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Micro-level structural change decomposition of carbon productivity: Application to electricity generation in Finland

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ABSTRACT

The transition to renewable energy can lead to major structural changes within the energy sector: climate policies encourage the entry of cleaner producers while at the same time driving polluting firms out of the market. However, previous macro-level structural decompositions of carbon intensity and carbon productivity fail to capture the underlying micro-level dynamics, such as firm entry and exit, industry switching, and the reallocation of emissions between firms. The purpose of this study is to fill this gap by presenting a novel micro-level structural change decomposition of carbon productivity. Using comprehensive firm-level register data of the greenhouse gas emissions in the Finnish electricity generation industry in 2000–2019, we find that more efficient allocation of carbon emissions across firms was the main driver of carbon productivity growth in Finnish electricity generation during the study period. We also find that structural change, especially the entry of new firms, played a significant role in the carbon productivity development of this industry.

1. Introduction

The burning of fossil fuels, such as coal, oil, and natural gas, to generate energy is the main source of anthropogenic greenhouse gas (GHG) emissions. Mitigating climate change by reducing GHG emissions has become a major policy objective since the early 1990s. The first commitment period of the Kyoto Protocol started in 2008, and since then, a significant proportion of research and development activities and capital in the European Union (EU) and other Annex I parties to the agreement investments has been devoted to GHG abatement.

To monitor the performance of climate change mitigation programs and their economic costs over time, commonly used performance indicators include *carbon productivity*, generally defined as the economic output per unit of GHG emissions (e.g., Ekins et al., 2012; Jung et al., 2021; Sun et al., 2021; Murshed et al., 2022), and its inverse *carbon intensity* (GHG emissions per output; e.g., Richter and Schiersch, 2017; Liu et al., 2018; Pan et al., 2022).[1] The vast majority of previous studies on carbon productivity and carbon intensity operate at the macro-level of countries and regions (e.g., Hu and Liu, 2016; Bai et al., 2019; Bagchi et al., 2022). There is growing interest in measuring carbon productivity at the firm level; however, firm-level GHG emissions data are not always easily accessible to researchers.[2] To address this issue, many previous studies estimate firm-specific GHG emissions based on fuel consumption data (e.g., Cao and Karplus, 2014; Richter and Schiersch, 2017; Li and Wang, 2019; Li et al., 2022).

In addition to monitoring carbon intensity and productivity over time, a growing stream of literature examines the underlying drivers of carbon productivity by decomposing these performance indicators into subcomponents to capture the underlying drivers of technological change and technical efficiency. These studies are typically based on index decomposition analysis (Liu and Ang, 2003; Meng and Niu, 2012; Hu and Liu, 2016; Bai et al., 2019), production theory (Zhou and Ang, 2008; Liu et al., 2022), or a combination of different approaches (Lin and Du, 2014; Wang et al., 2018; Li et al., 2022). Another stream of literature focuses on disentangling the impacts of structural change in the economy by applying structural decomposition analysis (e.g., Wang

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[1] Carbon productivity is also sometimes referred to as carbon efficiency of production.

[2] In his description of the European Union Transaction Log (EUTL) database, Abrell (2022) notes that "Accessing the data is rather burdensome as data access is inconvenient and, more important, the relation between different elements of the EUTL is missing". Recently, Koch and Themann (2022) utilized EUTL to identify firms that are regulated by the EU ETS to examine the causal effect of the regulation on total factor productivity of the firms.

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et al., 2017; Kulionis and Wood, 2020; Lin and Teng, 2022). However, previous structural change decompositions that operate at the macro-level of countries and regions do not capture underlying micro-level dynamics, such as the entry of new firms that use cleaner technology or the exit of firms with polluting technology. In economics, micro-level dynamics, such as the market entry and exit of firms, are recognized as an important source of total factor productivity growth at the aggregate level (Syverson, 2011; Bartelsman et al., 2013). To the best of our knowledge, however, the influence of micro-level structural changes on carbon productivity or carbon intensity has not been studied before.

The purpose of this study is to fill this gap and shed explicit light on the contribution of firm-level dynamics on carbon productivity by using comprehensive firm-level register data and a recently developed structural change decomposition. More specifically, we utilize comprehensive register data on GHG emissions that cover all Finnish electricity generation firms that participate in the European Union Emissions Trading System (EU ETS).[3] Because electricity generation is subject to the EU ETS regulation, GHG emissions of all power plants with a net heat excess of 20 MW are carefully monitored and recorded at the plant level. To measure carbon productivity at the micro level of the firm, we use unique firm identification codes to merge the firm-level GHG data with the economic data available in the business register of Statistics Finland.

Our study is the first to apply the micro-level structural change decomposition method in the present context of carbon productivity. Similar structural change decompositions have been previously applied in the context of total factor productivity and labor productivity, but since the ongoing sustainable transition will likely cause structural changes in the energy industry, we find it important to examine how structural change affects carbon productivity in particular. The decomposition of carbon productivity proposed in this paper builds upon the seminal work of Olley and Pakes (1996), which has been further extended by Kuosmanen and Kuosmanen (2021, 2024) to incorporate the entry and exit of firms as well as industry switching by continuing firms.[4]

From a methodological point of view, it is not directly obvious which of a number of alternative structural change decompositions known in the literature is the most suitable one in the present context of carbon productivity. The recent paper by Bruhn et al. (2023) sharply criticizes the common practice of using log-transformed productivity values, showing that the use of logs may lead to an inaccurate aggregate growth rate, an inaccurate description of the micro sources of aggregate growth, or both. To avoid the problematic logs, Kuosmanen and Kuosmanen (2021, 2024) developed an exact decomposition, which remains the only known structural change decomposition in the literature that

a) guarantees consistent aggregation of firm-level productivity measures at the industry level,
b) is applicable to both static and inter-temporal settings, and
c) does not depend on the arbitrary choice of market shares or any other share weights of firms.

To gain further insight into the industry dynamics, we also estimate probit regression models in which the market entry (or exit) of firms is explained by observed firm-level characteristics. A deeper understanding of the attributes associated with firm entry and exit enables us to better interpret the observed structural changes and their influence on carbon productivity of the industry. Interestingly, our empirical findings are at odds with the usual perception of firm exit occurring through bankruptcy, along the lines of the Schumpeterian notion of creative destruction.

The remainder of this paper is organized as follows. To motivate our empirical strategy and provide some background for the empirical results, the next section begins with a brief overview of Finnish electricity generation firms. Section 3 presents the structural change decomposition of carbon productivity. Section 4 describes the data and key variables. The decomposition results are presented and discussed in Section 5. Section 6 concludes.

2. Overview of the industry

This section presents a brief review of recent development of GHG emissions, structural changes, and the resulting growth of carbon productivity in the electricity generation industry in Finland. This will illustrate the importance of the empirical phenomena which motivate our empirical strategy and provide some background for the empirical results.

The energy sector is one of the main sources of global GHG emissions around the world. In Finland, the process of energy transition is already well on the way and has triggered considerable structural changes, particularly in the electricity generation industry. These developments provide a strong empirical motivation to examine the role of firm-level dynamics behind carbon productivity growth.

Fig. 1 illustrates the importance of electricity generation (i.e., the 4-digit NACE industry 3511 Production of electricity) as the source of GHG emissions in Finland and puts it to the broader perspective of the abatement of industrial GHG emissions. Although the emissions from electricity generation (the broken grey line in Fig. 1) have decreased in absolute terms, in relative terms, the share of electricity generation in the total industrial emissions has increased over time because other industries have managed to reduce GHG emissions more sharply. In 2019, the share of electricity generation reached 28 % of total GHG emissions. Fig. 1 also illustrates that the electricity generation industry is the largest emitter of GHG within the energy sector (the 2-digit NACE code 35). Finally, Fig. 1 illustrates that our sample of electricity-generating EU ETS firms covers 70–80 % of the total GHG emissions of the entire energy sector.

In the Finnish Standard Industrial Classification TOL 2008, the 4-digit electricity generation industry is further decomposed into the 5-digit industries listed in Table 1. To provide an overview of the major structural changes that occurred in this industry, Table 1 reports the number of electricity generation firms by the TOL 2008 classification operating in Finland in the years 2000 and 2020. These numbers are based on business register data, which exhaustively cover all enterprises in Finland, including firms that do not participate in the EU ETS.

Table 1 highlights that all five subdivisions of the electricity generation industry attracted many new firms during the first two decades of the 21st century, stressing the importance of market entry as a potential source of carbon productivity growth. In particular, the fast-growing wind-power segment within subdivision 35111 attracted many new entrants, including startups, but also established firms that switched from other sub-industries to wind power. Note that the growth of subdivision 35111 can be fully attributed to the wind power segment: the hydroelectric plants of Finland were built during the 19th and 20th centuries, and no new hydroelectric plants were introduced during 2000–2020.[5] The detailed Finnish TOL 2008 industry classification at the 5-digit level enables us to examine the structural changes that occurred in the electricity generation industry over the last two decades.

[3] For a more detailed discussion and critical assessment of the EU ETS, see e.g. Böhringer (2014), Gulbrandsen et al. (2019), and Sato et al. (2022).

[4] Within electricity generation, industry switching can occur, for example, when a firm that operates coal-fired power plants invests in renewable wind and solar power to such a large extent that its industry classification (NACE code) changes.

[5] The number of firms in the nuclear subdivision 35114 increased due to startups that applied for the approval to build new nuclear generators, but only one of the projects proceeded to the construction stage.

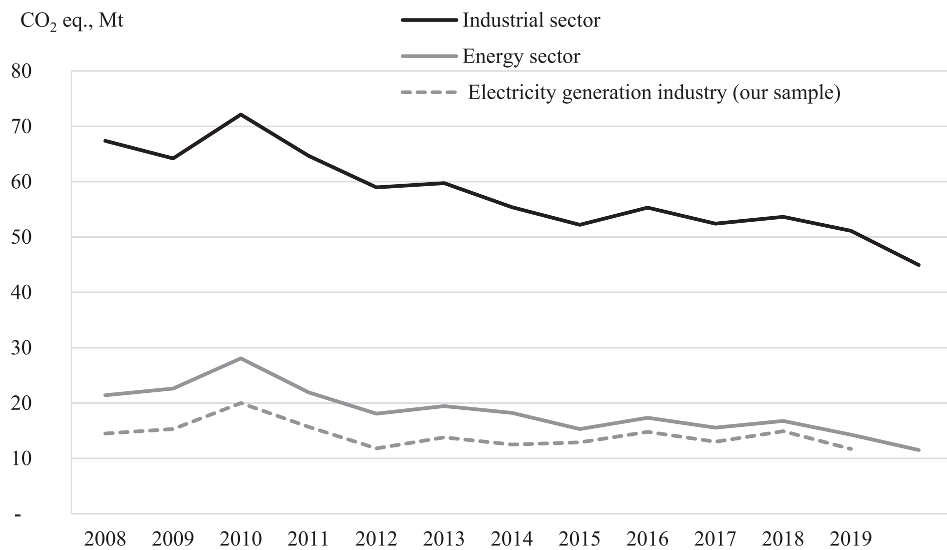

Fig. 1. GHG emissions of Finland's industrial sector (all NACE activities; the black line), the energy sector (D 35 Electricity, gas, steam and air conditioning supply; the solid grey line), and Production of electricity industry (3511; the broken grey line) in 2008–2020, measured in Mt of CO_2 equivalents.
Data sources: EUROSTAT air emissions accounts (solid lines) for 2008–2020 and the national greenhouse gas inventory of Statistics Finland (broken line) for 2008–2019.

Table 1
The number of electricity generation firms in Finland in 2000 and 2020.

Subdivision of electricity generation industry 3511	2000	2020
35111 Production of electricity with hydropower and wind power	43	239
35112 Separate production of electricity with thermal power	5	11
35113 Combined heat and power production	32	66
35114 Production of electricity with nuclear power	2	6
35115 Heat and power production for industry	15	23

Source: Business register database of Statistics Finland.

3. Methods

3.1. Structural change decomposition of carbon productivity

As carbon productivity is a partial productivity measure (analogous to labor productivity), the existing structural change decompositions of total factor productivity can be adapted to carbon productivity. Consider an industry consisting of N_t firms in period t, and note that the number of firms can change over time due to entry and exit. The carbon productivity of firm i in period t is defined as the ratio of output (y_{it}) to GHG emissions (g_{it}) as follows:

$$c_{it} = \frac{y_{it}}{g_{it}}. \tag{1}$$

Note that the carbon intensity is simply the inverse $1/c_{it}$. Therefore, the structural change decomposition introduced next is directly applicable to the carbon intensity; however, the results and interpretations of the decomposition are generally not the same.

The carbon productivity of the industry in period t is defined as

$$C_t = \frac{Y_t}{G_t} = \frac{\sum_{i=1}^{N_t} y_{it}}{\sum_{i=1}^{N_t} g_{it}} \tag{2}$$

where Y_t is the total output of the industry in period t and G_t is the total emissions generated by the industry. To link the firm-level and the industry level, it is helpful to restate the carbon productivity of the industry as a share-weighted average of firm-level carbon productivity measures, formally,

$$C_t = \sum_{i=1}^{N_t} \frac{y_{it}}{g_{it}} \frac{g_{it}}{G_t} = \sum_{i=1}^{N_t} s_{it} c_{it}, \tag{3}$$

where $s_{it} = \frac{g_{it}}{G_t}$ is the share of firm i in the total GHG emissions of the industry in year t. Note that the use of GHG emissions shares guarantees a consistent aggregation of firm-level carbon productivity indicators at the industry level. If one inverts the indicators to measure carbon intensity, then one should use the output shares ($\frac{y_{it}}{Y_t}$) as the share weights s to ensure consistency of aggregation. Because the share weights are different, the decompositions of carbon productivity and intensity generally differ. In this study, we focus on carbon productivity, leaving the decomposition of carbon intensity as an interesting avenue for future research.

Following Olley and Pakes (1996), we can re-express the aggregate carbon productivity of an industry as

$$C_t = \overline{c}_t + cov(s_{it}, c_{it}). \tag{4}$$

The right-hand side of Eq. (4) breaks down the industry's carbon productivity into two components. The first component is the unweighted average of the carbon productivity of all the firms observed in year t, which would be equal to the industry productivity in the counterfactual scenario where all firms emit an equal amount of the GHG emissions. The second covariance term, which can be positive or negative, captures the effect of the GHG allocation between firms on the carbon productivity of the industry. If the covariance term is negative, low-productivity firms tend to emit a larger share of their emissions. By contrast, a positive value of the covariance term indicates that high-productivity firms tend to have a larger share of emissions than low-productivity firms.

Following Kuosmanen and Kuosmanen (2021, 2024),[6] we can further break down the average carbon productivity $\overline{c}_t$ to capture changes in the industry composition through entry and exit, as well as industry switching. To this end, we classify firms in the industry into four mutually exclusive groups:

(a) continuing firms remaining in the same sub-industry,
(b) continuing firms that switch to another sub-industry,
(c) exiting firms observed in period t but not in period $t+1$,

[6] Similar classification is used in other productivity studies such as in Maliranta (2003), Böckerman and Maliranta (2007), Hyytinen and Maliranta (2013), Maliranta and Määttänen (2015), and Melitz and Polanec (2015).

(d) new entrants in period $t+1$.

The union of all continuing firms in groups (a) and (b) forms set S of all surviving firms. Further, firms in group (a) form the set Sn of surviving non-switchers, which is used as the baseline for quantifying structural change effects. As noted by Olley and Pakes (1996), studies based on balanced panel data of firms focus exclusively on group (a).

Applying this classification, the carbon productivity of the industry in period t can be written as the sum of the four components as follows:

$$C_t = \bar{c}_{Sn,t} + \left(\bar{c}_{S,t} - \bar{c}_{Sn,t}\right) + \left(\bar{c}_t - \bar{c}_{S,t}\right) + \left(C_t - \bar{c}_t\right). \tag{5}$$

The first component on the right-hand side of Eq. (5) is the average carbon productivity of non-switching continuing (surviving) firms, which forms the baseline. The second component captures the effect of industry switching by comparing the average carbon productivity of all continuing firms S and its subset Sn, consisting of non-switching continuing firms. For industry switching, we refer to the observed change in the 5-digit industry classification of the firm within the 4-digit electricity generation industry. Industry switching is common in many industries (Kuosmanen et al., 2022). Note that if switching is not explicitly considered, then its contribution is mixed with the continuing non-switching firms or the contribution of entry and exit.

From the vantage point of the base period t, the third component of (5) captures the productivity effect of exiting firms by comparing the average carbon productivity of all firms and all continuing firms. Note that exiting firms might completely close down or continue operations in sectors other than electricity generation. This component represents the contribution of firm entry from the perspective of the target period $t+1$. Firm entry can occur through newly established firms or existing firms switching from another industry to electricity generation. Finally, the fourth component captures the reallocation of carbon emissions across all firms, which is facilitated by the EU ETS emissions trading scheme. Instead of using the covariance formulation by Olley and Pakes (1996), we use the equivalent formulation based on the difference between the carbon productivity of the industry and the unweighted average carbon productivity of all firms (see Kuosmanen and Kuosmanen, 2021, for further details).

The static decomposition (5) of the level of carbon productivity can be extended to carbon productivity growth as follows:

$$\Delta C = \Delta\bar{c}_{Sn} + \Delta INS + \Delta INT + \Delta ENX + \Delta ALL \tag{6}$$

where

$\Delta C = \frac{C_t}{C_{t-1}}$ *(carbon productivity change of the industry),*

$\Delta\bar{c}_{Sn} = \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}}$ *(carbon productivity change of continuing firms in the same sub-industry),*

$\Delta INS = \frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}} - \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}}$ *(contribution of intra-industry switching of sub-industry),*

$\Delta ENX = \frac{\bar{c}_t}{\bar{c}_{t-1}} - \frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}}$ *(contribution of firm entry and exit),*

$\Delta ALL = \frac{C_t}{C_{t-1}} - \frac{\bar{c}_t}{\bar{c}_{t-1}}$ *(contribution of reallocation of emissions).*

Intertemporal decomposition (6) allows us to break down the carbon productivity growth of the industry into multiple components expressed as percentage changes. In this case, the component ΔENX represents the net contribution of firm entry and exit.

3.2. Probit regression

To gain further insight into the industry dynamics in the context of carbon productivity, we also employ the probit regression models to gain a better understanding of the attributes that correlate with firm entry and exit. The probit analysis can help sharpen our interpretation of the observed structural changes and their contribution on carbon productivity.

More specifically, we estimate two probit models, specified as follows:

$$Pr\left(Exit_{i,t+2} = 1\right) = \Phi(\alpha + \boldsymbol{\beta}\boldsymbol{X}_{it} + \varepsilon_{it}) \tag{7}$$

$$Pr\Big(Entry_{i,t-2} = 1\Big) = \Phi(\alpha + \boldsymbol{\beta}\boldsymbol{X}_{it} + \varepsilon_{it})$$

where, $Exit_{i,t+2}$ is a binary indicator for firm i having exited by period time $t+2$ (1 for exiting firms, 0 for continuing firms), and $Entry_{i,t-2}$ is similarly defined (1 for the firm having entered after period t–2, 0 for continuing firms). Note that the firm characteristics are unobservable for the entering firms prior to entry and for the exiting firms after the exit. Therefore, we consider a two-period lead prior to exit and a two-period lag after entry. In other words, firm exit in our probit model refers to a situation where a firm that operates in period t is no longer observed in our register data after two years in period $t+2$. Analogously, the group of entering firms refers to firms that have less than two years observed records in the register data.

In the probit model, the exit and entry probabilities are modeled assuming the standard normal distribution: Φ denotes the standard normal cumulative distributive function. The coefficients $\boldsymbol{\beta}$ are the parameters of interest. Vector $\mathbf{X}$ includes observed firm-level characteristics such as the firm size, financial health (e.g., liquidity, capital structure and debt) (e.g., Cefis et al., 2022) as well as employee characteristics (Koch et al., 2013); these variables are introduced in more detail in the next section. In addition, the model includes a constant α and the random error term ε that has the standard normal distribution.

4. Data

4.1. Data sources

Our empirical study is based on comprehensive firm-level register data on GHG emissions from the National Greenhouse Gas Inventory of Statistics Finland.[7] This yearly panel data covers the period 2000–2019 and includes all electricity-generating firms that participate in the EU ETS, the first large-scale GHG emissions trading scheme in the world. According to EU directives, all power plants with a net heat excess of 20 MW must participate in the EU ETS. In Finland, the EU ETS regulations are administered by the Finnish Energy Authority. Every plant subject to EU ETS regulation is required to have a monitoring system approved by the Energy Authority. The firm-level data of the national greenhouse gas inventory used in this study were based on plant-level monitoring information submitted to the Energy Authority.

To calculate carbon productivity, we match the register data of GHG emissions with the Financial Statement panel data of Statistics Finland using unique firm identification codes. The Financial Statement panel data include the most essential profit and loss accounts and the balance sheet data of firms.[8] These data include relevant information regarding industry codes and economic data, which allow us to compute the value added by each firm. Therefore, we use value added as the output measure and define carbon productivity as the ratio of value added and GHG emissions.[9] Note that the business register data exhaustively cover all independent business enterprises in virtually all industries. Enterprises with at least 20 employees are included in the direct data collection, and the data of smaller enterprises and non-respondent enterprises are

[7] Further information on the Greenhouse gas inventory is available at: https://www.tilastokeskus.fi/tup/khkinv/index_en.html.

[8] Further information on the Financial Statement Data Panel of Statistics Finland is available at: https://taika.stat.fi/en/aineistokuvaus.html#!?dataid=FIRM_19862020_jua_FSSpaneeli_001.xml.

[9] In electricity generation industry, carbon intensity is often measured using the net energy generation (in kWh) as a physical output. Unfortunately, we cannot match the register data of GHG emissions to the physical energy output, so we resort to the economic output in terms of value added in this study.

derived from administrative records, such as tax registers.

For the probit regressions, we link diverse data sources using firm identification codes to construct a unique matched dataset that combines firm-level GHG emissions with detailed background characteristics. We incorporate data from the Business Register database, which provides firm-level information on location and firm age (in years). The financial characteristics include the total revenue, labor input (measured in full-time equivalents, FTE), capital stock (in millions of euros, M€), equity ratio (total equity divided by total assets), and current ratio (the firm's ability to cover short-term liabilities). We also obtained details on foreign ownership from the Foreign Affiliates Statistics and export data from Finnish customs. Firm-level employee characteristics, including the average age of employees and their work experience, were obtained from the FIRM enterprise-specific personnel characteristics data. Individual-level FLEED and FOLK registers were also utilized to gather data on education level and field at the individual employee level, according to the ISCED educational classification. At the firm level, this allows us to identify the share of firm's workers with a Master's degree or equivalent level in the fields of science, technology, engineering, or mathematics (henceforth abbreviated as STEM).

The merged data used in the empirical analysis in the next section include only firms that participate in the EU ETS. Note that renewable producers with zero emissions (e.g., firms specializing in wind power) are not included in the sample because their carbon productivity is undefined. Further, we classify entry, exit, and industry switching based on the business register data of all firms and not just the subset of EU ETS-participating firms. This ensures that entry to and exit from the EU ETS regulation is not misclassified as entry or exit. The total sample size of our study comprised 802 observations from 87 electricity generation firms operating in Finland from 2000 to 2019.

4.2. Three time periods

To capture structural change in carbon productivity and to ensure comparability over time, we examined carbon productivity during the following three distinct periods, analogous to Kuosmanen and Kuosmanen (2024) and Kuosmanen and Maczulskij (2024):

1) 2000–2006,
2) 2007–2012,
3) 2013–2019.

The segmentation into three distinct subperiods of 6–7 years length is motivated by the following four reasons.

First, considering medium-term perspective instead of insisting on yearly changes enables one to better capture the contributions of structural changes, such as entry/exit and industry switching, which are relatively rare events in a single year (cf., Holm, 2014; Kuosmanen and Kuosmanen, 2021, 2024; Kuosmanen and Maczulskij, 2024).

Second, the present segmentation into three subperiods ensures data comparability throughout each subperiod. It is important to note that Statistics Finland conducted major revisions to the Financial Statement Data Panel in years 2006 and 2013, which may affect comparability of data before and after the revision.[10] Therefore, we have chosen these years of data revisions as the first years of the second and the third subperiod, respectively, to ensure that the data standards remain consistent throughout each subperiod.

Third, the three periods match well with the macroeconomic conditions in Finland. The first period 2000–2006 was characterized by rapid economic growth in Finland. The second period 2007–2012 includes the global recession in 2008–2009 followed by a decline in Finland's GDP due to sluggish exports in 2011–2012 (referred to as "double recessions").[11] The final period 2013–2019 was characterized by a slow recovery.

Fourth, the selected periods also match reasonably well with the first three phases of the EU ETS. Note that the firm-level data of the Finnish GHG inventory reach back to the year 2000, but the EU ETS was launched only in January 2005. There was a need to monitor GHG emissions before the first pilot phase of the EU ETS in 2005–2007 (phase 1) because initially the emission allowances were given for free in proportion to historical emission levels (the approach known as "grandfathering"; e.g., Sato et al., 2022). Therefore, our first study period includes the years leading up to the launch of the EU ETS, and the first years of the pilot phase. During phase 2 of the EU ETS in 2008–2012 (covered by our second study period), the total volume of allowances remained at a similar level as in phase 1, but up to 10 % of emission allowances were auctioned. In phase 3 in the years 2013–2020 (our third study period), auctioning became the default allocation mechanism, especially in the electricity sector. Further, the total volume of allowances was notably decreased, creating more scarcity of emission allowances.

5. Results

5.1. Average carbon productivity by subgroup and subperiods

The structural change decomposition of carbon productivity introduced in Section 3 is based on partitioning the sample into four mutually exclusive subgroups. To gain insight, we first compare the average carbon productivity of these four subgroups before proceeding to the decomposition analysis.

The left panel of Table 2 presents the average level of carbon productivity in the four subgroups of firms in the first and the last years of the three distinct periods introduced in Section 4.2.[12] The right panel of Table 2 indicates the relative sizes of the subgroups as the percentage of firms classified to each subgroup.

During the first study period of 2000–2006, the electricity generation industry experienced major structural changes in the form of entry, exit, and industry switching, as the subgroup shares in the right panel of Table 2 indicate. In 2006, almost one-third of the observed sample were new firms that had entered the market between the years 2000 and 2006, another one-third had switched sub-industry within electricity generation, and the remaining one-third were continuing firms in the same segment.

Moving to the left panel of Table 2, we observe that the carbon productivity of the firms that continue to operate within the same industry nearly doubled, but unfortunately, the carbon productivity of those firms that switched industries declined sharply. This suggests that these firms underperformed, and industry switching may have served as an alternative to the market exit. Worse yet, the subgroup of exiting firms had the highest average carbon productivity of all subgroups in 2000, while the subgroup of entering firms in 2006 had considerably lower average carbon productivity (recall that our sample excludes renewable producers with zero emissions). Based on the group averages, the subgroup of firms continuing in the same industry exhibited a positive development of carbon productivity, whereas firm entry, exit, and industry switching had a major negative effect on the carbon productivity of the industry. Since market competition is considered the main driver of the entry, exit, and switching decisions of the firms, these figures suggest that carbon productivity did not help to enhance competitive advantage in this industry during this period. Further, it is

[10] More detailed information of the revisions conducted on the financial statement statistics are available at the following link: https://taika.stat.fi/en/aineistokuvaus.html#!?dataid=FIRM_19862020_jua_FSSpaneeli_001.xml.

[11] For further information, see the Bank of Finland (2018).

[12] To alleviate the influence of extreme outliers, the empirical distribution of carbon productivity has been trimmed at the 5th and the 95th percentiles before computing the subgroup averages.

Table 2
Average carbon productivity in the four subgroups of firms (left panel) and the relative sizes of the subgroups (right panel).

	Carbon productivity*				Subgroup size (% of firms in the sample)			
Year	*Same industry*	*Industry switch*	*Exit*	*Entry*	*Same industry*	*Industry switch*	*Exit*	*Entry*
2000	200.2	131.7	347.8		38.5	30.8	30.8	
2006	393.6	41.6		49.2	35.5	32.3		32.3
2007	342.2	109.8	36.2		74.3	14.3	11.4	
2012	131.4	808.7		42.2	71.1	18.4		10.5
2013	237.8	1281.7	943.1		75.0	12.5	12.5	
2019	281.8	183.1		91.9	74.4	9.3		16.3

* Carbon productivity measured as value added (euros, prices of 2015) per tonne of GHG (CO_2 equivalents).

interesting to note that these major structural changes in the Finnish electricity generation industry took place between 2000 and 2006, leading up to the launch of the EU ETS in 2005, well before the financial crisis and the period referred to as the Great Recession.

During the second period of 2007–2012, associated with the Great Recession and the second phase of the EU ETS, somewhat surprisingly, the industry structure remained much more stable since more than 70 % of the sample continued in the same sub-industry according to the right panel of Table 2. Interestingly, inter-industry switching was very common in this industry during this period. Regarding the average carbon productivity figures reported on the left panel of Table 2, we see that the performance of firms continuing in the same industry deteriorated sharply during this period, but in contrast, the firms that switched industries achieved major growth in their carbon productivity. Moreover, the average carbon productivity of the subgroup of entering firms during this period was somewhat higher than that of firms that exited during this period.

During the last period of 2013–2019, approximately three-quarters of our sample consist of firms continuing in the same sub-industry. In this period, new startups were a more common form of entry to this industry than industry switching of existing firms. Regarding the average carbon productivity, the situation is similar to that seen in the first period: firms continuing in the same industry were the main driver of carbon productivity growth, whereas carbon productivity of industry switchers dropped, and the exiting firms had on average higher carbon productivity than the entering firms. The carbon productivity decomposition, to be examined in the next section, helps to empirically quantify the effects of these structural changes more systematically on the carbon productivity development of the industry.

To summarize, the share of continuing firms increased between 2000 and 2019, while firm exit, entry and industry switching declined. This indicates higher survival rates of new firms during the second and third subperiods, which are temporarily associated with phases II and III of the EU ETS. Previous studies have demonstrated that the implementation of the EU ETS improved various firm-level metrics, such as investments, green research and development (R&D), revenues and productivity (e.g., Calel and Dechezleprêtre, 2016; Klemetsen et al., 2020; Dechezleprête et al., 2023).

5.2. Decomposing the level of carbon productivity

While the average carbon productivity levels reported in Table 2 for each subgroup in the first and the last year of each subperiod already reveal interesting patterns, to systematically quantify the effects of structural changes on industry productivity, we next apply the carbon productivity decomposition (5) introduced in Section 3. The decomposition of the levels of carbon productivity in the first and the last years of the three subperiods is presented in Table 3.

The first four rows of Table 3 present the components of the carbon productivity decomposition in the same ordering as on the right-hand side of Eq. (5). The starting point of the decomposition is the average carbon productivity of the subgroup of firms that continued operating in the same industry; the values indicated on the first row of Table 3 are the

Table 3
Structural change decomposition of the levels of carbon productivity in the Finnish electricity generation industry.

	Period 1		Period 2		Period 3	
	2000	2006	2007	2012	2013	2019
Average carbon productivity of firms continuing in the same industry	200.2	393.6	342.2	131.4	237.8	281.8
+ effect of industry switching	−30.4	−167.6	−37.5	139.4	149.1	−11.0
+ effect of entering firms		−57.0		−24.1		−29.1
+ effect of exiting firms	54.8		−30.7		69.5	
+ effect of GHG allocation	−186.9	−111.0	−211.3	−159.5	−375.1	−131.0
= Carbon productivity of the industry	37.7	57.9	62.7	87.3	81.4	110.7

Note: Carbon productivity is measured as value added (euros, prices of 2015) per tonne of GHG (CO_2 equivalents).

same as those on the first column of Table 2. Note, however, that the average carbon productivity of this subgroup is not the same as the carbon productivity of the industry: the average carbon productivity of the continuing firms is much higher than the carbon productivity of the industry indicated on the bottom row of Table 3, which corresponds to the left-hand side of Eq. (5). To bridge this gap, we need to consider the structural effects reported on the second, third, and fourth rows of Table 3.

The contribution of industry switching is measured by comparing the average carbon productivity of all continuing firms and that of the subset of continuing firms in the same industry. The second row of Table 3 indicates that the industry switching contributed negatively to carbon productivity, particularly during the first period when approximately one-third of the firms in our sample switched sub-industry within the electricity generation industry. In the years 2012 and 2013, however, industry switching had a large positive contribution to the carbon productivity of electricity generation.

The contributions of firm exit and firm entry are similarly measured by comparing the sample averages of all observations and that of all continuing firms. The third row indicates that the entry of new firms had a negative contribution in all three periods considered. Recall from Table 2 that the average carbon productivity in the subgroup of entering firms was lower than that of the continuing firms in each of the three periods. In contrast, the average carbon productivity of exiting firms on the fourth row of Table 3 was very high during the first and last periods: the positive effect in Table 3 captures the impact of these high-productivity firms staying in operation during the first year of the period. Unfortunately, this subgroup of firms will later exit the market, which will be duly taken into account in the inter-temporal decomposition to be presented in Section 5.3.

The fifth row of Table 3 is the Olley-Pakes allocation component, in other words, the covariance term of Eq. (4). This component captures the allocation of GHG emissions across all firms. The large negative values indicate a negative correlation between GHG emissions and carbon productivity. In other words, firms with low carbon productivity generated the largest amounts of GHG emissions, as might be expected.

When the first five rows of Table 3 are summed up, we arrive at the carbon productivity of the whole industry, as indicated in the bottom row of Table 3. Despite the large offsetting effects of structural changes indicated in Table 3, we see a clear increasing trend in the values of the bottom row over time, consistent with Figure 1. This observation motivates us to consider the contribution of structural change to the growth of carbon productivity over time.

5.3. Decomposing the growth of carbon productivity over time

The productivity decomposition introduced in Section 3 applies to both the levels and changes in carbon productivity. In this sub-section, we turn attention to the carbon productivity change and apply the intertemporal decomposition presented in Eq. (6).

Table 4 presents the results of the inter-temporal carbon productivity decomposition. Note that Table 4 is organized analogously to Table 3, where the key difference is that the numbers reported in Table 4 represent the average yearly percentage changes of the components during the three subperiods. Similar to Table 3, the first four rows of the table sum up to the aggregate carbon productivity change of the industry, as reported on the bottom row of Table 4.

Our starting point is again the average carbon productivity change of the firms that continue to operate in the same industry. This subgroup of firms achieved an extremely high yearly growth of 16 % during the first period but experienced a major decline during the second period (associated with the Great Recession). The growth of carbon productivity resumed in this subgroup during the third period but at a more modest average rate of 3 % per year.

The effects of industry switching and the net effect of the entry and exit capture the contributions of changes in the industry composition. Interestingly, both these components had large negative contributions of approximately 10 % per year during the first period, in which almost one-third of firms in the sample were assigned to each of these subgroups. Perhaps somewhat surprisingly, the industry switching and the entry and exit effects both had a positive contribution to carbon productivity growth during the second period that coincided with the Great Recession. However, during the third subperiod, the industry switching and the entry and exit effects both turned negative, but the magnitude of these structural changes was smaller due to the smaller frequency of entry, exit, and industry switching.

Perhaps the most interesting result of the inter-temporal decomposition is the large positive contribution of the Olley-Pakes reallocation component, as reported in the fourth row of Table 4. This effect remained consistently large and positive throughout all three time periods. While in Table 3 we found the level of the allocation component to be negative, importantly, its absolute value decreased during each of the three subperiods. Comparing the four components of the decomposition, we find that the improved allocation of GHG emissions to more carbon-productive electricity-generating firms was the most important driver of carbon productivity growth in the Finnish electricity generation industry.

Table 4

Structural change decomposition of the average yearly change in carbon productivity in the Finnish electricity generation industry (% per year).

	Period 1	Period 2	Period 3
	2000–2006	2007–2012	2013–2019
Average carbon productivity change of firms continuing in the same industry	16.10	−12.32	3.09
+ effect of industry switching	−10.58	10.10	−8.09
+ effect of entry and exit	−9.64	0.23	−2.84
+ effect of GHG allocation	13.09	9.85	13.86
= Carbon productivity change of the industry	8.97	7.86	6.02

The improved allocation of GHG emissions is likely associated with the economic incentives created by the tradeable emissions allowances. Recall that our sample of firms consists of electricity-generating firms that participated in the EU ETS regulation. Even though the market prices of allowances were relatively low during this period, except for the first and the last years of the study period, the fact that GHG emissions have a positive opportunity cost and that emission allowances can be traded between firms can help the market mechanism to allocate the GHG emissions to more productive uses.

Previous firm-level studies on carbon pricing indicate that ETS regulations stimulated green investments and R&D, although initial free allowances in the EU ETS may have hindered low-carbon investments (Calel and Dechezleprêtre, 2016; Teixidó et al., 2019). Based on our empirical results, the improved allocation of GHG emissions between firms was the main source of carbon productivity growth in this industry during the entire study period, although the increased carbon productivity within continuing firms also played a role, except during the financial crisis.

5.4. Probit analysis

The purpose of this section is to shed some further light on the rather counterintuitive finding that the average carbon productivity of exiting firms was considerably higher than that of continuing firms or entering firms during the first and last subperiods (Table 2). This resulted in a large negative contribution from entry and exit during those subperiods in the intertemporal decomposition presented in Table 4. To this end, we estimate the probit models (see Eq. (7)) to examine what types of firm characteristics are temporarily associated with market exit or entry.

Table 5 presents the maximum likelihood estimates of the coefficients of the probit models for the exit and entry probabilities. For both models, two alternative specifications “with emissions” and “without emissions” are considered. Our baseline model “with emissions” includes the GHG emissions as an explanatory variable, and hence the sample consists of firms for which GHG emissions data are available. As a robustness check, we also consider the model “without emissions”, which excludes the GHG emissions from the explanatory variables in order to cover a somewhat larger sample of firms, including those electricity generating firms for which the GHG emissions data are unavailable, which were excluded from the carbon productivity decompositions.

Our main finding in Table 5 is that the exit probability has a significant positive association with the current ratio and the total revenue. These findings are at odds with the conventional perception of market exit occurring through bankruptcy. Note that the current ratio is a liquidity measure commonly used to track how well a company is able to meet its short-term debt obligations. Therefore, the probit results suggest that the exiting firms were not at particularly high risk of insolvency, rather, such firms with high liquidity would appear as attractive targets for mergers and acquisitions. It seems likely that most exiting firms in our sample chose to voluntarily exit through mergers and acquisitions instead of closing down completely. If this is true, then it is fortunate that the exiting firms with extremely high carbon productivity levels (recall Table 2) continue to operate as sub-units of some larger firms. Such mergers and acquisitions would help explain the exceptionally high carbon productivity growth (on average 16 % per year) of the continuing firms within the same subindustry during the first subperiod. If market exit mainly occurred through mergers and acquisitions

Table 5
Probit results for firm entry and exit.

Variables	Exit		Entry	
	With emissions	Without emissions	With emissions	Without emissions
Revenue (M€)	0.011**	0.012**	−0.001	−0.000
	(0.005)	(0.005)	(0.005)	(0.004)
Number of employees (FTE)	0.001	0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)
GHG emissions (1000 t)	−0.001	–	0.000	–
	(0.001)	–	(0.001)	–
Exporter dummy	0.168	0.288	0.041	0.279
	(0.605)	(0.505)	(0.704)	(0.543)
Capital (M€)	−0.003	−0.006**	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)
Equity ratio	−0.002	−0.006	−0.003	−0.002
	(0.007)	(0.007)	(0.008)	(0.007)
Current ratio	0.215**	0.209**	−0.001	0.080**
	(0.107)	(0.102)	(0.138)	(0.039)
Firm age (years)	−0.008	−0.010	−0.030*	−0.029**
	(0.011)	(0.011)	(0.016)	(0.013)
Uusimaa region dummy	−0.542	−0.490	0.824**	0.861**
	(0.509)	(0.463)	(0.416)	(0.391)
Foreign firm dummy	−0.098	−0.161	−0.058	−0.099
	(0.763)	(0.738)	(0.874)	(0.860)
Workers' average age (years)	0.005	−0.035	0.068*	0.051
	(0.043)	(0.036)	(0.037)	(0.036)
Work experience (years)	0.001	−0.000	−0.001	−0.001
	(0.003)	(0.002)	(0.002)	(0.002)
Education (years)	0.080	−0.016	0.163	0.183
	(0.213)	(0.190)	(0.236)	(0.211)
Share of STEM workers	−5.668*	−4.805*	−2.507	−3.439*
	(2.950)	(2.795)	(2.327)	(1.931)
Constant	−1.141	2.232	−3.619	−3.296
	(4.096)	(3.490)	(3.646)	(3.397)
Sub-industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N	213	229	201	217

Notes: FTE = full-time equivalents. Standard errors are reported in parentheses. Statistical significance denoted as ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

in this specific industry, as it seems likely, then the negative contribution of entry and exit in the first and third subperiods must be mainly attributed to a rather low level of average carbon productivity among the entering firms. Although the exiting firms are financially quite strong, the results also suggest a limited focus on technical expertise and innovation, as measured by the share of STEM workers in a firm.

Considering the factors associated with market entry, a statistically significant positive association is found with the dummy variable for Uusimaa region, and in the model without GHG emissions, also with the current ratio. Uusimaa region includes the metropolitan area of Helsinki and has the highest population of all regions in Finland, so it is not surprising to find that new entrants are likely located in that region. The probit estimates also confirm a trivial result that the firm age is negatively associated with the firm entry; recall that the sub-group of entering firms are less than two years old by construction.

It is also worth noting in Table 5 that the GHG emissions appear to have no association whatsoever with either exit or entry.[13] This would suggest that the various incentives and regulations to decrease GHG emissions were not strong enough to drive dirtier firms out of business or to attract cleaner firms to enter the market. This can help explain the rather low average level of carbon productivity among the subgroup of entering firms. Regarding the direction of causality, we must stress that even if the climate policy measures had no effect on the market entry and exit decisions of the firms, our decomposition results demonstrate that the entry and exit decisions did considerably influence the allocation of GHG emissions across firms, which in turn had large effects on the carbon productivity growth of the industry. In other words, while structural changes influence carbon productivity, it does not seem that carbon productivity or GHG emissions were significant drivers of structural change.

6. Conclusions

This study is the first attempt to quantify the impacts of micro-level structural changes such as firm entry and exit, industry switching, and resource allocation on the level and growth of carbon productivity. Our methodological contribution was to adapt an existing micro-level structural change decomposition of total factor productivity to the present context of carbon productivity. The proposed decomposition builds upon the seminal work by Olley and Pakes (1996) and its recent extensions by Kuosmanen and Kuosmanen (2021, 2024), which guarantee a consistent aggregation of firm-level carbon productivity (or carbon intensity) indicators to the aggregate level of an industry or a sector. The proposed micro-level decomposition can be applied to any industry or sector for which firm- or plant-level CO_2 emission data are available, or can be reliably estimated from the fuel consumption data.

Our empirical contribution was to utilize comprehensive firm-level register data of the GHG emissions in the Finnish electricity generation industry to decompose the aggregate carbon productivity growth of the industry into four components: carbon productivity growth of the continuing firms in the same sub-industry, the contribution of firms that switched sub-industry, the entry and exit effect, and the effect of emission allocation across electricity generation firms. We found that more efficient allocation of carbon emissions across firms was the main driver of carbon productivity growth of the industry. However, increased carbon productivity within continuing non-switching firms also played a positive role, except during the financial crisis. This implies that more mature continuing firms are better positioned to address the challenges generated by the green transition, for example, by investing in green technology and R&D (Aghion et al., 2012; Ma and Zimmermann, 2023).

Firm entry and exit as well as industry switching had a positive contribution to the carbon productivity growth during the period of 2007–2012 associated with the Great Recession. But somewhat unexpectedly, industry switching and the net entry and exit had a negative contribution to carbon productivity change during the first period 2000–2006 and the last period 2013–2019. According to our merged GHG emissions and economic data, the average carbon productivity of the exiting firms was considerably higher than that of the group of new entrants. Additional probit estimations indicate that the exiting firms were associated with significantly higher current ratio and total revenue than the continuing firms. This would suggest that the observed market exits in this industry occurred more likely through mergers and acquisitions than through bankruptcy. A more thorough investigation of the influence of low-carbon mergers and acquisitions (e.g., Lu et al., 2024) on carbon productivity development is left as a promising avenue for future research.

A better understanding of the underlying micro-level structural dynamics would be important to design effective policy measures to reduce GHG emissions and to facilitate the transition to carbon-neutral energy systems. Our structural change decomposition indicates that the improved allocation of GHG emissions had the largest and the most stable positive contribution to the carbon productivity growth of the industry. In this respect, our study provides further evidence to support emissions trading as a potentially effective policy measure that can enhance carbon productivity by facilitating a more efficient allocation of GHG emissions across firms.

[13] We have tested that the probit results remain robust even if we substituting the GHG emissions by carbon productivity.

From the policy perspective, it is important to understand that policy measures designed for existing firms may prove ineffective, if the market exit and entry dynamics are ignored. The results of our structural change decomposition indicate that the carbon productivity growth of the Finnish electricity generation industry was slowed down by very large negative contributions from industry switching (i.e., firms switching from one sub-industry to another) and the market entry and exit, especially during the period 2000–2006 (combined effect −20 % per year), but also in 2013–2019 (−11 % per year). The results of the probit analysis further suggest that the GHG emissions had no association with the observed entry and exit decisions of firms. Our results suggest that there is a need for policy measures to stimulate creative destruction, targeted to attract cleaner firms to enter the market that have potential to drive dirtier firms out of business.

Perhaps most alarmingly, the average carbon productivity of new firms entering the market was notably lower than that of continuing or exiting firms. Based on the probit analysis, such a poor average performance in terms of carbon productivity is unrelated to the financial constraints of new firms. Possible alternative explanations include a limited capacity to implement environmental regulations and a lack of commitment to green management practices. A better understanding of the underlying causes of low carbon productivity of new firms would be essential to develop more effective policy tools. This is left as an interesting challenge for future research.

Considering the ongoing green transition and Finland's ambitious target of carbon neutrality by the year 2035, we expect to see further measures to enhance the growth of carbon productivity, not only in electricity generation but also in manufacturing industries. It is important to acknowledge that such policy measures can cause major structural changes in all energy-intensive industries, including market entry and exit of firms, industry switching, as well as reallocation of GHG emissions between continuing firms. Supporting productivity growth and the green transition simultaneously is a major policy challenge, which requires further attention. We hope that this work presents a valuable step in this direction, showing how the established tools of productivity analysis can be adapted to carbon productivity.

We conclude by noting several interesting avenues for future research. From a methodological point of view, the causal interpretation of the counterfactual components of the structural change decompositions as well as potential endogeneity biases in the decomposition methods would clearly warrant further research. Moreover, drawing a sharper distinction of different types of firm exit through mergers and acquisitions instead of voluntary or involuntary liquidation would call for further attention. From an empirical point of view, availability of high-quality register-based emissions data at the firm level opens up many interesting opportunities to shed further light on the underlying mechanisms behind the observed development of carbon productivity or carbon intensity. One promising empirical direction worth noting concerns the use of quasi-experimental research designs to estimate causal effects of policy measures targeted at reducing the GHG emissions, including both the intended effects on the emissions as well as unintended effects on firm performance and productivity.

CRediT authorship contribution statement

Natalia Kuosmanen: Conceptualization, Software, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Timo Kuosmanen:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Terhi Maczulskij:** Software, Resources, Data curation, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Timo Kuosmanen reports financial support was provided by Finnish Prime Minister's Office. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data used in the study are located on a server administered by Statistics Finland. The analysis was performed via a remote access system to Statistics Finland's research laboratory (FIONA). For additional information follow https://www.stat.fi/tup/mikroaineistot/etakaytto_en.html. A license to use statistical data can be applied from Statistics Finland (https://www.tilastokeskus.fi/index_en.html).

References

Abrell, J., 2022. Database for the European Union Transaction Log. https://euets.info/static//download/Description_EUTL_database.pdf. Retrieved: 27 March 2022.

Aghion, P., Askenazy, P., Berman, N., Cette, G., Eymard, L., 2012. Credit constraints and the cyclicality of R&D investment: evidence from France. J. Eur. Econ. Assoc. 10 (5), 1001–1024.

Bagchi, P., Sahu, S.K., Kumar, A., Tan, K.H., 2022. Analysis of carbon productivity for firms in the manufacturing sector of India. Technol. Forecast. Soc. Chang. 178, 121606.

Bai, C., Du, K., Yu, Y., Feng, C., 2019. Understanding the trend of total factor carbon productivity in the world: insights from convergence analysis. Energy Econ. 81, 698–708.

Bank of Finland, 2018. Euro countries recovered from crisis at different paces. In: Bank of Finland Bulletin available at https://www.bofbulletin.fi/en/2018/1/euro-countries-recovered-from-crisis-at-different-paces/ (Accessed 23rd December 2024).

Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: the role of allocation and selection. Am. Econ. Rev. 103 (1), 305–334.

Böckerman, P., Maliranta, M., 2007. The micro-level dynamics of regional productivity growth: the source of divergence in Finland. Reg. Sci. Urban Econ. 37 (2), 165–182.

Böhringer, C., 2014. Two decades of European climate policy: a critical appraisal. Rev. Environ. Econ. Policy 8 (1), 1–17.

Bruhn, S., Grebel, T., Nesta, L., 2023. The fallacy in productivity decomposition. J. Evol. Econ. 33, 797–835.

Calel, R., Dechezleprêtre, A., 2016. Environmental policy and directed technological change: evidence from the European carbon market. Rev. Econ. Stat. 98, 173–191.

Cao, J., Karplus, V.J., 2014. Firm-level determinants of energy and carbon intensity in China. Energy Policy 75, 167–178.

Cefis, E., Bettinelli, C., Coad, A., Marsili, O., 2022. Understanding firm exit: a systematic literature review. Small Bus. Econ. 59, 423–446.

Dechezleprête, A., Nachtigall, D., Venmans, F., 2023. The joint impact of the European Union emissions trading system on carbon emissions and economic performance. J. Environ. Econ. Manag. 118, 102758.

Ekins, P., Pollitt, H., Summerton, P., Chewpreecha, U., 2012. Increasing carbon and material productivity through environmental tax reform. Energy Policy 42, 365–376.

Gulbrandsen, L.H., Wettestad, J., Victor, D.G., Underdal, A., 2019. The political roots of divergence in carbon market design: implications for linking. Clim. Pol. 19 (4), 427–438.

Holm, J.R., 2014. The significance of structural transformation to productivity growth. J. Evol. Econ. 24 (5), 1009–1036.

Hu, X., Liu, C., 2016. Carbon productivity: a case study in the Australia construction industry. J. Clean. Prod. 112, 2354–2362.

Hyytinen, A., Maliranta, M., 2013. Firm lifecycles and evolution of industry productivity. Res. Policy 42 (5), 1080–1098.

Jung, H., Song, S., Ahn, Y.H., Hwang, H., Song, C.K., 2021. Effects of emission trading schemes on corporate carbon productivity and implications for firm-level responses. Sci. Rep. 11 (1), 1–10.
Klemetsen, M., Rosendahl, K.E., Jakobsen, A.L., 2020. The impacts of the EU ETS on Norwegian plants' environmental and economic performance. Clim. Chang. Econ. 11 (01), 2050006.
Koch, N., Themann, M., 2022. Catching up and falling behind: cross-country evidence on the impact of the EU ETS on firm productivity. Resour. Energy Econ. 69, 101315.
Koch, A., Späth, J., Strotmann, H., 2013. The role of employees for post-entry firm growth. Small Bus. Econ. 41, 733–755.
Kulionis, V., Wood, R., 2020. Explaining decoupling in high income countries: a structural decomposition analysis of the change in energy footprint from 1970 to 2009. Energy 194, 116909.
Kuosmanen, T., 2022. Misallocation of labor and capital in Finland's business sector. Publications of the Government's Analysis, Assessment and Research Activities 2022, p. 44.
Kuosmanen, T., Kuosmanen, N., 2021. Structural change decomposition of productivity without share weights. Struct. Chang. Econ. Dyn. 59, 120–127.
Kuosmanen, N., Kuosmanen, T., 2024. Inter-industry and intra-industry switching as sources of productivity growth: structural change of Finland's ICT industries. J. Prod. Anal. 61, 107–120.
Kuosmanen, N., Maczulskij, T., 2024. Going green while getting lean: decomposing carbon and total green factor productivity. J. Environ. Manag. 352, 120046.
Kuosmanen, N., Kuosmanen, T., Ali-Yrkkö, J., Pajarinen, M., 2022. Renewal of Companies: Industry Switching as a Form of Structural Change, vol. No. 126. The Research Institute of the Finnish Economy.
Li, S., Wang, S., 2019. Examining the effects of socioeconomic development on China's carbon productivity: a panel data analysis. Sci. Total Environ. 659, 681–690.
Li, J., Meng, G., Li, C., Du, K., 2022. Tracking carbon intensity changes between China and Japan: based on the decomposition technique. J. Clean. Prod. 349, 131090.
Lin, B., Du, K., 2014. Decomposing energy intensity change: a combination of index decomposition analysis and production-theoretical decomposition analysis. Appl. Energy 129, 158–165.
Lin, B., Teng, Y., 2022. Structural path and decomposition analysis of sectoral carbon emission changes in China. Energy 261 B, 125331.
Liu, F.L., Ang, B.W., 2003. Eight methods for decomposing the aggregate energy-intensity of industry. Appl. Energy 76 (1–3), 15–23.
Liu, K., Bai, H., Yin, S., Lin, B., 2018. Factor substitution and decomposition of carbon intensity in China's heavy industry. Energy 145, 582–591.
Liu, X., Hang, Y., Wang, Q., Chiu, C.R., Zhou, D., 2022. The role of energy consumption in global carbon intensity change: a meta-frontier-based production-theoretical decomposition analysis. Energy Econ. 109, 105968.
Lu, J., Li, H., Guo, F., 2024. Low-carbon mergers and acquisitions as a driver for higher energy efficiency: evidence from China's high energy-consuming companies. Energy 290, 130116.
Ma, Y., Zimmermann, K., 2023. Monetary Policy and Innovation, vol. No. w31698. National Bureau of Economic Research.
Maliranta, M., 2003. Micro level dynamics of productivity growth. In: An Empirical Analysis of the Great Leap in Finnish Manufacturing Productivity in 1975-2000. ETLA A.
Maliranta, M., Määttänen, N., 2015. An augmented static Olley-Pakes productivity decomposition with entry and exit: measurement and interpretation. Economica 82, 1372–1416.
Melitz, M.J., Polanec, S., 2015. Dynamic Olley-Pakes productivity decomposition with entry and exit. RAND J. Econ. 46 (2), 362–375.
Meng, M., Niu, D., 2012. Three-dimensional decomposition models for carbon productivity. Energy 46 (1), 179–187.
Murshed, M., Apergis, N., Alam, M.S., Khan, U., Mahmud, S., 2022. The impacts of renewable energy, financial inclusivity, globalization, economic growth, and urbanization on carbon productivity: evidence from net moderation and mediation effects of energy efficiency gains. Renew. Energy 196, 824–838.
Olley, G., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.
Pan, X., Guo, S., Xu, H., Tian, M., Pan, X., Chu, J., 2022. China's carbon intensity factor decomposition and carbon emission decoupling analysis. Energy 239 C, 122175.
Richter, P.M., Schiersch, A., 2017. CO_2 emission intensity and exporting: evidence from firm-level data. Eur. Econ. Rev. 98, 373–391.
Sato, M., Rafaty, R., Calel, R., Grubb, M., 2022. Allocation, allocation, allocation! The political economy of the development of the European Union emissions trading system. WIREs Clim. Chang. 13 (5), e796.
Sun, L.X., Xia, Y.S., Feng, C., 2021. Income gap and global carbon productivity inequality: a meta-frontier data envelopment analysis. Sust. Prod. Consum. 26, 548–557.
Syverson, C., 2011. What determines productivity? J. Econ. Lit. 49 (2), 326–365.
Teixidó, J., Verde, S., Nicolli, F., 2019. The impact of the EU emission trading system on low-carbon technological change: the empirical evidence. Ecol. Econ. 164, 106347.
Wang, H., Ang, B.W., Su, B., 2017. Multiplicative structural decomposition analysis of energy and emission intensities: some methodological issues. Energy 123, 47–63.
Wang, Q., Hang, Y., Su, B., Zhou, P., 2018. Contributions to sector-level carbon intensity change: an integrated decomposition analysis. Energy Econ. 70, 12–25.
Zhou, P., Ang, B.W., 2008. Decomposition of aggregate CO_2 emissions: a production-theoretical approach. Energy Econ. 30 (3), 1054–1067.