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ABSTRACT

The Role of Firm Dynamics in the Green Transition: Carbon Productivity Decomposition in Finnish Manufacturing*

This paper explores 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 appeared to be inefficient, with a negative impact on carbon productivity growth over the study period. Our analysis also revealed a positive relationship between labor-intensive firms and carbon productivity, but firms with a larger market share tended to be less productive in terms of carbon use.

JEL Classification: D24, L60, Q54

Keywords: carbon productivity, decomposition analysis, firm dynamics, firm-level data, manufacturing sector

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1. Introduction

A major cause of climate change is greenhouse gas (GHG) emissions (Solomon, 2007). These GHGs trap heat in the Earth's atmosphere, causing the planet's surface temperature to rise and leading to a range of negative impacts, including more frequent heatwaves, droughts, and extreme weather events. Transitioning to a more sustainable, low-carbon economy is a critical global challenge in addressing this issue and mitigating the impacts of climate change. This transition involves reducing GHG emissions and increasing the use of clean energy sources, such as solar and wind power. It also involves the development of more efficient and eco-friendly technologies and adopting more sustainable management practices in various sectors of the economy.

Understanding the factors that drive or hinder this transition at the firm level is crucial for developing effective policies and strategies to accelerate the shift towards a green economy. Firm dynamics or the processes and activities within firms that drive change play a crucial role in this transition. This includes the internal operations of firms, such as decision-making, resource allocation, and innovation, as well as the interactions between firms, the entry of new firms into a market and the exit of existing firms. The entry and exit of firms significantly shape market dynamics and can have important implications for the economy as a whole. Understanding these drivers can help policy makers and stakeholders develop targeted interventions to promote a more sustainable, low-carbon economy.

In this study, we examine the role of firm dynamics in the green transition by analyzing carbon productivity decomposition in Finnish manufacturing. Carbon productivity refers to the amount of economic output that is generated for each unit of carbon dioxide (CO_2)

emissions (e.g., Sun et al., 2021; Murshed et al., 2022).[1] It is a performance measure describing a firm's ability to produce goods while minimizing its GHG emissions. As climate change becomes an increasingly pressing issue, many companies and governments are focusing on improving carbon productivity in order to reduce their carbon footprint and mitigate the impacts of global warming. 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 Wang, 2019). By decomposing carbon productivity into its various drivers, this study aims to identify the specific factors that contribute to changes in carbon productivity and understand how firm dynamics can facilitate or hinder the green transition.

Empirical research in this field has been limited by the lack of suitable microdata. Previous work in this area has primarily used macro-level data on countries and regions to decompose changes in carbon productivity or 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). While there has been an increase in firm-level analyses in recent years, these studies tend to focus on examining the determinants of firm-level factors on carbon productivity growth (e.g., Cao and Karplus, 2014; Jung et al., 2021; Bagchi et al., 2022). However, no studies have investigated the role of firm dynamics in the green transition or the effects of structural change on carbon productivity growth. Our paper aims to address this gap in the literature and improve our understanding of the underlying mechanism in order to design effective policy responses to achieve stringent climate goals and promote the green transition.

[1] 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).

This paper uses firm-level emissions data on all the Finnish manufacturing firms that are part of the EU Emissions Trading System (EU ETS) to assess carbon productivity at the micro level. The data, which includes 5,269 firm-year observations from 2000–2019, is derived from matching the administrative emissions data with the firm-level Financial Statement data of Statistics Finland using unique firm-identification codes. These register-based data eliminate the risks of nonresponse and measurement errors associated with self-reported measures. We apply a structural change decomposition of carbon productivity, which is based on the seminal study by Olley and Pakes (1996) and its extension by Kuosmanen and Kuosmanen (2021).[2] This decomposition method allows for the consistent aggregation of productivity measures at the firm level to those at the industry level and is applicable for analyzing both levels and changes in productivity over time.

Our results reveal a U-shaped trend in carbon productivity growth between 2000 and 2019. We find that firms that remained in the same industry had positive impact on carbon productivity growth of the sector over the analyzed periods, and this effect increased over time. However, the positive impact of these non-switching firms was nearly cancelled out by the negative effects of firm entry/exit and the allocation of emissions across firms. Specifically, the negative contribution of allocation suggests that emissions were allocated toward less productive firms. Additionally, we observe that exiting firms had higher carbon productivity compared to continuing and new entering firms. Furthermore, we find that firm-specific characteristics such as number of employees and labor productivity had a positive

[2] Kuosmanen, N., Maczulskij, T. and Kuosmanen, T. (2022a) conducted a study on carbon productivity growth in the Finnish electricity generation industry using firm-level emission data from this industry. They analyzed how different factors contribute to changes in the industry's carbon productivity over time and how these changes vary across different types of firms.

relationship with carbon productivity, while firms' turnover and market share has a negative relationship with carbon productivity.

The remainder of the paper is organized as follows. In Section 2, we contextualize our analysis within the existing literature. In Section 3, we introduce the decomposition method of carbon productivity. In Section 4, we describe the data used in the study. In Sections 5 and 6, we present the decomposition and regression results, respectively. Finally, in Section 7, we present our conclusions.

2. Related literature

The majority of research on the determinants of carbon productivity growth has been 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 region (e.g., Li and Wang, 2019). These studies have found that carbon productivity has increased more in developed countries compared to developing countries (He and Su, 2011; Bai et al., 2019). Additionally, studies have found that consumption-based carbon intensity (the inverse of carbon productivity) has been higher in developing countries and lower in developed countries (Xiao et al., 2020).

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 findings showed that R&D investments and GDP per capita tend to be associated with higher carbon productivity, whereas economies with foreign-trade dependence and higher energy intensity tend to have lower carbon productivity. Li and Wang (2019) applied spatial-analysis techniques and panel-data models to regional data to examine variations in carbon productivity among Chinese provinces. They found that factors such as technology level, trade openness, GDP per capita, and foreign direct investment contribute to higher carbon productivity. Additionally, research has shown that environmental-tax reform has a positive impact on carbon productivity in EU countries (Ekins et al., 2012).

Several studies have 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).[3] These studies have primarily applied insights from index decomposition analysis or production theory.[4] The findings of many of these studies have shown that carbon-productivity growth is mainly driven by technological change (Meng and Niu, 2012; Hu and Liu, 2016; Wang et al., 2018; Bai et al., 2019), while the global reduction in carbon intensity has largely been due to decreased energy intensity (Liu et al., 2022) and improved thermal efficiency in electricity generation (Ang and Su, 2016). Moreover, capital and labor-energy substitutions, as well as energy structure, have reduced the carbon-intensity gap between Japan and China (Li et al., 2022).

While the macro-perspective is important and provides important insights, it is also essential to understand the driving forces behind the evolution of carbon productivity from the perspective of individual firms. There has been an increase in firm-level studies on this topic in recent years, but only a small body of research has thoroughly examined the issue. Some studies have analyzed the correlation between various firm-level factors and carbon

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[3] Shen et al. (2017) proposed a decomposition method to analyze the green productivity growth of a group of 30 OECD countries from 1971 to 2011. The decomposition breaks down productivity changes into three components: technological progress, technical efficiency change, and structural efficiency change.

[4] Energy consumption is a primary contributor to emissions, and so energy intensity and carbon intensity are related but not interchangeable. Although different decomposition methods have been used to analyze energy intensity (e.g., Liu and Ang, 2003; Lin and Du, 2014; Tan and Lin, 2018), the focus of our paper is on studies that examine carbon productivity (or carbon intensity, which is its inverse).

productivity growth (e.g., Cao and Karplus, 2014; Jung et al., 2021; Bagchi et al., 2022). For instance, Cao and Karplus (2014) examined the determinants of carbon intensity in Chinese firms and found that changes in carbon intensity were largely driven by changes in energy use, but firm size and firm ownership also played a role, with state-owned firms having higher carbon intensity compared to joint ventures. Further, Brännlund et al. (2014) examined the impact of climate policy and found that CO_2 tax has significantly contributed to the decline in carbon intensity among Swedish manufacturing firms.

Richter and Schiersch (2017) recently conducted a study to test the hypothesis that exporting firms have better environmental performance than nonexporting firms. Their results showed a positive relationship between German firms' export intensity and carbon productivity. Jung et al. (2021) also found that carbon productivity is higher in firms participating in the emissions-trading scheme, as well as in more profitable and innovative firms, and in firms where management has experience in environmental fields.[5] Bagchi et al. (2022) used data on Indian manufacturing firms and found that export and technological intensities, in particular, 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.

While there has been some empirical research on micro-level factors that are associated with carbon productivity, there is still a need for more in-depth analysis of the underlying mechanisms and processes driving carbon productivity at the firm level. In what follows, we address this gap in the literature by examining the contribution of structural

[5] Mahapatra et al. (2021) examined the association of carbon footprint and firm-level factors, including internal initiatives, using data on 77 firms from the Global 500 list. The results showed that reduction of emissions *per se* are not associated with a superior financial performance.

change and firm dynamics on carbon productivity using unique emission data on Finnish manufacturing firms.

3. Carbon productivity decomposition

Carbon productivity, which is a partial productivity measure similar to labor productivity, can be analyzed using existing structural change decompositions of productivity. Consider a sector (or an industry) of the economy with N_t operating firms in a given period t. Note that the number of firms in the sector may vary over time due to market entry and exit. The carbon productivity of a firm i in this period can be calculated by dividing its output y_{it} (e.g., firms' value added) by its GHG emissions c_{it}:

$$c_{it} = \frac{y_{it}}{e_{it}}. \quad (1)$$

By linking the firm-level and the industry-level, carbon productivity of the sector can be defined as a share-weighted average of firm-level carbon-productivity measures (c_{it}) as:

$$C_t = \sum_{i=1}^{N_t} s_{it} c_{it}. \quad (2)$$

In Eq. (2), $s_{it} = \frac{e_{it}}{E_t}$ represent the share of firm i in the total GHG emissions (E_t) of the sector in year t. The use of the shares ensures consistent aggregation of firm-level carbon productivities to the sector level. Following Olley and Pakes (1996), the aggregate carbon productivity of the sector can be further decomposed into two components:

$$C_t = \bar{c}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta c_{it} = \bar{c}_t + \text{cov}(s_{it}, c_{it}), \quad (3)$$

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. (3) indicates, carbon productivity of the sector 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. To address this issue, we follow Kuosmanen and Kuosmanen (2021) and decompose the average carbon productivity $\bar{c}_t$ to capture changes in the composition of the sector through entry and exit as well as industry switching. This implies dividing the firms of the sector into mutually exclusive groups: [6]

(a) continuing firms operating from period t to period $t + 1$,

(b) new entrants in period $t+1$,

(c) exiting firms observed in period t but not in period $t + 1$.

[6] Other productivity studies, such as those conducted by Maliranta (2003), Böckerman and Maliranta (2007), Hyytinen and Maliranta (2013), and Maliranta and Määttänen (2015), have employed a classification similar to the one being discussed.

The set of continuing firms (*S*) includes continuing industry-non-switching firms (*Sn*) and continuing industry-switching firms ($S - Sn$).[7] Applying this classification, carbon productivity of the sector in period *t* can be written as a sum of four components:

$$C_t = \bar{c}_{Sn,t} + (\bar{c}_{S,t} - \bar{c}_{Sn,t}) + (\bar{c}_t - \bar{c}_{S,t}) + (C_t - \bar{c}_t). \quad (4)$$

The *first* term on the right-hand side of Eq (4) represents the average carbon productivity of continuing firms that have not changed industries within the considered sector, also known as non-switching continuing firms. The *second* term captures the effect of industry switching and is identified by comparing the average carbon productivity of all the continuing firms to that of the non-switching continuing firms. Note that if the switching effect is not considered explicitly, its contribution is combined with the effects of continuing non-switching firms and the contribution of entry and exit. The *third* term accounts for the productivity impact of firms entering and exiting the sector and is calculated by comparing the average carbon productivity of all the firms to that of the continuing firms. The *fourth* term captures the allocation of emissions among all the firms, and is represented by the difference between the sector's carbon productivity and the unweighted average carbon productivity of all the firms.

[7] In addition to traditional forms of structural change such as market entry and exit, industry switching represents another way that companies can renew and adapt. This type of change can indicate a company's growth and expansion, or its strategy to survive economic downturns. According to several studies (Bernard et al., 2010, 2016; Maliranta and Valmari, 2017; Kuosmanen et al. 2022b), product switching, which can lead to industry switching for firms, is very common and frequently occurs in manufacturing and other industries. Industry switching can be identified by analyzing changes in the numerical codes assigned to firms according to classifications of economic activities (such as NACE Rev. 2).

The decomposition of the level of carbon productivity in Eq. (4) can be also expressed as the carbon productivity growth, where the sector's carbon productivity growth is decomposed into four components expressed as percentage changes:

$$\frac{C_t}{C_{t-1}} = \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}} + \left[\frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}} - \frac{\bar{c}_{Sn,t}}{\bar{c}_{Sn,t-1}}\right] + \left[\frac{\bar{c}_t}{\bar{c}_{t-1}} - \frac{\bar{c}_{S,t}}{\bar{c}_{S,t-1}}\right] + \left[\frac{C_t}{C_{t-1}} - \frac{\bar{c}_t}{\bar{c}_{t-1}}\right]. \qquad (5)$$

Similar to Eq (4), in Eq. (5), the subscript (S) refers to the continuing firms and (S_n) refers to the continuing non-switching firms in periods t and t–1. The right-hand side of the equation consists of four terms: the *first* measures the carbon productivity change of the continuing non-switching firms, the *second* measures the contribution of the continuing industry-switching firms to aggregate carbon productivity growth, the *third* captures the impact of firms' entry and exit on carbon productivity of the sector, and the *fourth* captures the allocation of emissions among firms. In total, the equation represents the sector's carbon productivity growth is the sum of these four terms.

4. Data

4.1 Data sources

The present study examines the carbon productivity of firms in the Finnish manufacturing sector during the period 2000–2019. Carbon productivity is calculated as the ratio of a firm's value added (VA) to its GHG emissions. Observations with missing values or zero emissions are excluded from the analysis, as 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.[8] As the official statistical authority for Finland, Statistics Finland is required to submit GHG inventories under the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and EU regulations. This inventory annually reports GHG emissions and removals and serves as a foundation for climate policy planning and monitoring. The emission data include units participating in the EU ETS[9] and provide annual reporting of both carbon dioxide and GHG emissions in CO_2 eq. at the establishment and firm levels. In our analysis, we utilize firm-level data and GHG emissions in CO_2 eq. Our data's coverage of the Finnish manufacturing sector's GHG emissions is approximately 99% according to a comparison with Eurostat's aggregate figures for the sector. Our emissions data are thus representative of the entire Finnish manufacturing sector.

The data on VA were obtained from Statistics Finland’s Financial Statement panel data. These panel data provide comprehensive coverage of all independent business enterprises across a wide range of industries and include key profit and loss account and balance sheet data for firms, such as industry code, number of employees, VA, and other firm-specific information. All enterprises with at least 20 employees are directly included in the data collection, while data for smaller enterprises and non-respondent enterprises are derived from administrative sources like business taxation registers.

Linking these two sources of information using firm-identification codes allows us to create a unique matched dataset where firm-level emission records are combined with the business-register datasets containing detailed information on firms’ financial statistics. After

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

[9] All firms in energy-intensive sectors are required to participate in the EU ETS and report their emissions. For more information on sectors and gases covered in the EU ETS, see: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en.

matching the emissions data with the Financial Statement panel data, we obtained 5,269 yearly observations representing 602 manufacturing firms operating in 2000–2019. It is important to note that we classify market entry, exit and industry switching based on the business register data of all firms, not just a subset of EU ETS participating firms. This ensures that exit from and entry to the EU ETS regulation are not misclassified as market entry or exit.

In Table 1, we present the characteristics of our sample. Value added (VA) is measured in millions of euros, greenhouse gas (GHG) emissions are in thousands of tonnes of CO_2 equivalent (CO_2 eq.), and carbon productivity (CP) is in thousands of euros per tonne of CO_2 eq. To facilitate comparison across years, VA and carbon productivity were deflated using the GDP deflator for Finland (with 2015 as the base year). The number of observations in the subsamples ranges from 247 to 276 annually. The average carbon productivity for the firms was 31,000 euros per tonne of CO_2 eq. in 2000 and 694,000 euros per tonne of CO_2 eq. in 2019. During the study period, we observed significant variations in the average carbon productivity among the firms in our sample. This variation could be attributed to certain firms with high value added but low GHG emissions.

[Table 1 here]

4.2 Carbon productivity of the manufacturing sector

Figure 1 illustrates the carbon productivity of the Finnish manufacturing sector for the period from 2000 to 2019 calculated based on our firm-level emission data. It is evident from the graph that there is a distinct U-shaped trend in carbon productivity over this period. From 2000 to 2009, there was a significant decrease in carbon productivity, followed by an increase in more recent years. However, even with this latter positive trend, the sector's carbon productivity has not reached its highest recorded value from 2000 (890 euros per tonne of GHG emissions).

[Figure 1 here]

To further understand the evolution of carbon productivity, Figure 2 presents trends in VA and GHG emissions separately. The figure indicates that changes in carbon productivity are not solely due to a reduction in GHG emissions or an improvement in environmental performance, but also to fluctuations in VA. The decline in carbon productivity may also be attributed to the decrease in industrial output resulting from the financial crisis that occurred at that time. The 2008 global financial crisis turned into an economic crisis in the eurozone, causing a sharp drop in industrial output and subsequently leading to a significant decrease in emissions. However, there has been a continuous reduction in emissions since 2009, which can be partly attributed to the ongoing decline in industrial output but also to the implementation of measures to improve carbon use efficiency.

[Figure 2 here]

4.3 Average carbon productivity by subperiods and subgroups

The present study spans the two decades from 2000 to 2019. In order to capture the effects of firm dynamics on carbon productivity, we focus on three subperiods of six to seven years each: 2000–2006, 2007–2012, and 2013–2019. There are three reasons for this division of the study period. Firstly, medium-term time periods are preferred over short-term analysis (e.g., analysis of yearly changes) as they are able to capture structural changes such as firm entry, exit, and industry switching. Secondly, the chosen periods include different economic up- and downturns, including the period of growth, the Great Recession, and the subsequent recession and slow recovery. Lastly, these periods correspond to 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).[10]

As previously mentioned, the decomposition of carbon productivity in Section 3 is based on dividing the sample of firms into mutually exclusive subgroups: continuing firms, entering firms, and exiting firms. In this subsection, we seek to gain a deeper understanding of the firms included in our sample by examining the average carbon productivities of firms in these subgroups. As a supplement, Appendix A presents additional firm-specific characteristics such as the median size and age of firms from different subgroups.

Panel A of Table 2 reports the relative shares of firms in the first and last years of each subperiod, as well as for the four subgroups of firms: non-switching continuing firms, continuing firms that switched industries, exiting firms, and entering firms. As the panel shows, the manufacturing sector experienced major structural change in the form of industry switching and entry and exit, particularly during the first subperiod (2000–2006). During this time, almost 23% of the firms left the market and were replaced by new entrants, while approximately 9% of the firms switched to a different industry. Meanwhile, nearly 70% of the firms continued to operate in the same industry. The structural changes were less pronounced during the second (2007–2012) and third (2013–2019) subperiods with approximately 80% of the firms remaining in the same industry, 5% of the continuing firms switching industries, and 10%–13% of firms being new entrants.

[10] The Finnish GHG inventory includes firm-level data dating back to 1999. However, the EU ETS was not implemented until 2005. To accurately allocate emission allowances during the initial "grandfathering" phase (in which allowances were distributed based on historical emission levels, see e.g., Sato et al., 2022), it was necessary to track GHG emissions prior to the launch of the EU ETS in 2005–2007.

Further, panel B of Table 2 reports the average level of carbon productivity (in thousand euros per tonne of CO_2 eq., in 2015 prices) for the four subgroups of firms during the first and last years of the three subperiods. The continuing, exiting, and entering firms exhibit significant differences in their average carbon productivity. The average levels of carbon productivity for continuing firms were low during the first subperiod, but increased in the second and third subperiods, reaching an average of approximately 112 thousand euros per tonne of emissions in 2019. The average carbon productivity of the continuing firms that have switched industries has remained relatively stable (30–40 thousand euros per tonne of emissions), except in 2019 when it reached nearly 90 thousand euros per tonne of emissions. The average carbon productivity was relatively high for 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 and third subperiods, the productivity of the exiting firms was quite high compared to all the other groups. This suggests that many firms with high carbon productivity operating in 2013 exited the market by 2019.

[Table 2 here]

To this end, based on the group averages presented in Table 2, the positive development of carbon productivity (shown in Figure 1) after 2009 was largely driven by the subgroup of firms that remained in the same industry, while market entry and exit had a major negative impact on the sector's carbon productivity. This may have been partially due to the global recession triggered by the US financial crisis and resulting in the European debt crisis. In Finland, for instance, the recession led to a structural crisis in the manufacturing sector, which faced numerous mutually independent, exceptionally strong, and negative changes in the global market situation (Holmström et al., 2014).

5. Results of structural-change decomposition

5.1 Decomposing the level of carbon productivity

Applying the carbon productivity decomposition – i.e., Eq. (4) – introduced in Section 3, we next examine the effects of structural changes on the carbon productivity of the Finnish manufacturing sector. Table 3 presents the decomposition of carbon productivity levels in the first and last years of the three subperiods. Column (1) of Table 3 shows the carbon productivity of the entire sector, which is the sum of the four components of the carbon productivity decomposition listed in the same order as in the right-hand side of Eq. (4). 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 Table 3, is the contribution of industry switching, which was positive during 2000–2006 but negative during 2007–2012 and 2013–2019, due to the negative measures of VA 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. 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 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 gradually increased, 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. (5), 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, with all numbers expressed as average yearly percentage changes of the components during the three subperiods. The sum of the components shown in columns (2) to (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 provide insight into 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, which accelerated even further during the second and third subperiods, reaching an average rate of 24% per year in the third period. Structural change also played a significant role in aggregate growth. The third and fourth columns of Table 4 report the contributions of industry switching by 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 particularly strong during 2013–2019 (approximately -9%), due to lower average carbon productivity among entering firms and higher average carbon productivity among exiting firms during that period (see Table 2). The allocation component (the last column of Table 4), which measures the allocation of emissions across firms, remained consistently large and negative throughout all subperiods, nearly doubling in the third subperiod compared to the first two. This negative value indicates that emissions were allocated towards less productive firms in terms of carbon productivity.

[Table 4 here]

The analysis of carbon productivity in the Finnish manufacturing sector reveals that the aggregate carbon productivity change was negative during 2000–2006 but improved during 2007–2012 and 2013–2019. The main driver of carbon productivity growth was the group of firms that continued to operate in the same industry. However, the negative contribution of entry and exit, combined with the negative effect of emission allocation, largely offset the positive impact of these continuing firms.

6. Extension: factors contributing to firm-level carbon productivity

The results of the decomposition analysis presented above show 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:

$$\log(CP_{ft}) = \alpha' X_{ft} + \beta' I_{ft} + \tau_t + \varepsilon_{ft}, \quad (6)$$

where the dependent variable is the logarithmic form of carbon productivity for firm *f* in year *t*. The vector *X* includes firm-level characteristics measured in year *t*, including the logarithmic forms of firm's labor productivity (value added per number of employees), the number of employees and sales. Accordingly, the control vector is augmented with firms' age, the current ratio (current assets divided by current liabilities), and the market share of firms (the ratio of the firm's turnover to the total aggregate turnover of all manufacturing firms). The market share term can be seen as a measure of a firm's size relative to its market and its competitors, or in other words, as a proxy variable for competitiveness. The model also includes 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 5,140 observations of manufacturing firms in 2000–2019. The descriptive statistics of the sample are included in Appendix B, and the results of the regression are reported in Table 5. The regression results show that, among the firm-specific factors, all variables 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 associated with a 0.9% increase in carbon productivity, and a 1% increase in labor productivity is associated with a 0.7% increase in carbon productivity.

[Table 5 here]

The coefficients of turnover and market share are negative and statistically significant, indicating that firms with higher sales (turnover) and larger market share are less efficient in terms of carbon use. A 1% increase in turnover is associated with a 0.5% decrease in carbon productivity, and a 1%-point increase in market share is associated with a 0.9% decrease in carbon productivity. One possible explanation for this negative relationship is that manufacturing firms with higher turnover and larger market share have access to cheaper European Union Allowances for CO_2 emissions, rather than reducing their own emissions. However, this situation may change in the near future due to recent spikes in allowance prices for CO_2 emissions. Additionally, the situation may persist due to the EU ETS design, in which some sectors with high carbon intensity and trade intensity may qualify for free allowances under the EU ETS, which could also affect the cost of emitting CO_2 and contribute to this relationship.[11]

There is a positive correlation between firms' age and carbon productivity, which suggests that older firms are making greater efforts to reduce their carbon emissions. However, the association is not economically that significant. For example, a 10-year increase in a firm's age is associated with a mere 0.08% increase in carbon productivity. Regarding specific manufacturing sectors, the results show that many of the estimated coefficients are statistically significant. Industries such as the *manufacture of wood and wood products*, *machinery and equipment*, and *electrical and optical equipment* have positive and statistically significant coefficients (at the 1% significance level), indicating that carbon productivity is higher in these industries compared to the reference industry, which is the *manufacture of food products, beverages, and tobacco*. On the other hand, 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 compared to the reference industry.

[11] In 2013, the manufacturing industry received 80% of its allowances for free. However, this proportion decreased steadily over the years and by 2020, the industry only received 30% of its allowances for free (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).

7. Conclusions

The Finnish manufacturing sector has undergone a green transition in recent years, with many firms working to reduce their GHG emissions. In this study, we investigate the role of firm dynamics - such as entry, exit, and productivity improvement - in driving this transition. We use a panel of Finnish manufacturing firms, linking GHG emissions data and financial performance data to study carbon productivity at the firm level and consistently aggregate these measures at the sector level. By applying a structural change decomposition, we decompose the sector's aggregate carbon productivity over the period 2000–2019 into components that capture the carbon productivity growth of continuing firms, the contributions of entering and exiting firms, and the allocation of GHG emissions among firms. This allows us to identify the specific contributions of different types of changes at the firm level to the sector's overall performance.

Understanding how different types of changes in the composition of firms - such as new entrants and exits - impact carbon productivity in the manufacturing sector is an important but understudied area. To our knowledge, our study represents one of the first attempts to address this gap by using firm-level GHG-emissions data. Previous research has mainly focused on carbon productivity at higher levels of aggregation, such as industries or countries, and has not explicitly examined the role of structural change. While there are some studies that have investigated how changes in technical efficiency and technology affect carbon productivity, none have specifically examined the impact of firms entering or exiting the market on carbon productivity in manufacturing.

Our analysis shows that the main factor driving the sector's carbon productivity growth was the strong performance of continuing firms. In contrast, the allocation of GHG emissions across firms and changes in the composition of firms had negative effects on carbon productivity growth, leading to declining productivity and worsening over time. Industry switching had a relatively small and negative effect on aggregate growth. Furthermore, we find that certain firm-specific characteristics are related to the carbon productivity of continuing firms. Larger firms and those with higher labor productivity tend to have higher carbon productivity, while firms with higher turnover and larger market share tend to have lower carbon productivity. These results are consistent with the idea that emission reduction efforts can lead to economic losses, as previously suggested by He et al. (2018).

Although our results indicate that continuing firms in the manufacturing sector perform well in terms of carbon productivity, further research is needed on the role of structural change. It is concerning that the average carbon productivity of firms entering the sector is lower than that of firms exiting the sector, and the sector's carbon productivity could be improved significantly by reallocating emissions to more carbon-productive firms. However, this may be challenging due to the diverse nature of the manufacturing sector. Future research should focus on understanding the effects of structural change in specific industries.

The policy implications of this paper are significant. Policymakers should take into account the heterogeneity of firm-level carbon productivity when designing policy. To maximize the benefits of current carbon productivity growth, more effort should be directed at improving the carbon productivity of firms entering the sector. The government can support this by providing technological assistance and financial compensation to these firms, as well as to continuing firms to offset the potential economic costs of emission reduction efforts. There has been debate in Finland about the optimal level for a carbon tax (Khastar et al., 2020). Although a carbon tax can be effective in reducing emissions, it may also have negative impacts on social welfare.

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Figures and Tables

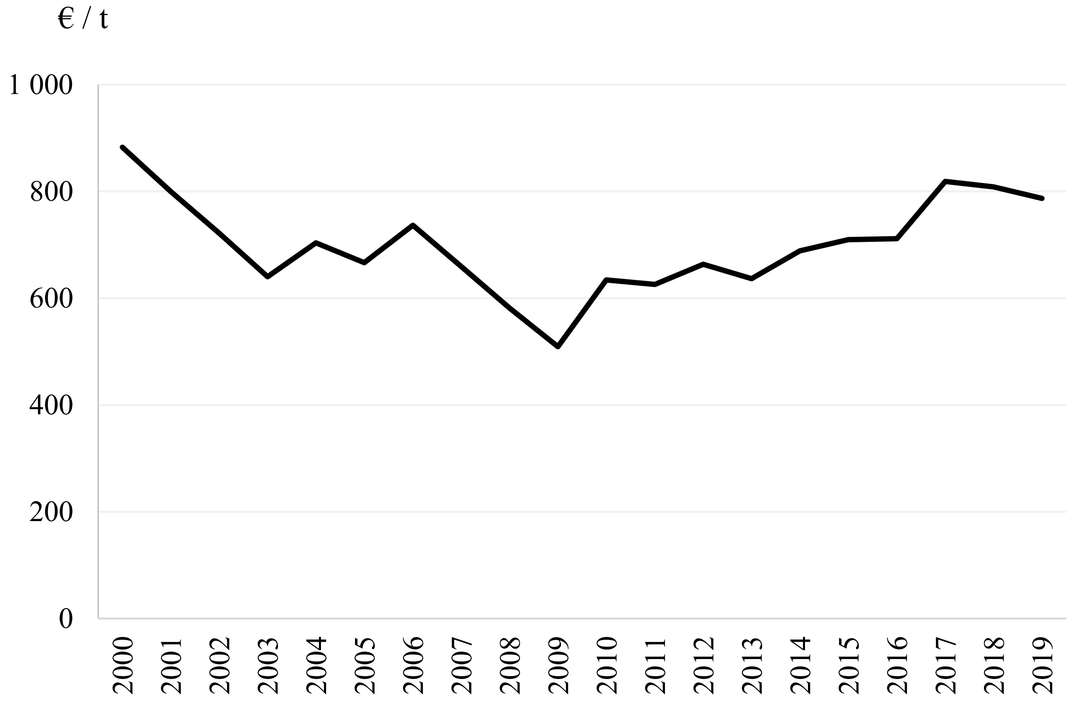

Figure 1. Carbon productivity of the Finnish manufacturing sector in 2000–2019, measured in euros per tonne of GHG (prices of 2015, GHGs in CO_2 equivalents).

Source: Authors' calculations based on Statistics Finland's data.

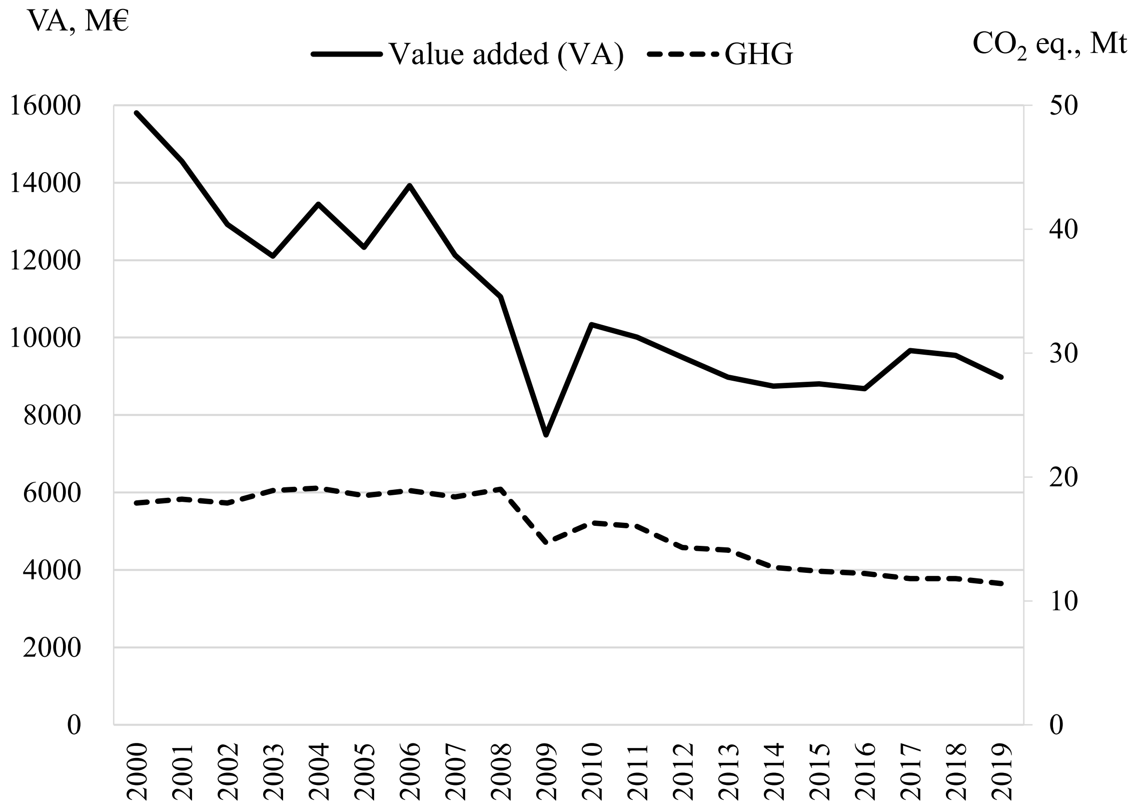

Figure 2. Value added (left axis; the solid line) and GHG emissions (right axis; the broken line), measured in M€ (prices of 2015) and Mt of CO_2 equivalents, respectively, of the Finnish manufacturing sector in 2000–2019.

Data sources: The National Greenhouse Gas Inventory and Financial Statement panel data of Statistics Finland.

Table 1. Descriptive statistics of the key variables.

	No of Obs.	**VA**		**GHG**		**CP**	
		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

Note: Value added (VA) is expressed in million euros in 2015 prices, GHG emissions are measured in thousand tonnes of CO_2 eq, and carbon productivity (CP) is measured in thousands of euros (in 2015 prices) per tonne of CO_2 eq.

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

	Non-switching continuing firms	*Industry-switching continuing 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		
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 levels of carbon productivity (CP) in the Finnish manufacturing sector.

	Sector's CP level	Aver. CP of non-switching continuing firms	Effect of industry switching	Effect of entry and exit	Effect of GHG allocation
	(1)	(2)	(3)	(4)	(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 (thousand euros, 2015 prices) per tonne of GHG (in CO_2 eq.).

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

	Sector's CP change	Aver. CP change of non-switching continuing firms	Effect of industry switching	Effect of entry and exit	Effect of GHG allocation
	(1)	(2)	(3)	(4)	(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

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

	Coef.	Std.Err.
Log (Labor productivity)	0.691 ***	0.122
Log (Employees)	0.873 ***	0.138
Log (Turnover)	-0.523 ***	0.120
Market share	-0.867 ***	0.220
Current ratio	0.001	0.001
Firm age	0.008 **	0.004
Manufacture of		
textiles and textile products	-0.598 *	0.310
leather and leather products	-0.781 ***	0.223
wood and wood products	1.417 ***	0.246
pulp and paper products, publishing and printing	-1.079 ***	0.316
coke, refined petroleum products, and nuclear fuel	0.335	1.214
chemicals, chemical products, and man-made fibers	0.106	0.339
rubber and plastic products	0.183	0.343
other nonmetallic mineral products	-1.834 ***	0.388
basic metal and fabricated metal products	-0.203	0.276
machinery and equipment	1.846 ***	0.359
electrical and optical equipment	0.951 ***	0.349
transport equipment	0.193	0.399
other products	0.741 *	0.419
Year indicators (19)	Yes	
R^2	0.263	
Observations	5,140	

Note: The dependent variable is the logarithm of carbon productivity. 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. Median size of firms by firm type and year.

	Non-switching continuing firms	*Industry-switching continuing firms*	*Exiting firms*	*Entering firms*
Firm size (number of employees)				
2000	210.4	178.5	255.0	
2006	175.0	135.0		156.6
2007	157.9	94.7	114.0	
2012	116.3	76.3		102.3
2013	109.4	156.8	81.6	
2019	92.1	135.7		94.4

Table A2. Median age of firms by firm type and year.

	Non-switching continuing firms	*Industry-switching continuing firms*	*Exiting firms*	*Entering firms*
2000	8.0	11.0	9.0	
2006	12.0	11.0		2.0
2007	13.0	13.0	12.0	
2012	18.0	18.0		2.0
2013	18.0	18.0	13.0	
2019	24.5	16.5		3.0

Appendix B

Table B1. Descriptive statistics of the sample used in the regressions.

Variable	Mean	Std. Dev.
Carbon productivity (M€/t of CO_2 eq.)	0.581	20.00
Labor productivity (M€/person)	0.099	0.163
Number of employees (in full-time-equivalent units)	421.2	891.51
Turnover (M€)	217.14	742.73
Market share (%)	0.20	0.512
Current ratio	2.67	27.91
Age of firms	22.5	20.83
Manufacture of		
food products, beverages, and tobacco	0.145	0.351
textiles and textile products	0.032	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	0.113	0.318
coke, refined petroleum products, and nuclear fuel	0.005	0.068
chemicals, chemical products, and man-made fibers	0.150	0.358
rubber and plastic products	0.064	0.245
other nonmetallic mineral products	0.089	0.286
basic metal and fabricated metal products	0.168	0.373
machinery and equipment	0.042	0.201
electrical and optical equipment	0.009	0.092
transport equipment	0.021	0.143
other products	0.036	0.186