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The Role of Firm Dynamics in the Green Transition

CARBON PRODUCTIVITY DECOMPOSITION IN FINNISH MANUFACTURING

Abstract

This paper investigates the importance of firm dynamics, including entry and exit and the allocation of carbon emissions across firms, on the green transition. Using the 2000–2019 firm-level register data on greenhouse gas emissions matched with the Financial Statement data in the Finnish manufacturing sector, we examine the sources of carbon-productivity growth and assess the relative contributions of structural change and firm dynamics. We find that continuing firms were the main drivers of carbon productivity growth whereas the contribution of entering and exiting firms was negative. In addition, the allocation of emissions across firms seems to be inefficient; its impact on carbon productivity growth was negative over the study period. Moreover, we find that there is a positive relationship between labor-intensive firms and carbon productivity but that firms with a larger market share tend to be less productive in terms of carbon use.

Natalia Kuosmanen
Etla Economic Research, Finland
natalia.kuosmanen@etla.fi

Terhi Maczulskij (Corresponding author)
Etla Economic Research, Finland and
IZA Institute of Labor Economics, Germany
terhi.maczulskij@etla.fi

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Tiivistelmä

Rakennemuutos ja vihreä siirtymä: hiilituottavuuden osatekijät Suomen teollisuudessa

Tässä artikkelissa tutkitaan teollisuuden rakennemuutoksen ja yritysten uusiutumisen yhteyttä hiilituottavuuden kasvussa. Tutkimuksessa hyödynnetään teollisuuden yritystason tietoja kasvihuonekaasupäästöistä ja tilinpäätöstiedoista vuosille 2000–2019. Menetelmänä käytetään niin kutsuttua hajotelmamenetelmää, jonka avulla hiilituottavuuden kehitys voidaan jakaa kolmeen osaan: keskimääräiseen jatkavien yritysten hiilituottavuuden muutokseen, uusien ja poistuvien yritysten kontribuutioon sekä kasvihuonekaasupäästöjen kohdentumiseen yritysten kesken. Tulosten perusteella toimintaansa jatkaneet yritykset olivat hiilituottavuuden kasvun tärkein veturi, kun taas osa tehokkaimmista yrityksistä oli jostain syystä kannattamattomia ja poistui markkinoilta. Lisäksi kasvihuonekaasupäästöjen kohdentuminen yritysten kesken näyttää olevan tehotonta. Tämä tarkoittaa sitä, että päästöt kohdentuivat saastuttavimpiin yrityksiin ja päästöjen vähentäminen tapahtui jo ennestään vähäpäästöisten yritysten toimesta. Lisäksi hiilituottavuus kulkee käsi kädessä työn tuottavuuden kanssa, mutta suhde kilpailukykyyn on päinvastainen.

Ph.D. **Natalia Kuosmanen** is a Chief Research Scientist at ETLA Economic Research.

Ph.D. **Terhi Maczulskij** is a Chief Research Scientist at ETLA Economic Research and a Research Fellow at IZA.

MMT **Natalia Kuosmanen** on Elinkeinoelämän tutkimuslaitoksen tutkimuspäällikkö.

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Asiasanat: Hiilituottavuus, Hajotelmamenetelmä, Rakennemuutos, Yritystason aineisto, Teollisuus

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1. Introduction

A major cause of climate change is greenhouse gas (GHG) emissions (Solomon, 2007). According to the Government Programme, Finland aims to be carbon neutral by year 2035.[1] Further, the new Climate Change Act, which came into force in 2022, has set ambitious targets for reducing emissions by 80% by 2040, compared to the levels in 1990 (Ministry of the Environment, 2022). To meet its carbon neutrality goals, Finland must strengthen its efforts to fight climate change and reduce CO_2 emissions. Therefore, it is crucial to understand the driving forces behind the emission changes.

The contribution of the manufacturing sector to Finland’s total GHG emissions was 22% in 2020 (Statistics Finland, 2022). Figure 1 depicts the GHG emissions generated by the manufacturing sector between 2000 and 2019. Although this sector is responsible for the great majority of total emissions at the national level, it has been able to decrease its emissions by approximately 2% annually between 2000 and 2019. The emission levels remained fairly constant between 2000 and 2008: approximately 18 million tonnes of carbon dioxide equivalent (CO_2 eq.) annually. As the 2008 global financial crisis turned into an economic crisis in the eurozone countries, industrial output declined sharply, which led to a sharp decline in emissions. Since 2009, there has been continuous emission reduction; although this reduction is partly due to the continuous decline in industrial output, it is also due to improved carbon use.

“Figure 1 here”

According to the requirements of sustainable development and economic growth, improving carbon productivity is a key pathway to addressing climate change (He and Su, 2011; Li and

[1] Climate Neutral Finland 2035, Ministry of the Environment: https://ym.fi/en/climate-neutral-finland-2035.

Wang, 2019). Carbon productivity is a performance measure generally defined as economic output per unit of GHG emissions (e.g., Sun et al., 2021; Murshed et al., 2022).[2] Recent work on this issue has used mostly macro-level data on countries and regions to decompose changes in carbon productivity (or in its inverse, carbon intensity) into components such as efficiency and technological innovation (see e.g., Meng and Niu, 2012; Hu and Liu, 2016; Wang et al., 2018; Bai et al., 2019).

The lack of suitable microdata has limited empirical research in this field. Although the number of firm-level analyses has increased in recent years, they are focused mostly on examining the determinants of firm-level factors and carbon productivity growth (e.g., Cao and Karplus, 2014; Jung et al., 2021; Bagchi et al., 2022). Yet, no studies have addressed the role of firm dynamics in the green transition or, more specifically, the effects of structural change on carbon productivity growth. The purpose of our paper is to fill this gap. This issue is highly relevant for designing effective policy responses to reach stringent climate goals. A better understanding of the underlying mechanism may help to improve environmental-policy measures and promote the green transition.

In this paper, we use the original firm-level emissions data on all the Finnish manufacturing firms that belong to the EU Emissions Trading System (EU ETS). To assess carbon productivity at the micro level of the firm, we match the administrative emissions data with the firm-level Financial Statement data using unique firm-identification codes. Note that all the information is register based, which eliminates the risks of nonresponse and measurement errors associated with self-reported measures. The data include 5,269 firm-year observations over the period 2000–2019. We apply a structural change decomposition of carbon productivity, which is based on the seminal study by Olley and Pakes (1996) and

[2] The concept of carbon productivity, defined as the ratio of gross domestic product to emissions at the national level, was first introduced by Kaya and Yokobori (1999).

its extension by Kuosmanen and Kuosmanen (2021).[3] This method enables consistent aggregation of productivity measures at the firm level to those at the industry level and is applicable to both the levels and changes of productivity over time.

Our results show a clear U-shaped trend in carbon productivity growth between 2000 and 2019. We find that the contribution of firms that continued to operate in the same industry is positive over the analyzed periods and that it has increased over time. However, the components of entry/exit and the allocation of emissions across firms nearly cancel out the positive effect of nonswitching continuing firms. The negative contribution of allocation implies that emissions were allocated toward less productive firms. It is also concerning that exiting firms exhibit higher carbon productivity compared to surviving and new entering firms. Moreover, we find that firm-specific characteristics, such as number of employees and labor productivity, are positively related to carbon productivity whereas firms' turnover and market share are negatively related to carbon productivity.

The rest of the paper is organized as follows. Section 2 situates our analysis in the context of relevant literature. Section 3 describes the decomposition method. Section 4 presents the data used in the study. Section 5 and 6 present the decomposition results and the regression results, respectively, and Section 7 presents our conclusions.

[3] Kuosmanen, Maczulskij, and Kuosmanen (2022a) have examined carbon productivity growth using data on the Finnish energy sector.

2. Literature review

To a great extent, current research on the determinants of carbon productivity growth is conducted using macro-level data on countries and regions. For instance, a large body of literature has analyzed trends in carbon productivity growth across countries (He and Su, 2011; Ekins et al., 2012; Bai et al., 2019; Xiao et al., 2020) or in a single economy, often aggregated by industry or regional data (e.g., Li and Wang, 2019). These studies demonstrate that although carbon productivity has increased globally, it has increased much more in developed than in developing countries (He and Su, 2011; Bai et al., 2019). Similarly, Xiao et al. (2020) find that consumption-based carbon intensity (the inverse of carbon productivity) has been higher in developing countries and lower in developed countries.

Further, Bai et al. (2019) applied convergence analysis and a probit model to country-level data to examine which determinants converge to different groups of carbon productivity growth. Their results indicated that R&D investments and GDP per capita tend to converge to the group with high carbon productivity, whereas economies with foreign-trade dependence and higher energy intensity tend to converge to the low-carbon-productivity group. Li and Wang (2019) applied spatial-analysis techniques and panel-data models to regional data and quantified the variations in carbon productivity across Chinese provinces. They found that technology level, trade openness, GDP per capita, and foreign direct investments enhance carbon productivity. There is also a positive link between environmental-tax reform and carbon productivity in EU countries (Ekins et al., 2012).

Some studies went further and decomposed changes in carbon productivity or carbon intensity into underlying components, such as technical efficiency and technological change (e.g., Meng and Niu, 2012; Hu and Liu, 2016). These studies have primarily applied insights from index decomposition analysis or production theory.[4] The findings of many studies show that carbon-productivity growth has resulted mainly from technological change (Meng and Niu, 2012; Hu and Liu, 2016; Wang et al., 2018; Bai et al., 2019) whereas the global reduction in carbon intensity has resulted primarily from decreased energy intensity (Liu et al., 2022) and improvements in the thermal efficiency of electricity generation (Ang and Su, 2016). Moreover, both capital and labor-energy substitutions and energy structure have decreased the carbon-intensity gap between Japan and China (Li et al., 2022).

Although studies that focus on the macro level of countries and regions clearly provide important insights, it is important to understand the driving forces of the evolution of carbon productivity from the perspective of the micro level of firms. Even though recent years have witnessed a growth in firm-level studies of this issue, only a small body of research has examined it in depth. Some studies focused on correlation analyses of various firm-level factors and carbon productivity growth (e.g., Cao and Karplus, 2014; Jung et al., 2021; Bagchi et al., 2022). Cao and Karplus (2014) examined the firm-level determinants of carbon intensity using data on Chinese firms. The results showed that changes in carbon intensity were driven largely by changes in energy use but firm size and firm ownership also played a role. For example, state-owned firms exhibited higher carbon intensity compared to joint ventures. Brännlund et al. (2014) examined the effect of climate policy and found that CO_2 tax has been a significant reason for the decline in Swedish manufacturing firms' carbon intensity.

[4] Energy consumption is the main cause of emissions. Therefore, energy intensity and carbon intensity are related but not synonymous. Although different decomposition analyses are also used to examine energy intensity (e.g., Liu and Ang, 2003; Lin and Du, 2014; Tan and Lin, 2018), our paper concentrates on studies that examine carbon productivity (or carbon intensity, its inverse).

More recently, Richter and Schiersch (2017) tested the hypothesis that exporting firms perform better environmentally than nonexporting firms. Their results showed a positive relationship between German firms' export intensity and carbon productivity. Jung et al. (2021) showed that carbon productivity has been higher in firms under the emissions-trading scheme. They also found that carbon productivity has been higher in more profitable and innovative firms and in firms in which the management has experience in environmental fields. Bagchi et al. (2022) used data on firms in the manufacturing sector of India and found that especially export and technological intensities enhance carbon productivity. Lastly, Coderoni and Vanina (2022) used data on Italian farms and found a nonlinear relationship between carbon productivity and farms' economic performance.

Regarding the empirical research on the role of micro-level dynamics such as the market entry and exit of firms, studies of industry switching and of the allocation of emissions across firms are, to the best of our knowledge, still lacking. Our study addresses this gap by examining the contribution of such micro-level structural changes on carbon productivity using unique data on firms in Finland's manufacturing sector.

3. Carbon productivity decomposition

3.1 Decomposition of productivity level

Productivity decomposition in levels measures components of aggregate productivity (e.g., the productivity of an industry or a sector). One such approach was originally proposed by Olley and Pakes (1996), who decomposed industry-level productivity into the sum of an unweighted average productivity level of all firms and a covariance component representing the allocation of resources across firms. As in Olley and Pakes (1996) but for our context of carbon productivity, we first define the aggregate carbon productivity of a sector in period t as C_t. Assuming consistent aggregation, the sector's carbon productivity is a share-weighted average of firm-level carbon-productivity measures c_{it}, that is,

$$C_t = \sum_{i=1}^{N_t} s_{it} c_{it}. \quad (1)$$

In Eq. (1), $s_{it} = \frac{e_{it}}{E_t}$ is the share of firm i in the total GHG emissions of the sector in year t, and $c_{it} = \frac{y_{it}}{e_{it}}$ is the carbon productivity of firm i in period t defined as the ratio of the firm's value added (y_{it}) to its GHG emissions (e_{it}).

The sector's carbon productivity can be split into two components:

$$C_t = \bar{c}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta c_{it} = \bar{c}_t + \mathrm{cov}(s_{it}, c_{it}), \quad (2)$$

where $\bar{c}_t$ is the unweighted average of the carbon productivity of all the firms observed in period t and $\mathrm{cov}(s_{it}, c_{it})$ is a covariance term that captures the allocation of emissions across firms. A negative covariance term indicates that low-productivity firms tend to have a larger share of emissions than high-productivity firms, whereas a positive covariance term indicates that high-productivity firms tend to have a larger share of emissions than low-productivity firms. As Eq. (2) indicates, the sector's carbon productivity can grow either because of increases in the average carbon productivity of all the firms or because of a higher covariance value, which represents a shift of emissions from low-productivity to high-productivity firms.

The Olley–Pakes decomposition, however, does not explicitly consider the entry and exit of firms but attributes these firms to the covariance term. Following Kuosmanen and Kuosmanen (2021), we classify the sector's firms into four mutually exclusive groups:

entrants (E) in period t+1, exiting firms (X) observed in period t but not in period $t + 1$, and all continuing (surviving) firms S, which are subdivided into continuing nonswitching firms (Sn) and continuing industry-switching firms (S–Sn).[5] Applying this classification, the sector's carbon productivity in period t can be written as a sum of four components, as follows:

$$C_t = \bar{c}_{Sn,t} + (\bar{c}_{S,t} - \bar{c}_{Sn,t}) + (\bar{c}_t - \bar{c}_{S,t}) + (C_t - \bar{c}_t). \tag{3}$$

The *first* component on the right-hand side of Eq. (3) is the average carbon productivity of nonswitching continuing firms. The *second* component describes the effect of industry switching, which is very common in many industries (Kuosmanen et al., 2022b). We define industry switching as an observed change in the 5-digit industry classification of the firm in the manufacturing sector. This component is identified by comparing the average carbon productivity of all the continuing firms and that of the nonswitching continuing firms. Note that when the switching effect is not considered explicitly, its contribution is mixed with the effects of continuing nonswitching firms and the contribution of entry and exit. The *third* component captures the productivity impact of entry and exit by comparing the average carbon productivity of all the firms and that of the continuing firms. Finally, the *fourth* component captures the allocation of emissions across all the firms. We measure this component as the difference between the sector's carbon productivity and the unweighted average carbon productivity of all the firms.

[5] A similar classification is used in other productivity studies, such as Maliranta (2003), Böckerman and Maliranta (2007), Hyytinen and Maliranta (2013), and Maliranta and Määttänen (2015).

3.2 Decomposition of productivity change

Decomposition of productivity change measures sources of aggregate productivity growth (Baily et al., 1992; Griliches and Regev, 1995; Melitz and Polanec, 2015). Using the same classification of firms, we decompose the sector's carbon productivity growth into four components expressed as percentage changes:

$$\frac{C_t}{C_{t-1}} = \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}} + \left[\frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}} - \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}}\right] + \left[\frac{\bar{c}_t}{\bar{c}_{t-1}} - \frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}}\right] + \left[\frac{C_t}{C_{t-1}} - \frac{\bar{c}_t}{\bar{c}_{t-1}}\right], \tag{4}$$

where subscript S refers to the surviving firms and S_n refers to the surviving nonswitching firms in periods t and t–1. The first component on the right-hand side is the carbon productivity change of the continuing nonswitching firms. The second component measures the contribution of the continuing industry-switching firms to aggregate carbon productivity growth. The third component captures the contribution of firms' entry and exit, and the fourth component captures the allocation of emissions across firms. Thus, the sector's carbon productivity growth is the sum of these four components.

4. Data

4.1 Data sources

This study focuses on the Finnish manufacturing sector during the period 2000–2019. The analysis is based on firm-level values of carbon productivity computed as the ratio of a firm's value added (VA) to its GHG emissions. Observations with missing values and observations with zero emissions were excluded, because carbon productivity cannot be computed for those observations. The higher the value of carbon productivity, the more efficient the firm is in its use of emissions. To obtain the required microdata, we rely on two data sources.

The GHG emission microdata come from the National Greenhouse Gas Inventory of Statistics Finland.[6] This inventory annually reports GHG emissions and removals and provides an information base for the planning and monitoring of climate policy. Under the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and EU regulations, Statistics Finland is the general authority for the official statistics of Finland and is responsible for GHG-inventory submissions. The emissions data include units that belong to the EU ETS and report both carbon dioxide and GHG emissions in CO_2 eq. at the establishment and firm levels annually. In this study, we utilize firm-level data and GHG emissions in CO_2 eq. Comparing our GHG-emissions data with Eurostat's aggregate figures for the manufacturing sector's GHG emissions, we find that our data's coverage is about 99% that of Eurostat's data. Our emissions data are thus representative of the entire Finnish manufacturing sector.

The data on VA are drawn from Statistics Finland's Financial Statement panel data. These panel data provide exhaustive coverage of all the independent business enterprises in almost all industries and include the most essential loss-and-profit-account and balance-sheet data of firms (e.g., industry code, number of personnel, VA, and other firm-related information). All enterprises with at least 20 employees are included in the direct data collection, and the data on smaller enterprises and nonrespondent enterprises are derived from administrative records, such as business taxation registers.

Linking these two sources of information through firms' ID codes allows us to create a unique matched dataset in which firm-level emission records are combined with the

[6] Information on the Greenhouse Gas Inventory: https://www.tilastokeskus.fi/tup/khkinv/index_en.html.

business-register datasets containing detailed information on firms' financial statistics. After matching the emissions data with the Financial Statement panel data, we arrive at 5,269 yearly observations representing 602 manufacturing firms operating in 2000–2019. We describe our sample in Table 1. VA is presented in millions of euros, GHG emissions in thousands of tonnes of CO_2 eq., and carbon productivity in thousands of euros per tonne of CO_2 eq. VA and carbon productivity were deflated using the GDP deflator for Finland (with 2015 as the base year) to allow for comparison across years. The number of observations in the subsamples varies between 247 and 276 annually. The average carbon productivity for the firms was 31,000 euros per tonne of CO_2 eq. in 2000 and increased to 694,000 euros per tonne of CO_2 eq. in 2019. As the table highlights, there are large variations between the averages during the study period.

˄Table 1 here˴

4.2 Carbon productivity of the manufacturing sector

Figure 2 plots the carbon productivity of the manufacturing sector for the period 2000–2019 calculated based on our firm-level data. As noted above, our emissions data are representative of the entire Finnish manufacturing sector. It should be noted that there is a clear U-shaped trend in carbon productivity over time: it decreased considerably from 2000 to 2009 and then increased in more recent years. Despite this latter positive trend, the sector's carbon productivity has yet to not reached its highest value that was observed in 2000 (890 euros per tonne of GHG emissions).

The underlying trends of VA and GHG emissions of the manufacturing sector are presented in Figure 3. The figure reveals that the increasing trend in carbon productivity after 2009 is not solely a phenomenon of decreased emissions and improvements in environmental performance but that it is also due to the decreasing VA. As mentioned in the Introduction, this may be the result of the decline of industrial output because of the financial crisis taking place at that time.

"Figures 2 and 3 here"

4.3 Average carbon productivity by subperiods and subgroups

The study period covers the 20 years from 2000 to 2019. To better capture the effects of firm dynamics on carbon productivity, we focus on three subperiods lasting six to seven years: 2000–2006, 2007–2012, and 2013–2019. We use these subperiods for three reasons. First, we choose medium-run time periods because short-run analysis (e.g., analysis of yearly changes) is unable to capture structural changes such as firm entry, firm exit, and industry switching. Second, the periods include different economic up- and downturns, including the growth period, the Great Recession, and the follow-up recession and slow recovery. Third, these periods are closely linked with the first three phases of the EU ETS: the pilot phase, or phase 1 (2005–2007), phase 2 (2008–2012), and phase 3 (2013–2020).[7]

Recall that the decomposition of carbon productivity presented in Section 3 is based on partitioning the sample of firms into four mutually exclusive subgroups. Before we

[7] The firm-level data on the Finnish GHG inventory reach back to 1999, but the EU ETS was launched in January 2005. Because the emission allowances were initially given for free in proportion to historical emission levels (an approach known as "grandfathering"; e.g., Sato et al., 2022), there was a need to monitor GHG emissions prior to the pilot phase (phase 1) of the EU ETS in 2005–2007.

present the results in the subsequent sections, we compare the average carbon productivity of these four subgroups to gain further insight.

Panel A of Table 2 reports the relative shares of firms by each subperiod's first and last year and by four subgroups of firms: nonswitching surviving firms, surviving firms that switched industries, exiting firms, and entering firms. As the panel shows, the manufacturing sector experienced major structural change in the form of both industry switching and entry and exit, especially during the first subperiod (2000–2006). At that time, almost 23% of the firms exited the market and were replaced by new entering firms, and approximately 9% of the firms switched to another industry. Finally, nearly 70% of the firms continued to operate in the same industry. Structural change was weaker during the second (2007–2012) and third (2013–2019) subperiods. Approximately 80% of the firms continued to operate in the same industry, 5% of the surviving firms switched to a different industry, and 10%–13% of the firms were new entering firms.

Further, panel B of Table 2 reports the average level of carbon productivity (in thousands of euros per tonne of CO_2 eq., in 2015 prices) in the four subgroups of firms during the first and last years of the three subperiods. The surviving, exiting, and entering firms differ significantly in terms of average carbon productivity. The average levels of carbon productivity were low among the continuing firms in the first subperiod of 2000–2006 but increased in the second and third subperiods, reaching an average level of about 112,000 euros per tonne of emissions in 2019. The average carbon productivity of the surviving firms that have switched industries has been relatively stable (30,000–40,000 euros per tonne of emissions), except in 2019, when it reached nearly 90,000 euros per tonne of emissions. The average carbon productivity was relatively high in both the exiting and entering firms. The productivity of the entering firms was somewhat higher than that of the exiting firms, but only in the first subperiod. It is concerning that in the second (2007–2012) and third (2013–

2019) subperiods, the productivity of the exiting firms was quite high compared to all the other groups. This implies that many high-carbon-productivity firms operating in 2013 exited the market by 2019.

To this end, based on the group averages presented in Table 2, the positive development of carbon productivity (depicted in Figure 2) after 2009 was achieved by the subgroup of firms that continued to operate in the same industry, whereas market entry and exit had a major negative effect on the sector's carbon productivity. This may have resulted in part from the global recession that originated in the US financial crisis and led to the European debt crisis. In Finland, for instance, the recession led to the structural crisis in the manufacturing sector, which suffered from a number of mutually independent, exceptionally strong, and negative changes in the world-market situation (Holmström et al., 2014).

ˆTable 2 hereˋ

5. Results of structural-change decomposition

5.1 Decomposing the level of carbon productivity

Applying the carbon productivity decomposition—i.e., Eq. (3)—introduced in Section 3, we next examine the effects of structural changes on the carbon productivity of the Finnish manufacturing sector. Table 3 reports the decomposition of the levels of carbon productivity in the first and last years of the three subperiods.

Column (1) of the Table 3 indicates the carbon productivity of the entire sector, which is the sum of the four components of the carbon productivity decomposition in the same order as on the right-hand side of Eq. (3). *The first component* in column (2) is the average carbon productivity of the subgroup of firms that continued operating in the same industry. Note that these figures are the same as those in the first column of Panel B in Table 2. *The second component* indicated in column (3) of the table is the contribution of industry switching, which 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 contribution of the industry-switching firms was positive during 2000–2006 but negative during 2007–2012 and 2013–2019, which is due to the negative measures of VA prevailing in this subgroup of firms. However, the relative contribution of industry switching to the carbon productivity of the sector was quite modest.

The third component shown in column (4) is the net contribution of entry and exit, which is measured by comparing the sample averages of all observations and that of all continuing firms. The contribution of firm entry and exit was positive, except in 2012, when the average carbon productivity of entering firms was at its lowest. Lastly, *the fourth component* shown in column (5) is the contribution of the allocation of emissions across firms, or the Olley–Pakes allocation component. It was negative in all years, indicating a negative correlation between GHG emissions and carbon productivity. This means that firms with low carbon productivity are responsible for the largest amounts of GHG emissions. Overall, the carbon productivity of the sector decreased steadily from 2000 to 2007, after which it increased slowly, despite the large offsetting effects of the allocation of emissions.

Table 3 here

5.2 Decomposing the growth of carbon productivity over time

Applying Eq. (4), we next consider the contributions of structural-change components to the growth of the sector's carbon productivity over time. Table 4 presents the results of the intertemporal carbon productivity decomposition. All numbers are expressed as average yearly percentage changes of the components during the three subperiods. As in Table 3, the sum of the components shown in columns (2)–(5) of Table 4 represents the sector's aggregate carbon productivity change, which is reported in column (1).

The sector's aggregate carbon productivity change was negative during 2000–2006 (approximately 3% per year) but turned positive during 2007–2012 (approximately 1% per year) and improved even further during 2013–2019 (approximately 4% per year). Decomposing the sector's carbon productivity into its components can shed light on the underlying firm dynamics and structural changes.

The average carbon productivity change of the firms that continued to operate in the same industry had a positive yearly growth of 8% during the first subperiod and accelerated even further during the second and third subperiods. The growth of carbon productivity in this subgroup during the third period reached an average rate of 25% per year. Further, structural change played a major role in aggregate growth. The third and fourth columns of Table 4 report the contributions of the industry switching of continuing firms and the net effect of entry and exit, respectively. We find that industry switching made a modest negative contribution to the sector's productivity growth in 2000–2006 and 2007–2012 but turned positive in 2013–2019. The contribution of entry and exit was negative in each subperiod, but the negative effect was particularly strong during 2013–2019, the last subperiod (approximately -9%). This effect is due to the lower average productivity of entering firms and the higher average productivity of exiting firms during that period (see Table 2).

The last column of Table 4 reports the allocation component, which remains consistently large and negative throughout all the subperiods. It nearly doubled during 2013–2019 compared to the two earlier time periods. The negative sign implies that emissions were allocated toward less productive firms in terms of carbon productivity.

Comparing the four components of the decomposition, we find that the surviving firms that continued to operate within the same industry were the main driver of carbon productivity growth in the Finnish manufacturing sector. However, the negative effect of entry and exit combined with the negative contribution of emission allocation largely canceled out the positive effect of these continuing firms.

Table 4 here

6. Results of the regression analysis

The decomposition results presented above revealed that carbon productivity has increased mainly among continuing firms. To gain further insight, in this section we explore the role of observed firm-specific characteristics using the following regression model:

$$\log(CP_{ft}) = \boldsymbol{\alpha}'X_{ft-1} + \beta' I_{ft-1} + \tau_t + \varepsilon_{ft}, \qquad (3)$$

where the dependent variable is carbon productivity measured in logarithmic form of firm *f* in year *t*. Vector *X* includes the firm-level characteristics measured in year *t-1*, including the firm age, the current ratio (current assets divided by current liabilities), and the market share of firms (the ratio of the turnover of a firm to the total aggregate amount of the turnover of all manufacturing firms). The relative term of the market share can be seen as an indicator of the size of a firm in relation to its market and its competitors, or in other words, as an indicator of a firm's competitiveness. Finally, the model is augmented with controls for industry (13 indicators) and time effects (19 indicators). The standard errors are clustered at the firm level.

For this exercise, our sample drops to 4,962 observations of manufacturing firms in 2000–2019. The descriptive statistics of the sample are included in Appendix A. The results of the regression are reported in Table 5. For the firm-specific factors, all the estimates except for the current ratio are statistically significant. The coefficients of labor input and labor productivity are significantly positive, suggesting that larger firms (in terms of the number of employees) as well as firms with higher labor productivity have higher carbon productivity. More specifically, a 1% increase in labor input is related to a 0.7% increase in carbon productivity, and a 1% increase in labor productivity is related to a 0.3% increase in carbon productivity.

The coefficients of turnover and market share are negative and statistically significant, indicating that firms with higher sales and a larger market share are less efficient in terms of carbon use. The results show that a 1% increase in turnover is associated with a 0.4% decrease in carbon productivity. A market-share increase of one percentage point is associated with a nearly 7% reduction in carbon productivity. Although we did not have an expectation for the sign of this relationship, a possible explanation for the negative relationship is that manufacturing firms with higher turnover and a larger market share found it cheaper to use the European Union Allowances rather than cut their own emissions. On the one hand, this situation could change in the near future, because after many years of depressed carbon prices, allowance prices for CO_2 emissions spiked in 2022, which may affect the opportunity cost of emitting CO_2. On the other hand, the situation may persist due to the EU ETS design, in which some sectors with sufficiently high carbon intensity (low carbon productivity) and trade intensity qualify for free allowances; they therefore face different costs and can undercut their rivals.[8]

Firm age is positively correlated with carbon productivity, which indicates that older firms are making greater efforts to reduce their carbon emissions. Although the association is (marginally) statistically significant, it is not economically significant. For example, a 10-year increase in firm age is associated with only a 0.07% increase in carbon productivity. Regarding specific manufacturing sectors, the results show that many of the estimated coefficients are statistically significant. In particular, the estimates for industries such as the manufacture of wood and wood products, machinery and equipment, and electrical and optical equipment show positive and statistically significant coefficients (at the 1% significance level), indicating that carbon productivity is higher in these industries than in the reference industry, which is the manufacture of food products, beverages, and tobacco. In contrast, the estimates for industries such as the manufacturing textiles and textile products, leather and leather products, other nonmetallic mineral products, and pulp, paper, and paper products (plus publishing and printing) have negative and statistically significant coefficients, indicating that carbon productivity is lower in these industries than in the reference industry. The coefficients of all the year indicators are positive, and most of them are statistically significant at the 1% significance level (not reported in the table).

˄Table 5 here˴

7. Conclusions

[8] The manufacturing industry received 80% of its allowances for free in 2013. This proportion decreased gradually year-on-year, eventually reaching 30% in 2020 (European Commission, Allocation to industrial installations, https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation/allocation-industrial-installations_en).

We examine the role of firm dynamics such as entry, exit, and productivity improvement at the firm level in the green transition of the Finnish manufacturing sector. More specifically, we apply a productivity decomposition of structural change during the period 2000–2019 to a panel of Finnish manufacturing firms. The panel links two data sources, namely data on GHG emissions at the firm level and the Financial Statement data. The linked data allow us to examine carbon productivity dynamics at the firm level and consistently aggregate carbon productivity measures at the firm level to those at the sector level. Applying the structural-change decomposition, we break down the sector's aggregate carbon productivity into components that capture not only the productivity growth of continuing firms but also the contributions of the entry and exit of firms and the allocation of GHG emissions across firms.

Our results demonstrate that the main driver of the sector's carbon productivity growth was the strong performance of continuing firms. The allocation of GHG emissions across manufacturing firms and structural change in terms of firms' entry and exit had major negative effects on the sector's carbon productivity growth. These factors decreased the productivity growth of the sector and deteriorated over time. Industry switching made a relatively small and negative contribution to the aggregate growth. Finally, we explore whether certain firm-specific characteristics are related to the carbon productivity of the manufacturing firms. We find that larger firms (in terms of the number of employees) and those with higher levels of labor productivity show higher carbon productivity whereas firms with higher turnover and those with a larger market share show weaker carbon productivity.

To the best of our knowledge, our study represents one of the first attempts to estimate the contribution of structural change in manufacturing sector by utilizing firm-level GHG-emissions data. Most of the previous studies have focused on analyzing carbon productivity (or carbon intensity) at the industry, region, or country levels. Although several studies have investigated the effects of technical efficiency and technological change on carbon productivity growth (or change in carbon intensity), we know of no study that has examined the effect of firms' entry and exit on carbon productivity in the manufacturing sector.

Although our results demonstrate that continuing firms in the manufacturing sector perform very well in terms of carbon productivity, further research on structural change is clearly needed. It is concerning that the average carbon productivity of entering firms is lower than that of exiting firms. Further, the sector's carbon productivity could be improved significantly if emissions were reallocated to more carbon-productive firms. However, this might be challenging, because the manufacturing sector consists of a wide variety of industries. In future studies, it would be useful to examine the effects of structural changes in specific industries of the manufacturing sector.

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Figures and Tables

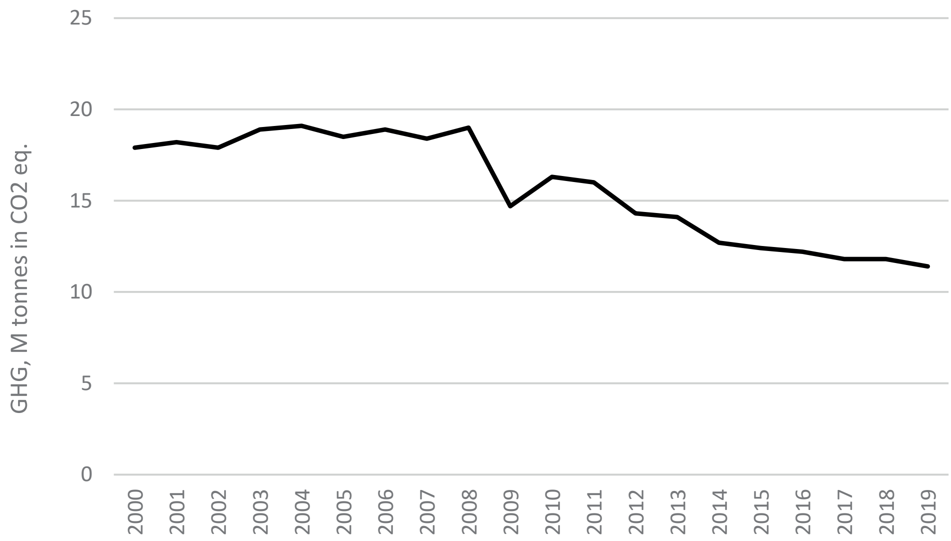

Figure 1. The Finnish manufacturing sector's GHG emissions in millions of tonnes of CO_2 eq. (source: emissions data).

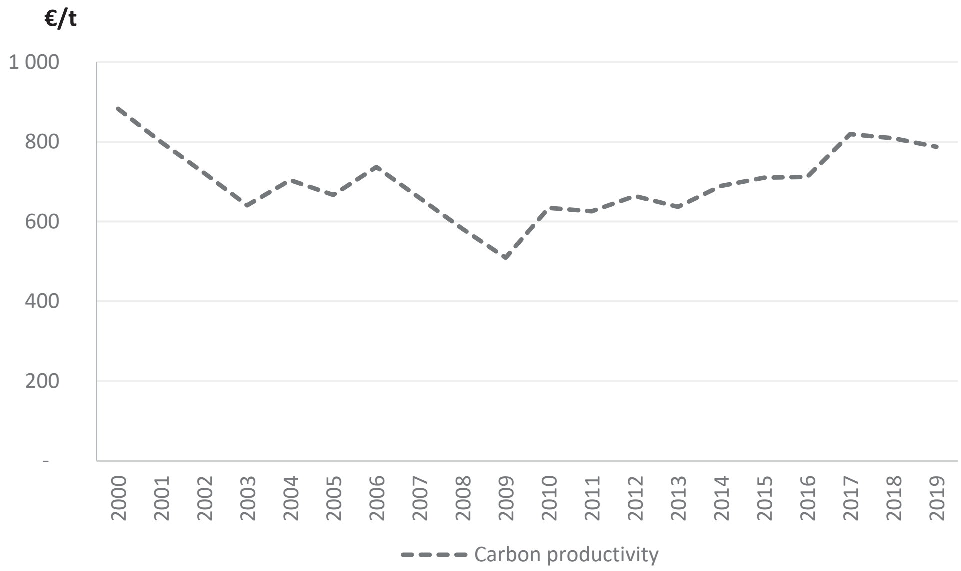

Figure 2. The Finnish manufacturing sector's carbon productivity in euros per tonne of CO_2 eq. (calculated by the authors based on Statistics Finland's data).

Figure 3. The Finnish manufacturing sector's VA in millions of euros (left axis) and total emissions in millions of tonnes of CO_2 eq. (right axis) (source: emissions data and Financial Statement data).

Table 1. Descriptive statistics of the key variables.

	Number of Obs.	**VA, M€ (in 2015 Prices)**		**GHG, 1,000 t**		**CP, 1,000 €/t (in 2015 Prices)**	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2000	274	57.9	168.4	65.4	364.3	31.2	110.8
2001	275	52.8	160.6	66.1	352.2	40.2	215.3
2002	269	48.1	147.8	66.5	355.5	51.7	736.7
2003	263	46.1	121.7	71.8	381.7	286.0	3499.2
2004	266	50.3	143.0	71.8	387.0	56.7	225.3
2005	271	45.3	130.6	68.4	377.4	49.7	248.8
2006	276	50.4	140.4	68.5	385.0	70.0	584.4
2007	273	44.4	116.1	67.5	382.3	156.4	1137.4
2008	269	41.1	122.3	70.5	387.0	73.7	367.4
2009	254	29.5	82.8	57.7	335.1	216.4	2482.5
2010	247	41.9	116.5	65.9	370.4	115.5	1097.9
2011	257	38.9	106.8	62.3	362.3	299.8	4050.6
2012	267	35.6	97.1	53.6	330.6	94.2	640.0
2013	258	34.8	89.3	54.8	333.0	196.7	1790.4
2014	257	34.0	86.2	49.3	277.0	5644.0	87093.5
2015	254	34.7	99.9	48.8	268.5	1259.5	13300.0
2016	260	33.4	96.4	47.0	250.7	819.7	7953.6
2017	253	38.2	107.0	46.7	234.5	441.1	4442.1
2018	258	37.0	105.0	45.8	233.5	938.4	7523.3
2019	268	33.5	96.7	42.5	223.6	693.8	8330.7

Table 2. Average carbon productivity (in 1,000 €/t) and relative shares of firms (in %) by year and firm type.

	Nonswitching surviving firms	Industry-switching surviving firms	Exiting firms	Entering firms
Panel A: Relative share of firms (%)				
2000	68.4	8.8	22.8	
2006	69.0	10.8		20.1
2007	77.6	5.6	16.8	
2012	84.4	5.3		10.3
2013	80.0	5.5	14.5	
2019	82.0	5.4		12.6
Panel B: Carbon productivity (1,000 €/t)				
2000	19.8	32.1	43	
2006	29.1	42.8		44.5
2007	39.8	40.8	49.8	
2012	64.1	28.4		23.7
2013	45.3	32.9	131.7	
2019	111.8	86.1		124.7

Table 3. Structural-change decomposition of the Finnish manufacturing sector's levels of carbon productivity.

	Carbon productivity of the sector (1)	Average carbon productivity of firms continuing in the same industry (2)	Effect of industry switching (3)	Effect of entry and exit (4)	Effect of GHG allocation (5)
2000	0.88	19.82	1.40	4.96	-25.30
2006	0.73	29.11	1.86	2.72	-32.96
2007	0.65	39.84	0.06	1.66	-40.91
2012	0.68	64.08	-2.13	-3.95	-57.33
2013	0.63	45.33	-0.79	12.65	-56.56
2019	0.77	111.78	-1.58	1.83	-111.26

Note: Carbon productivity is measured as VA (in thousands of euros, 2015 prices) per tonne of GHG (in CO_2 eq.).

Table 4. Structural-change decomposition of the average yearly change in the Finnish manufacturing sector's carbon productivity (% per year).

	Carbon-productivity change of the sector (1)	Average carbon-productivity change of firms continuing in the same industry (2)	Effect of industry switching (3)	Effect of entry and exit (4)	Effect of GHG allocation (5)
2000–2006	-2.82	7.81	-0.16	-2.88	-7.60
2007–2012	0.99	12.17	-1.12	-3.14	-6.92
2013–2019	3.81	24.43	0.14	-8.59	-12.18

Note: Carbon productivity is measured as VA (in thousands of euros, 2015 prices) per tonne of GHG (in CO_2 eq.).

Table 5. Relationship between firm-specific factors and carbon productivity.

	Coef.	Std.Err.
Log (Labor productivity)	0.313 **	0.127
Log (Labor)	0.709 ***	0.142
Log (Turnover)	-0.374 ***	0.125
Market share	-6.905 ***	1.775
Current ratio	0.001	0.001
Firm age	0.007 *	0.004
Manufacture of		
textiles and textile products	-0.583 *	0.321
leather and leather products	-1.029 ***	0.224
wood and wood products	1.287 ***	0.251
pulp and paper products, publishing and printing	-0.997 ***	0.324
coke, refined petroleum products, and nuclear fuel	0.656	1.144
chemicals, chemical products, and man-made fibers	0.223	0.342
rubber and plastic products	0.149	0.347
other nonmetallic mineral products	-1.760 ***	0.390
basic metal and fabricated metal products	-0.157	0.283
machinery and equipment	1.935 ***	0.369
electrical and optical equipment	1.058 ***	0.369
transport equipment	0.192	0.391
other products	0.641	0.437
Year indicators (19)	Yes	
R^2	0.072	
Observations	4,962	

Note: The dependent variable is the logarithm of carbon productivity in year *t*. The firm-level factors are measured in year *t*-1. The reference category for the industry is manufacture of food products, beverages, and tobacco. The standard errors are clustered at the firm level. *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$).

Appendix A

Table A1. Descriptive statistics of the sample used in the regressions.

Variable	Mean	Std. Dev.
Carbon productivity (M€/t of CO_2 eq.)	0.586	20.40
Labor productivity (M€/person)	0.097	0.107
Number of employees (in full-time-equivalent units)	423.93	897.47
Turnover (M€)	219.09	749.22
Market share (%)	1.92	6.56
Current ratio	2.70	28.41
Age of firms	28.10	20.83
Manufacture of		
food products, beverages, and tobacco	0.145	0.351
textiles and textile products	0.031	0.174
leather and leather products	0.001	0.025
wood and wood products	0.125	0.331
pulp, paper and paper products, publishing and printing	0.114	0.318
coke, refined petroleum products, and nuclear fuel	0.005	0.068
chemicals, chemical products, and man-made fibers	0.151	0.358
rubber and plastic products	0.064	0.245
other nonmetallic mineral products	0.090	0.286
basic metal and fabricated metal products	0.167	0.373
machinery and equipment	0.042	0.201
electrical and optical equipment	0.008	0.092
transport equipment	0.021	0.143
other products	0.036	0.186

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Tel. +358-9-609 900
www.etla.fi
firstname.lastname@etla.fi

Arkadiankatu 23 B
FIN-00100 Helsinki