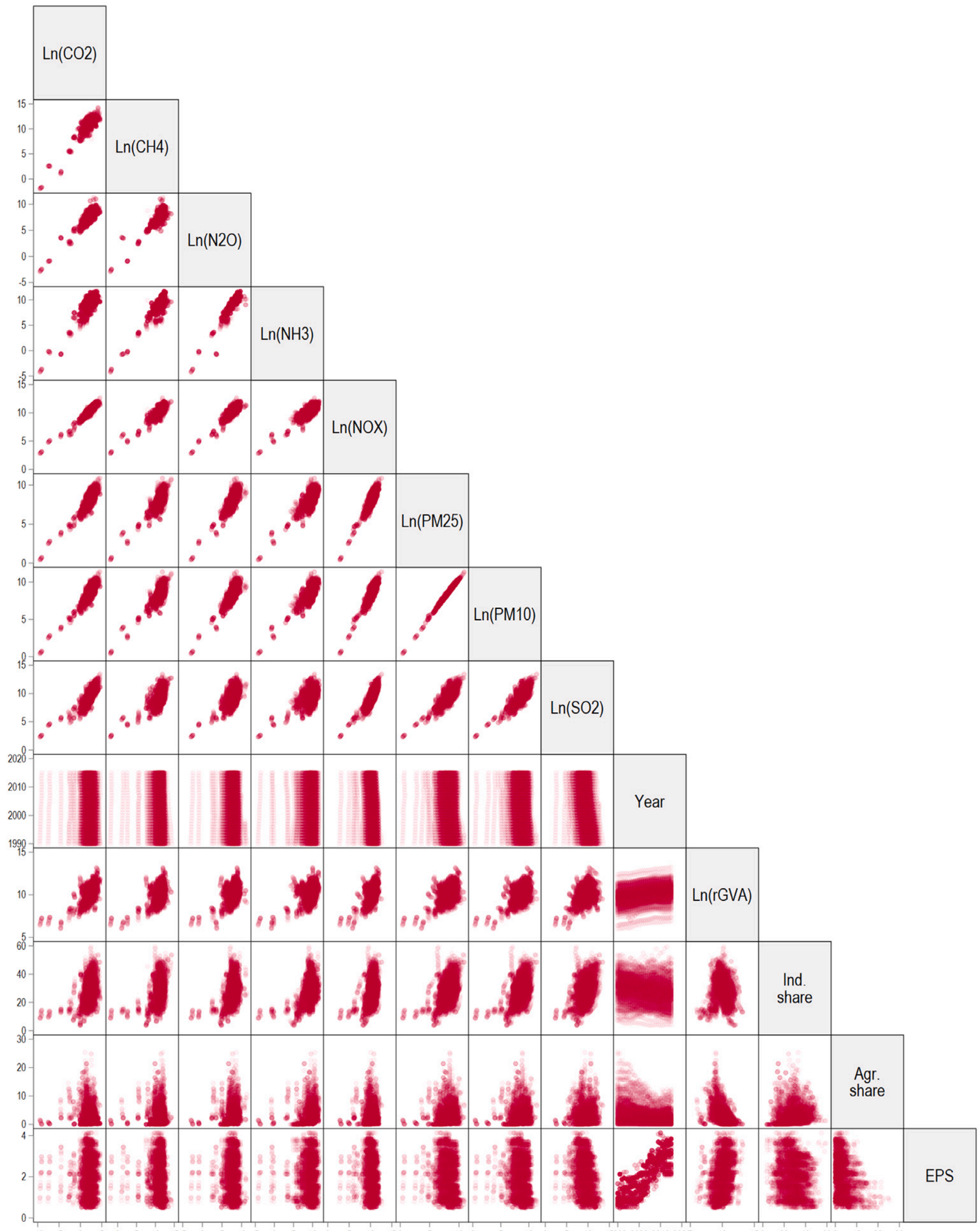


Fig. B.2. Matrix plot of various variables.

more detailed look at sector-specific activities that cause direct emissions. The EDGAR database also contains grid-level information on different air emission sectors that can be mapped on to various sector-specific economic activities for a more nuanced analysis. Additionally, the impact of environmental policies on socioeconomic variables can also be explored in detail. For example, one can go much deeper in understanding the impact of environmental policies on investment levels, labor market developments, demographic changes, and other well-being indicators. Most of these variables are easily accessible at the NUTS 2 level from ARDECO and the Eurostat. The EDGAR data can be utilized to identify how emissions and pollutants co-evolve spatially and temporally to help calculate the co-benefits of reducing key emissions (Zwickl et al., 2014; Boyce et al., 2016). Last, since these datasets are now regularly updated, the impact of more recent events like the COVID-19 and the impact of newer policies, like the Green New Deal, can be analyzed using the methods proposed in this paper.

The analysis presented in this paper also raises several new questions for future research. First, while the paper shows that environmental policies work, a discussion of the channels that cause these emissions to decline needs further evaluation. Regional analysis of environmental policies and emissions can also take a deeper look at institutional structures, changes in technologies, and shifts in sectoral compositions, and spillovers. For example, the role of European regional development funds, especially Cohesion Funds and Objective 1 funding (Becker et al., 2010, 2018), can be explored since they specify both the conditions for reducing emissions and simultaneously motivate large physical infrastructure investments that result in emissions (Delbeke and Vis, 2016). Second, the role of the geographic distribution of large emitters needs to be evaluated in terms of understanding the trade-offs between emissions reduction policies and economic development indicators like growth, employment, and investment levels. This might be more relevant for regions with a few high-polluting

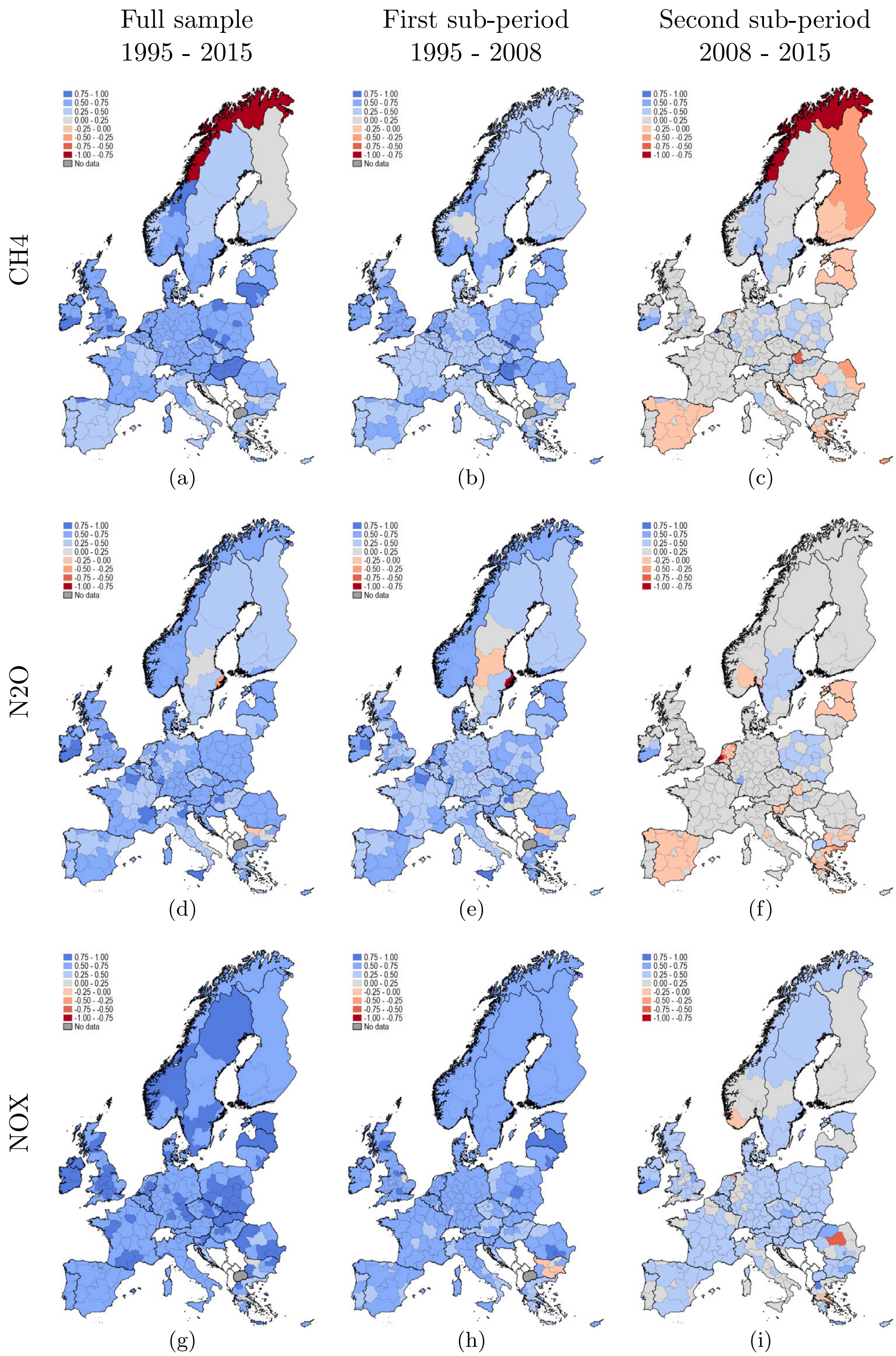


Fig. B.3. Decoupling of emissions and real GVA by time periods.

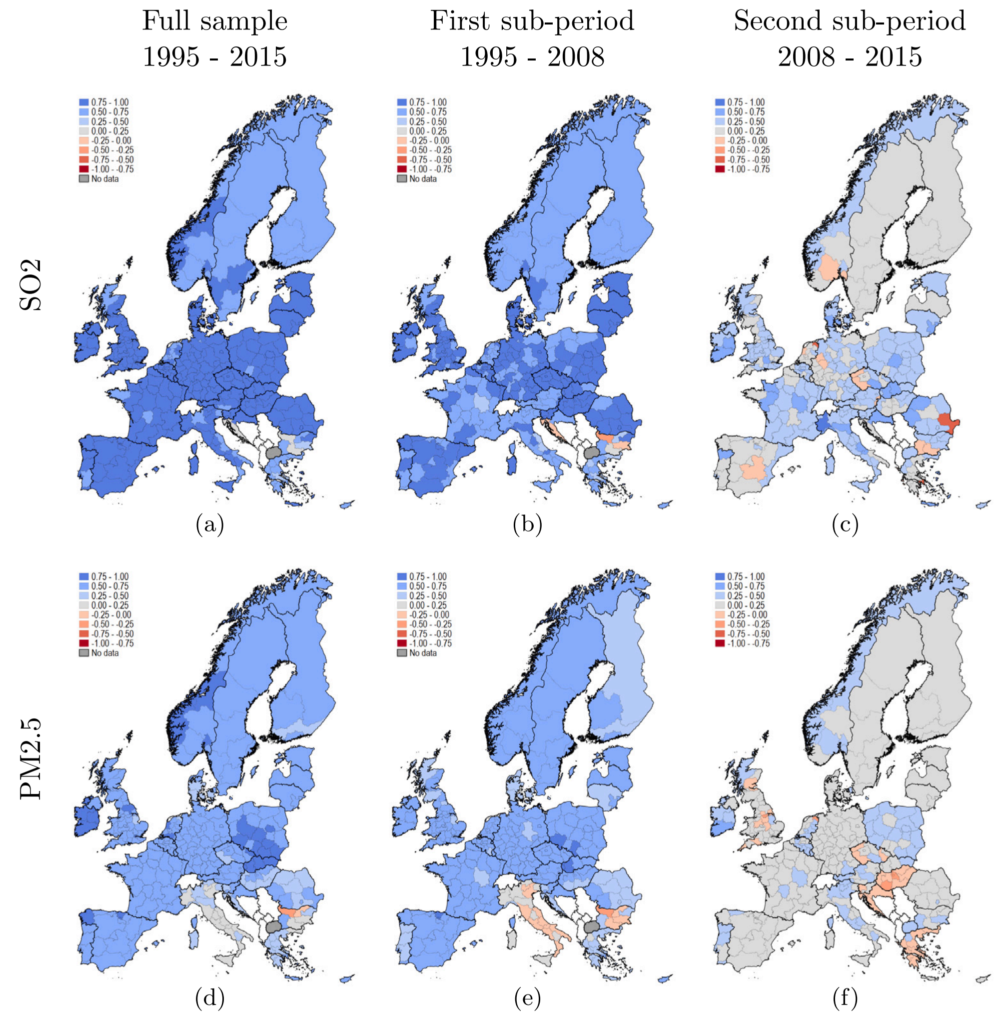


Fig. B.4. Decoupling of emissions and real GVA by time periods.

employers. And last, emission policies in one place can also affect other regions via value chains. Within EU regional spillovers can be analyzed using recently compiled regional input–output datasets (Lecca, P., Barbero, J., Christensen et al., 2018). Similarly impacts on upstream or downstream global values chains can be evaluated using recently available multi-region input–output (MRIO) tables (Maus et al., 2020). Such an analysis can also help identify carbon leakages, where strong environmental policies can force high-polluting firms to relocate, or outsource production, to regions with fewer regulations (Chitnis et al., 2014). Lastly, further decoupling analyses can benefit from fine-grained datasets and well-identified causal mechanisms that can better help inform policies for the heterogeneous EU regions.

CRediT authorship contribution statement

Asjad Naqvi: Conceptualization, Methodology, Data curation, Visualization, Investigation, Writing and editing original and revised draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Emission grids to NUTS 2 mapping

In order to combine the economic and the emission layers, EDGAR grids are overlaid with NUTS 2 boundaries, and the map projections of both layers are homogenized. For this study, the standard European ETRS 1989 LAEA coordinate system is used.

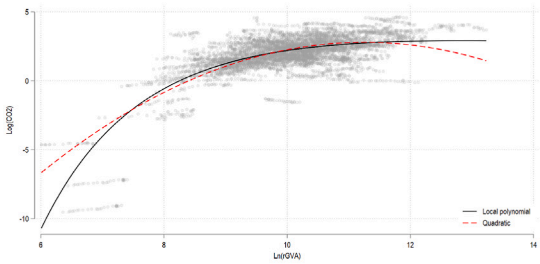
As shown in Fig. A.1, NUTS 2 administrative boundaries cut across the grids. Grids that split across two or more regions are split up based on the percentage share of the area that falls within NUTS 2 administrative boundaries. Since all the emission grids overlay perfectly, this exercise needs to be only done once to generate a grid-to-NUTS 2 crosswalk to allow the two datasets to merge. Using this crosswalk, the grid-level emissions data is aggregated to NUTS 2 regions as shown in Fig. 3.3.

Appendix B. Additional figures

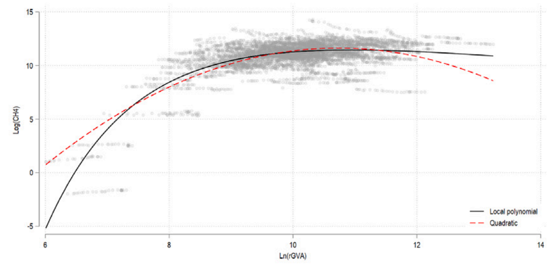
See Figs. B.1–B.5.

Appendix C. DiD versus TWFE estimates

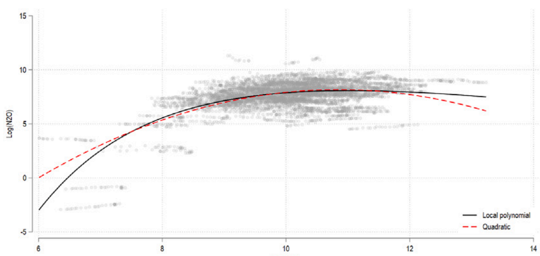
See Figs. C.1 and C.2.



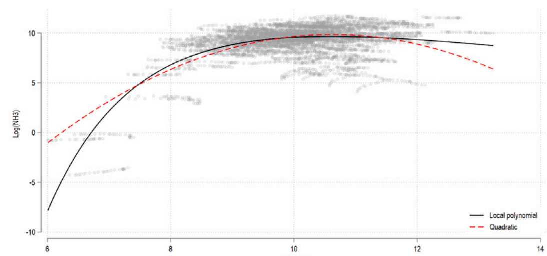
(a) CO2



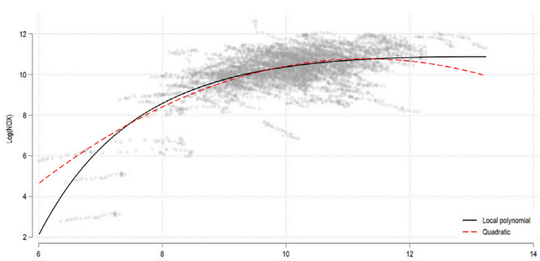
(b) CH4



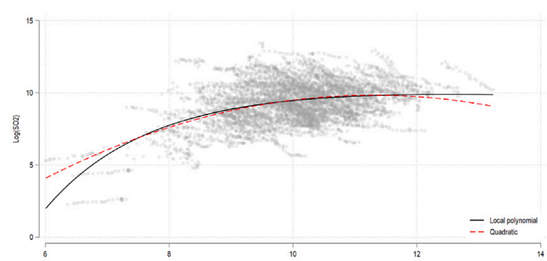
(c) N2O



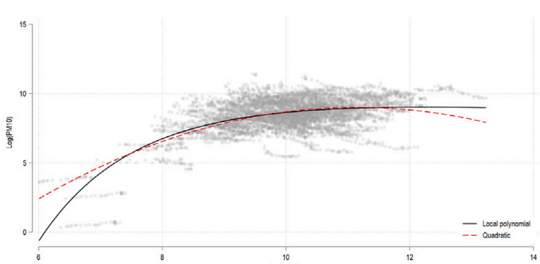
(d) NH3



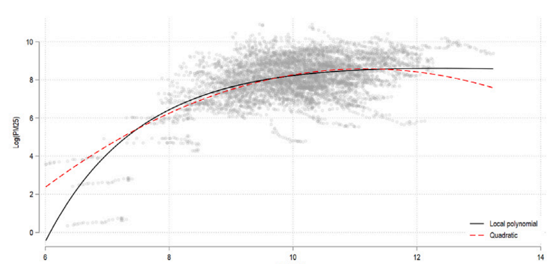
(e) NOX



(f) SO2

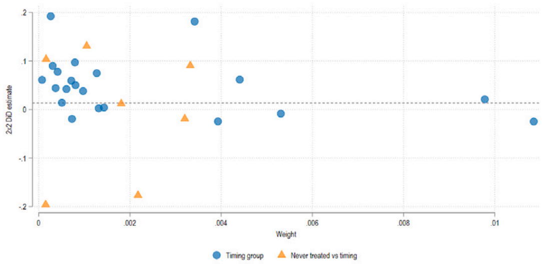


(g) PM10

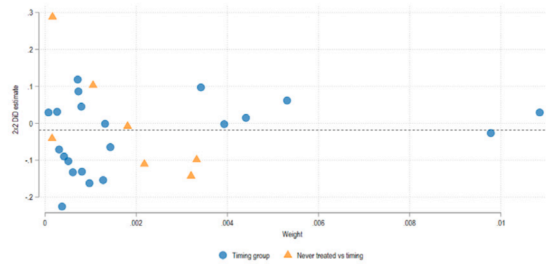


(h) PM2.5

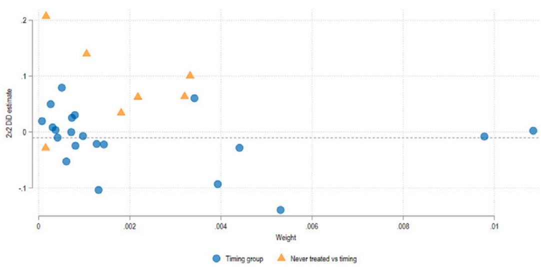
Fig. B.5. Emissions and output. Note: The local polynomial functions have a tighter fit than a quadratic function which by definition needs to have a turning point. Therefore an inverted U-shape in a local polynomial fit is a strong indicator of an EKC turning point.



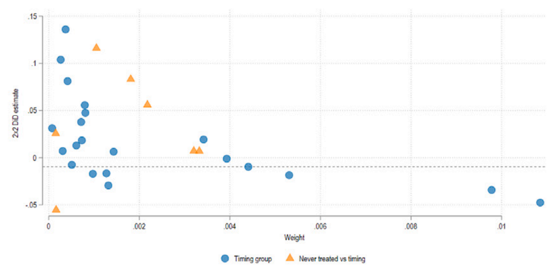
(a) CO2



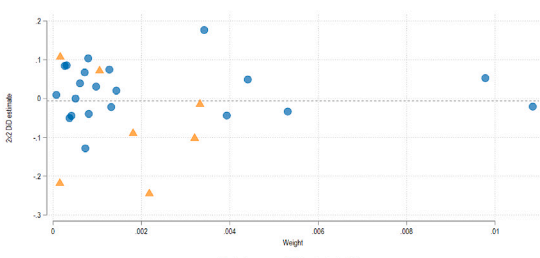
(b) CH4



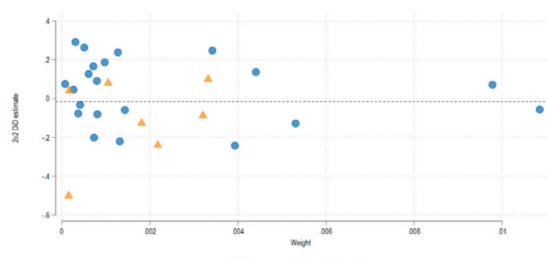
(c) N2O



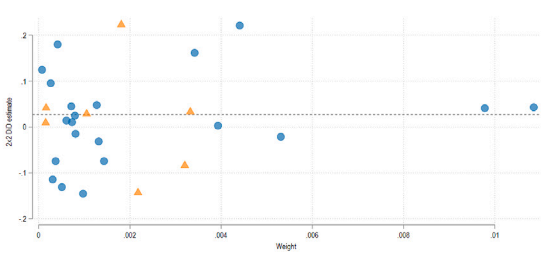
(d) NH3



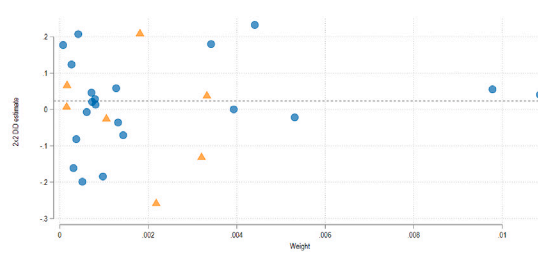
(e) NOX



(f) SO2

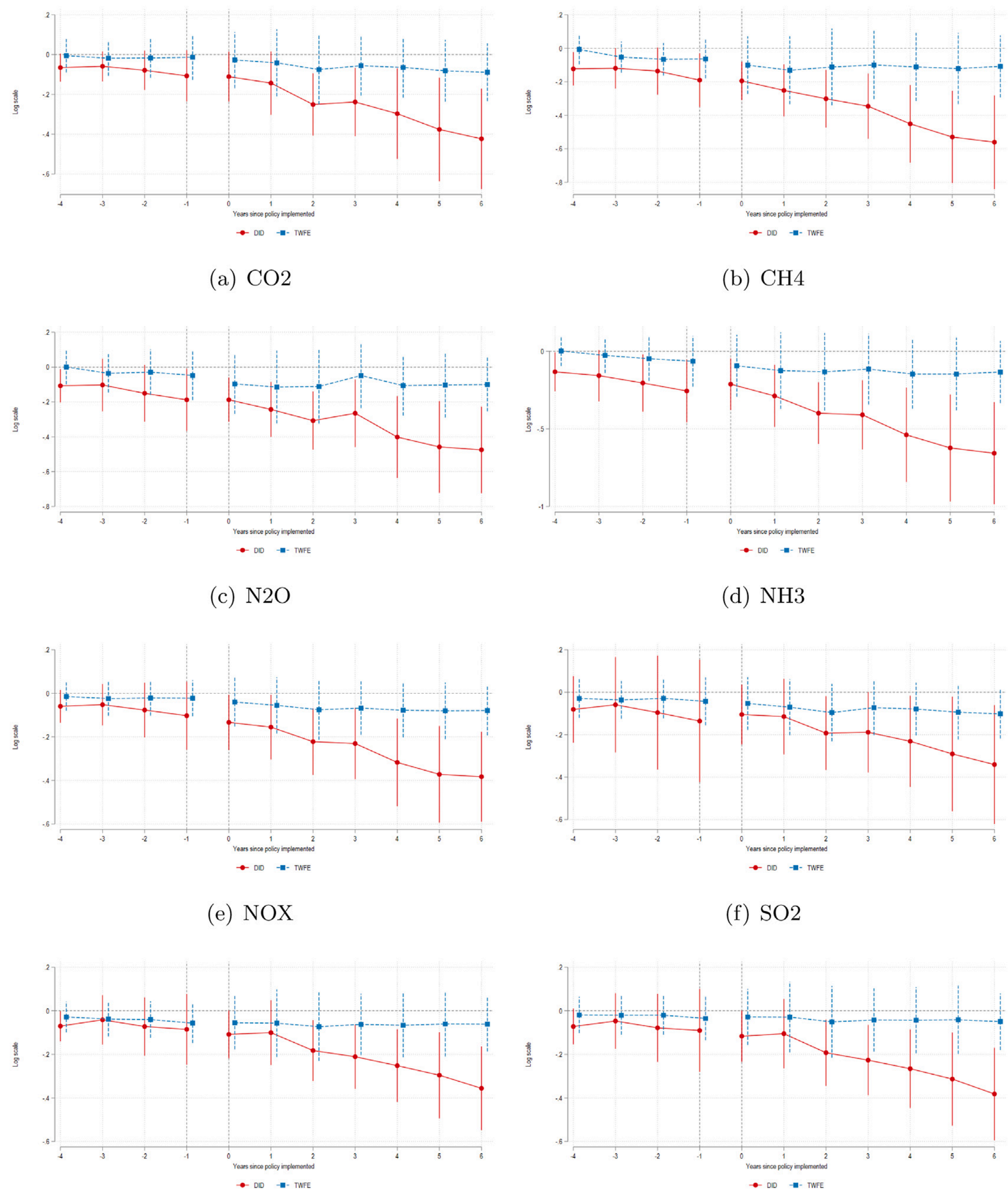


(g) PM10



(h) PM2.5

Fig. C.1. Bacon decomposition. Note: The *y*-axis shows the value of each timing cohort, and treated versus never treated groups in relation to the overall ATT effect. The *x*-axis shows the weight of each estimate. The higher the weight, the higher it will impact overall ATT estimates.



(a) CO2 (b) CH4

(c) N2O (d) NH3

(e) NOX (f) SO2

(g) PM10 (h) PM2.5

Fig. C.2. TWFE versus DiD event study plots. Note: The dotted blue lines show the classical DiD estimators which are all clustered around zero indicating that the method completely underestimates the impact of policies. These results can also be compared with the solid red lines which give DiD estimates using the Borusyak et al. (2021) method.

References

Abadie, A., 2005. Semiparametric difference-in-differences estimators. Rev. Econom. Stud. 72 (1), 1–19. http://dx.doi.org/10.1111/0034-6527.00321, URL: https://academic.oup.com/restud/article-lookup/doi/10.1111/0034-6527.00321.

Abraham, S., Sun, L., 2020. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. SSRN Electr. J http://dx.doi.org/10.2139/ssrn.3158747, URL: https://www.ssrn.com/abstract=3158747.

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The environment and directed technical change. Amer. Econ. Rev. 102 (1), 131–166. http://dx.doi.org/10.1257/aer.102.1.131, URL: http://pubs.aeaweb.org/doi/abs/10.1257/aer.102.1.131.

Akizu-Gardoki, O., Bueno, G., Wiedmann, T., Lopez-Guede, J.M., Arto, I.n., Hernandez, P., Moran, D., 2018. Decoupling between human development and energy consumption within footprint accounts. J. Cleaner Prod. 202, 1145–1157. http://dx.doi.org/10.1016/j.jclepro.2018.08.235, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652618325848.

ARDECO, 2020. Annual Regional Database of the European Commission. European Commission, URL: https://ec.europa.eu/knowledge4policy/territorial/ardeco-online{_}en.

Bacon, R.W., Bhattacharya, S., 2007. Growth and CO2 emissions: How do different countries fare? In: World Bank Environment Department Papers. 1, (113).

Baiocchi, G., Minx, J.C., 2010. Understanding changes in the uk's co2 emissions: A global perspective. Environ. Sci. Technol. 44 (4), 1177–1184. http://dx.doi.org/10.1021/es902662h, URL: https://pubs.acs.org/doi/10.1021/es902662h.

Bampatsou, C., Halkos, G., 2019. Economic growth, efficiency and environmental elasticity for the G7 countries. Energy Policy 130, 355–360. http://dx.doi.org/10.1016/j.enpol.2019.04.017, URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421519302563.

Becker, S.O., Egger, P.H., von Ehrlich, M., 2010. Going nuts: the effect of eu structural funds on regional performance. J. Public Economics 94 (9–10), 578–590. http://dx.doi.org/10.1016/j.jpubeco.2010.06.006, URL: http://dx.doi.org/10.1016/j.jpubeco.2010.06.006.

Becker, S.O., Egger, P.H., von Ehrlich, M., 2018. Effects of eu regional policy: 1989–2013. Reg. Sci. Urban Econ. 69 (November 2017), 143–152. http://dx.doi.org/10.1016/j.regsciurbeco.2017.12.001, URL: https://doi.org/10.1016/j.regsciurbeco.2017.12.001.

Beltrán-Esteve, M., Picazo-Tadeo, A.J., 2017. Assessing environmental performance in the European union: Eco-innovation versus catching-up. Energy Policy 104, 240–252. http://dx.doi.org/10.1016/j.enpol.2017.01.054, URL: https://linkinghub.elsevier.com/retrieve/pii/S030142151730071X.

van den Bergh, J.C., Kallis, G., 2012. Growth, a-growth or degrowth to stay within planetary boundaries? J. Economic Issues 46 (4), 909–920. http://dx.doi.org/10.2753/JEI0021-3624460404, URL: https://www.tandfonline.com/doi/full/10.2753/JEI0021-3624460404.

Berlemann, M., Wenzel, D., 2018. Hurricanes, economic growth and transmission channels. World Dev. 105, 231–247. http://dx.doi.org/10.1016/j.worlddev.2017.12.020, URL: https://linkinghub.elsevier.com/retrieve/pii/S0305750X17304138.

von Bismarck-Osten, C., Borusyak, K., Schoenberg, U., 2021. The role of schools in transmission of the sars-cov-2 virus: quasi-experimental evidence from germany. Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London, URL: https://econpapers.repec.org/RePEc:crm:wpaper:2022.

Borozan, D., 2018. Technical and total factor energy efficiency of european regions: a two-stage approach. Energy 152, 521–532. http://dx.doi.org/10.1016/j.energy.2018.03.159, URL: https://linkinghub.elsevier.com/retrieve/pii/S0360544218305681.

Borusyak, K., Jaravel, X., Spiess, J., 2021. Revisiting event study designs: robust and efficient estimation. In: University College London Working Paper. pp. 1–48.

Botta, E., Koźluk, T., 2014. Measuring environmental policy stringency in OECD countries. In: OECD Economics Department Working Papers No. 1177. p. 47. http://dx.doi.org/10.1787/5jxrjnc45gvg-en.

Boyce, J.K., Zwickl, K., Ash, M., 2016. Measuring environmental inequality. Ecol. Econom. 124, 114–123. http://dx.doi.org/10.1016/j.ecolecon.2016.01.014, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800916301264.

Brunel, C., Levinson, A., 2013. Measuring environmental regulatory stringency. In: OECD Trade and Environment Working Papers. http://dx.doi.org/10.1787/5k41t69f6f6d-en.

Burns, C., Eckersley, P., Tobin, P., 2020. EU Environmental policy in times of crisis. J. Eur. Public Policy 27 (1), 1–19. http://dx.doi.org/10.1080/13501763.2018.1561741, URL: https://www.tandfonline.com/doi/full/10.1080/13501763.2018.1561741.

Callaway, B., Sant'Anna, P.H., 2020. Difference-in-differences with multiple time periods. J. Econometrics http://dx.doi.org/10.1016/j.jeconom.2020.12.001, URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407620303948.

Carson, R.T., 2010. The environmental kuznets curve: seeking empirical regularity and theoretical structure. Rev. Environ. Econ. Policy 4 (1), 3–23. http://dx.doi.org/10.1093/reep/rep021, URL: https://www.journals.uchicago.edu/doi/10.1093/reep/rep021.

Cengiz, D., Dube, A., Lindner, A., Zipperer, B., 2019. The effect of minimum wages on low-wage jobs*. Q. J. Econ. 134 (3), 1405–1454. http://dx.doi.org/10.1093/qje/qjz014, URL: https://academic.oup.com/qje/article/134/3/1405/5484905.

de Chaisemartin, C., D'HaultfŒuille, X., 2018. Fuzzy differences-in-differences. Rev. Econom. Stud. 85 (2), 999–1028. http://dx.doi.org/10.1093/restud/rdx049, URL: https://academic.oup.com/restud/article/85/2/999/4096388.

de Chaisemartin, C., D'Haultfœuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. Amer. Econ. Rev. 110 (9), 2964–2996. http://dx.doi.org/10.1257/aer.20181169, URL: https://pubs.aeaweb.org/doi/10.1257/aer.20181169.

Chitnis, M., Sorrell, S., Druckman, A., Firth, S.K., Jackson, T., 2014. Who rebounds most? estimating direct and indirect rebound effects for different UK socioeconomic groups. Ecol. Econom. 106, 12–32. http://dx.doi.org/10.1016/j.ecolecon.2014.07.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800914002055.

Cohen, G., Jalles, J.T., Loungani, P., Marto, R., Wang, G., 2019. Decoupling of emissions and gdp: evidence from aggregate and provincial Chinese data. Energy Econ. 77, 105–118. http://dx.doi.org/10.1016/j.eneco.2018.03.030, URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988318301117.

Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Lo Vullo, E., Solazzo, E., Monforti-Ferrario, F., Olivier, J., Vignati, E., 2020a. EDGAR V5.0 global air pollutant emissions. In: Joint Research Centre (JRC). European Commission, http://dx.doi.org/10.2904/JRC_DATASET_EDGAR, URL: https://edgar.jrc.ec.europa.eu/overview.php?v=50{_}AP.

Crippa, M., Solazzo, E., Huang, G., Guizzardi, D., Koffi, E., Muntean, M., Schieberle, C., Friedrich, R., Janssens-Maenhout, G., 2020b. High resolution temporal profiles in the emissions database for global atmospheric research. Sci. Data 7 (1), 121. http://dx.doi.org/10.1038/s41597-020-0462-2, URL: http://www.nature.com/articles/s41597-020-0462-2.

Cruz, L., Dias, J., 2016. Energy and CO2 intensity changes in the EU-27: Decomposition into explanatory effects. Sustainable Cities Soc. 26, 486–495. http://dx.doi.org/10.1016/j.scs.2016.03.007, URL: https://linkinghub.elsevier.com/retrieve/pii/S2210670716300385.

Cunningham, S., 2021. Causal Inference: The Mixtape. Yale University Press, New Haven, URL: https://www.scunning.com/mixtape.html.

Davis, S.J., Caldeira, K., 2010. Consumption-based accounting of CO2 emissions. Proc. Natl. Acad. Sci. 107 (12), 5687–5692. http://dx.doi.org/10.1073/pnas.0906974107, URL: http://www.pnas.org/cgi/doi/10.1073/pnas.0906974107.

Delbeke, J., Vis, P., 2016. EU Climate Policy Explained. European Commission, Brussels.

Dube, A., 2019. Minimum wages and the distribution of family incomes. Am. Econ. J: Appl. Econ. 11 (4), 268–304. http://dx.doi.org/10.1257/app.20170085, URL: https://pubs.aeaweb.org/doi/10.1257/app.20170085.

EEA, 2020. European Union emission inventory report 1990–2018. Technical Report, European Environment Agency, URL: https://www.eea.europa.eu//publications/european-union-emission-inventory-report-1990-2018.

EEA, 2020a. Healthy environment, healthy lives: how the environment influences health and well-being in Europe. Technical Report, European Environment Agency.

Faehn, T., Bruvoll, A., 2009. Richer and cleaner–at others' expense? Resour. Energy Econ. 31 (2), 103–122. http://dx.doi.org/10.1016/j.reseneeco.2008.11.001, URL: https://linkinghub.elsevier.com/retrieve/pii/S0928765508000432.

Fanning, A.L., O'Neill, D.W., 2019. The wellbeing–consumption paradox: Happiness, health, income, and carbon emissions in growing versus non-growing economies. J. Cleaner Prod. 212, 810–821. http://dx.doi.org/10.1016/j.jclepro.2018.11.223, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652618336266.

Fernández-Amador, O., Francois, J.F., Oberdabernig, D.A., Tomberger, P., 2017. Carbon dioxide emissions and economic growth: An assessment based on production and consumption emission inventories. Ecol. Econom. 135, 269–279. http://dx.doi.org/10.1016/j.ecolecon.2017.01.004, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800916308837.

Gardner, J., 2021. Two-stage differences in differences. (April).

Gazheli, A., van den Bergh, J., Antal, M., 2016. How realistic is green growth? sectoral-level carbon intensity versus productivity. J. Cleaner Prod. 129, 449–467. http://dx.doi.org/10.1016/j.jclepro.2016.04.032, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652616302992.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econometrics http://dx.doi.org/10.1016/j.jeconom.2021.03.014, URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407621001445.

Gupta, S., 2015. Decoupling: a step toward sustainable development with reference to OECD countries. Int. J. Sust. Develop. World Ecology 22 (6), 510–519. http://dx.doi.org/10.1080/13504509.2015.1088485, URL: http://www.tandfonline.com/doi/full/10.1080/13504509.2015.1088485.

Haberl, H., Wiedenhofer, D., Pauliuk, S., Krausmann, F., Müller, D.B., Fischer-Kowalski, M., 2019. Contributions of sociometabolic research to sustainability science. Nat. Sust. 2 (3), 173–184. http://dx.doi.org/10.1038/s41893-019-0225-2, URL: http://www.nature.com/articles/s41893-019-0225-2.

Haberl, H., Wiedenhofer, D., Virág, D., Kalt, G., Plank, B., Brockway, P., Fishman, T., Hausknost, D., Krausmann, F., Leon-Gruchalski, B., Mayer, A., Pichler, M., Schaffartzik, A., Sousa, T., Streeck, J., Creutzig, F., 2020. A systematic review of the evidence on decoupling of GDP, resource use and GHG emissions, part II: synthesizing the insights. Environ. Res. Lett. 15 (6), 065003. http://dx.doi.org/10.1088/1748-9326/ab842a, URL: https://iopscience.iop.org/article/10.1088/1748-9326/ab842a.

Hickel, J., Kallis, G., 2020. Is green growth possible? New Political Economy 25 (4), 469–486. http://dx.doi.org/10.1080/13563467.2019.1598964, URL: https://www.tandfonline.com/doi/full/10.1080/13563467.2019.1598964.
Hsiang, S., 2016. Climate econometrics. Ann. Rev. Resource Econ 8 (1), 43–75. http://dx.doi.org/10.1146/annurev-resource-100815-095343, URL: http://www.annualreviews.org/doi/10.1146/annurev-resource-100815-095343.
Hsiang, S., Jina, A., 2014. The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones. Technical Report, National Bureau of Economic Research, Cambridge, MA, http://dx.doi.org/10.3386/w20352, URL: http://www.nber.org/papers/w20352.pdf.
IPCC, 2018. An ipcc special report on the impacts of global warming of 1.5c above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change. Technical Report, Inter-governmental Panel on Climate Change.
IPCC, 2021. Sixth assessment report. Technical Report, Inter-Governmental Panel on Climate Change, URL: https://www.ipcc.ch/report/ar6/wg1/.
Jackson, T., 2009. Prosperity Without Growth. Routledge, http://dx.doi.org/10.4324/9781849774338, URL: https://www.taylorfrancis.com/books/9781136546785.
Jackson, T., 2018. The post-growth challenge. In: Centre for the Understanding of Sustainable Prosperity. Technical Report, (12), Centre for the Understanding of Sustainable Prosperity, p. 39.
Knight, K., Schor, J., 2014. Economic growth and climate change: A cross-national analysis of territorial and consumption-based carbon emissions in high-income countries. Sustainability 6 (6), 3722–3731. http://dx.doi.org/10.3390/su6063722, URL: http://www.mdpi.com/2071-1050/6/6/3722.
Kojima, M., Bacon, R., 2009. Changes in CO2 emissions from energy use: {A} multicountry decomposition analysis. In: Extractive Industries for Development Series #11 the World Bank. (October), World Bank, Washington, DC, pp. 11–14.
de Koning, A., Bruckner, M., Lutter, S., Wood, R., Stadler, K., Tukker, A., 2015. Effect of aggregation and disaggregation on embodied material use of products in input–output analysis. Ecol. Econom. 116, 289–299. http://dx.doi.org/10.1016/j.ecolecon.2015.05.008, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800915002232.
Krausmann, F., Gingrich, S., Eisenmenger, N., Erb, K.-H., Haberl, H., Fischer-Kowalski, M., 2009. Growth in global materials use, gdp and population during the 20th century. Ecol. Econom. 68 (10), 2696–2705. http://dx.doi.org/10.1016/j.ecolecon.2009.05.007, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800909002158.
Krausmann, F., Schandl, H., Eisenmenger, N., Giljum, S., Jackson, T., 2017. Material flow accounting: measuring global material use for sustainable development. Ann. Rev. Environ. Resour 42 (1), 647–675. http://dx.doi.org/10.1146/annurev-environ-102016-060726, URL: http://www.annualreviews.org/doi/10.1146/annurev-environ-102016-060726.
Le Quéré, C., Korsbakken, J.I., Wilson, C., Tosun, J., Andrew, R., Andres, R.J., Canadell, J.G., Jordan, A., Peters, G.P., van Vuuren, D.P., 2019. Drivers of declining CO2 emissions in 18 developed economies. Nature Clim. Change 9 (3), 213–217. http://dx.doi.org/10.1038/s41558-019-0419-7, URL: http://www.nature.com/articles/s41558-019-0419-7.
Lecca, P., Barbero, J., Christensen, M., Conte, A., Di Comite, F., Diaz-Lanchas, J., Diukanova, O., Mandras, G., Persyn, D., Sakkas, S., 2018. RHOMOLO V3: A Spatial Modelling Framework. Technical Report, 29229 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-85886-4, Luxembourg, http://dx.doi.org/10.2760/671622.
Lenzen, M., 2016. Structural analyses of energy use and carbon emissions – an overview. Econ Syst Res 28 (2), 119–132. http://dx.doi.org/10.1080/09535314.2016.1170991, URL: http://www.tandfonline.com/doi/full/10.1080/09535314.2016.1170991.
Li, H., Grijalva, T., Berrens, R.P., 2007. Economic growth and environmental quality: A meta-analysis of environmental kuznets curve studies. Econ. Bull.
Liobikiene, G., Butkus, M., Bernatoniene, J., LiobikienÄŮ, G., Butkus, M., BernatonienÄŮ, J., 2016. Drivers of greenhouse gas emissions in the baltic states: decomposition analysis related to the implementation of Europe 2020 strategy. Renew. Sustain. Energy Rev. 54 (2016), 309–317. http://dx.doi.org/10.1016/j.rser.2015.10.028, URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032115011077.
Liu, L., Wang, Y., Xu, Y., 2020. A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. SSRN Electr. J 53 (9), 1689–1699. http://dx.doi.org/10.2139/ssrn.3555463, URL: https://www.ssrn.com/abstract=3555463.
López-Menéndez, A.J., Pérez, R., Moreno, B., 2014. Environmental costs and renewable energy: Re-visiting the environmental Kuznets curve. J. Environ. Manag. 145 (2014), 368–373. http://dx.doi.org/10.1016/j.jenvman.2014.07.017, URL: https://linkinghub.elsevier.com/retrieve/pii/S0301479714003612.
Malik, A., McBain, D., Wiedmann, T.O., Lenzen, M., Murray, J., 2019. Advancements in input-output models and indicators for consumption-based accounting. J. Ind. Ecol. 23 (2), 300–312. http://dx.doi.org/10.1111/jiec.12771, URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jiec.12771.
Maus, V., Giljum, S., Gutschlhofer, J., da Silva, D.M., Probst, M., Gass, S.L., Luckeneder, S., Lieber, M., McCallum, I., 2020. A global-scale data set of mining areas. Sci. Data http://dx.doi.org/10.1038/s41597-020-00624-w.
Naqvi, A., Zwickl, K., 2017. Fifty shades of green: Revisiting decoupling by economic sectors and air pollutants. Ecol. Econom. 133, 111–126. http://dx.doi.org/10.1016/j.ecolecon.2016.09.017, URL: http://dx.doi.org/10.1016/j.ecolecon.2016.09.017.
OECD, 2002. Sustainable development: Indicators to measure decoupling of environmnetal pressure from economic growth. In: OECD Report. Technical Report, Organisation for Economic Cooperation and Development.
OECD, 2018. Green growth indicators 2018. Technical Report, Organisation for Economic Co-operation and Development, http://dx.doi.org/10.1787/eco_surveys-ltu-2018-graph22-en, URL: https://www.oecd-ilibrary.org/economics/oecd-economic-surveys-lithuania-2018/green-growth-indicators{_}eco_surveys-ltu-2018-graph22-en.
Özokcu, S., Özdemir, O., 2017. Economic growth, energy, and environmental Kuznets curve. Renew. Sustain. Energy Rev. 72, 639–647. http://dx.doi.org/10.1016/j.rser.2017.01.059, URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032117300692.
Palm, V., Wood, R., Berglund, M., Dawkins, E., Finnveden, G., Schmidt, S., Steinbach, N., 2019. Environmental pressures from Swedish consumption – A hybrid multi-regional input-output approach. J. Cleaner Prod. 228, 634–644. http://dx.doi.org/10.1016/j.jclepro.2019.04.181, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652619312600.
Peters, G.P., 2008. From production-based to consumption-based national emission inventories. Ecol. Econom. 65 (1), 13–23. http://dx.doi.org/10.1016/j.ecolecon.2007.10.014, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800907005162.
Peters, G., Andrew, R., Canadell, J., Friedlingstein, P., Jackson, R., Korsbakken, J., Le Quéré, C., Peregon, A., 2020. Carbon dioxide emissions continue to grow amidst slowly emerging climate policies. Nature Clim. Change 10 (1), 3–6. http://dx.doi.org/10.1038/s41558-019-0659-6, URL: http://www.nature.com/articles/s41558-019-0659-6.
Peters, G.P., Minx, J.C., Weber, C.L., Edenhofer, O., 2011. Growth in emission transfers via international trade from 1990 to 2008. Proc. Natl. Acad. Sci. 108 (21), 8903–8908. http://dx.doi.org/10.1073/pnas.1006388108, URL: http://www.pnas.org/cgi/doi/10.1073/pnas.1006388108.
Raworth, K., 2017. Doughnut Economics: Seven Ways To Think Like a 21st Century Economist. Chelsea Green Publishing, VT.
Robaina-Alves, M., Moutinho, V., Macedo, P., 2015. A new frontier approach to model the eco-efficiency in European countries. J. Cleaner Prod. 103, 562–573. http://dx.doi.org/10.1016/j.jclepro.2015.01.038, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652615000426.
Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., Nykvist, B., de Wit, C.A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P.K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R.W., Fabry, V.J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P., Foley, J.A., 2009. A safe operating space for humanity. Nature 461 (7263), 472–475. http://dx.doi.org/10.1038/461472a, URL: http://www.nature.com/articles/461472a.
Roth, J., Sant'Anna, P.H., 2021. Efficient estimation for staggered rollout designs. pp. 1–52, URL: http://arxiv.org/abs/2102.01291.
Sanchez, L.F., Stern, D.I., 2016. Drivers of industrial and non-industrial greenhouse gas emissions. Ecol. Econom. 124, 17–24. http://dx.doi.org/10.1016/j.ecolecon.2016.01.008, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800915300859.
Sant'Anna, P.H., Zhao, J., 2020. Doubly robust difference-in-differences estimators. J. Econometrics 219 (1), 101–122. http://dx.doi.org/10.1016/j.jeconom.2020.06.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407620301901.
Schmidheiny, K., Siegloch, S., 2019. On event study designs and distributed-lag models: Equivalence, generalization and practical implications. CEPR Discus Pap (12079).
Shuai, C., Chen, X., Shen, L., Jiao, L., Wu, Y., Tan, Y., 2017. The turning points of carbon kuznets curve: Evidences from panel and time-series data of 164 countries. J. Cleaner Prod. 162, 1031–1047. http://dx.doi.org/10.1016/j.jclepro.2017.06.049, URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652617312192.
Simas, M., Pauliuk, S., Wood, R., Hertwich, E.G., Stadler, K., 2017. Correlation between production and consumption-based environmental indicators. Ecol. Indic. 76, 317–323. http://dx.doi.org/10.1016/j.ecolind.2017.01.026, URL: https://linkinghub.elsevier.com/retrieve/pii/S1470160X17300328.
Steffen, W., Richardson, K., Rockstrom, J., Cornell, S., Fetzer, I., Bennett, E., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.a., Folke, C., Gerten, D., Heinke, J., Mace, G., Persson, L.M., Ramanathan, V., Reyers, B., Sorlin, S., 2015. Planetary boundaries: Guiding human development on a changing planet. Science 347 (6223), http://dx.doi.org/10.1126/science.1259855, 1259855–1259855, URL: https://www.sciencemag.org/lookup/doi/10.1126/science.1259855.
Stern, D.I., 2004. The rise and fall of the environmental kuznets curve. World Dev. 32 (8), 1419–1439. http://dx.doi.org/10.1016/j.worlddev.2004.03.004, URL: https://linkinghub.elsevier.com/retrieve/pii/S0305750X04000798.
Stiglitz, J.E., Fitoussi, J.-P., Durand, M., 2018. beyond GDP: Measuring What Counts for Economic and Social Performance. OECD, Paris, pp. 1–144. http://dx.doi.org/10.1787/9789264307292-en, URL: https://www.oecd-ilibrary.org/economics/beyond-gdp{_}9789264307292-en.
Štreimikienė, D., Balezentis, T., 2016. Kaya identity for analysis of the main drivers of ghg emissions and feasibility to implement eu "20–20–20" targets in the baltic states. Renew. Sustain. Energy Rev. 58, 1108–1113. http://dx.doi.org/10.1016/j.rser.2015.12.311, URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032115016949.

Tapio, P., 2005. Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in finland between 1970 and 2001. Transp. Policy 12 (2), 137–151. http://dx.doi.org/10.1016/j.tranpol.2005.01.001, URL: https://linkinghub.elsevier.com/retrieve/pii/S0967070X05000028.

Torras, M., Boyce, J.K., 1998. Income, inequality, and pollution: a reassessment of the environmental kuznets curve. Ecol. Econom. 25 (2), 147–160. http://dx.doi.org/10.1016/S0921-8009(97)00177-8, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800997001778.

UNECE, 2020. Annual report 2019. Technical Report, United Nations Economic Commission for Europe, URL: https://unece.org/annual-report/publications/annual-report-2019.

UNEP, 2019. Global resources outlook 2019. In: Global Resources Outlook 2019. Technical Report, United National Environment Programme, http://dx.doi.org/10.18356/689a1a17-en, URL: https://www.resourcepanel.org/reports/global-resources-outlook.

Valadkhani, A., Roshdi, I., Smyth, R., 2016. A multiplicative environmental DEA approach to measure efficiency changes in the world's major polluters. Energy Econ. 54, 363–375. http://dx.doi.org/10.1016/j.eneco.2015.12.018, URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988316000086.

Victor, P.A., 2012. Growth, degrowth and climate change: a scenario analysis. Ecol. Econom. 84 (C), 206–212. http://dx.doi.org/10.1016/j.ecolecon.2011.04.013, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800911001662.

WHO, 2014. Seven million premature deaths annually linked to air pollution. URL: http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/.

Wiedenhofer, D., Virág, D., Kalt, G., Plank, B., Streeck, J., Pichler, M., Mayer, A., Krausmann, F., Brockway, P., Schaffartzik, A., Fishman, T., Hausknost, D., Leon-Gruchalski, B., Sousa, T., Creutzig, F., Haberl, H., 2020. A systematic review of the evidence on decoupling of GDP, resource use and GHG emissions, part I: bibliometric and conceptual mapping. Environ. Res. Lett. 15 (6), 063002. http://dx.doi.org/10.1088/1748-9326/ab8429, URL: https://iopscience.iop.org/article/10.1088/1748-9326/ab8429.

Wiedmann, T., Lenzen, M., 2018. Environmental and social footprints of international trade. Nat. Geosci. 11 (5), 314–321. http://dx.doi.org/10.1038/s41561-018-0113-9, URL: http://www.nature.com/articles/s41561-018-0113-9.

Zhang, C., Chen, W.-Q., Ruth, M., 2018. Measuring material efficiency: A review of the historical evolution of indicators, methodologies and findings. Resour. Conserv. Recy. 132, 79–92. http://dx.doi.org/10.1016/j.resconrec.2018.01.028, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921344918300284.

Zwickl, K., Ash, M., Boyce, J.K., 2014. Regional variation in environmental inequality: Industrial air toxics exposure in U.S. cities. Ecol. Econom. 107, 494–509. http://dx.doi.org/10.1016/j.ecolecon.2014.09.013, URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800914002833.