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Industrial characteristics and air emissions: Long-term determinants in the UK manufacturing sector

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ABSTRACT

Empirical assessments of the relationship between emissions from the industrial sector and the characteristics of the production process are surprisingly scarce in the literature for European countries, despite the industrial sector being one of the major air polluters. In our study, we assess long-term relationship between industrial process and air emissions by building on an existing empirical framework. Our work implies re-estimating published findings for the UK industrial sector on a bigger dataset, incorporating additional observed factors which can plausibly influence the level of emissions and taking into account, for the first time in the empirical literature, unobserved common factors through cross section dependence. In comparison to previous findings we conclude that production inputs, total factor productivity and economies of scale cannot be relied upon to reduce emissions from industrial sector. We provide evidence that reduction in emissions can be reliably delivered by reducing energy consumption, encouraging fuel substitution and by encouraging market competition so that one can counteract the increase in emissions related to higher level of capital investment. We observe considerable similarities in the relationship between market concentration on one side and industrial emissions and innovation on the other side. This is an interesting result in for the energy and environmental economic literature as the relationship between the level of emissions and market structure is a considerably under-researched area.

1. Introduction

Air pollution affects negatively human health in various ways. Particular matter exposition, for example, raises the risk of developing cardiovascular diseases and lung cancer (Guerreiro et al., 2016), ecosystems are affected by air pollution through acidification, eutrophication, and ground level ozone (Wald, 2016)[1] while greenhouse gases are the dominant cause of climate change (IPCC, 2014) with related impacts on health (Watts et al., 2015), the economy (Stern, 2008), and ecosystems (Walther et al., 2002). Cole et al. (2005), from now onwards CES (2005), drew attention to the shortage of studies assessing the relationship between industrial activity and air pollution outside of the United States and provided the first empirically investigation of this relationship in the UK manufacturing[2] sector using data from 1990 to 1998. Although the manufacturing sector is one of the major air polluters in Europe (ONS, 2016a; EEA, 2015), not many studies have responded to the task highlighted by CES (2005) so that this apparent lack of investigative effort is preventing a rigorous understanding of the historical determinants of emissions from the manufacturing sector, at least in Europe. In fact, many contributions focus only on national or regional CO_2 emissions rather than from the industrial sector, e.g. Li et al. (2017), Mussini and Grossi (2015), Omri (2013), Qi et al. (2016), Tajudeen et al. (2018). When focusing on the industrial sector, analysis has been often implemented by using decomposition analysis rather than econometric modelling, e.g. Dachraoui and Harchaoui (2006), Kim and Kim (2012), Liaskas et al. (2000), Tan and

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[1] Acidification occurs when acidic compounds in accord and air pollutants (such as PM_{10} and CO) are deposited on land and aquatic systems and harm soils, vegetation and wildlife. Acid rain precursors (such as NO_x and SO_2) result both to eutrophication and ground-level ozone, where the former affects the nutrients level and the wildlife in sensitive environment, while the latter damages plants, crops and forests and contributes in climate change along with greenhouse gases (such as CO_2 and N_2O).

[2] Despite the difference between the two sectors based on the international SIC taxonomy we will be using the term 'manufacturing' and 'industrial' interchangeably. The list of the industrial subsectors covered by this study can be seen in Table 1.

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Lin (2018), Wang et al. (2018), with Floros and Vlachou (2005) being a notable exception but only focusing on CO_2 rather than set of air emissions discussed in this article. CES (2005) found that emissions intensity is positively related to energy use, physical capital intensity and human capital intensity and negatively related to sector's average firm size and productivity. Research and development (R&D) expenditures were reported to have a mixed impact on emissions intensities, with the direction of the impact depending on the pollutants being assessed. Impact of capital expenditure was positive but non-statistically significant. Emissions were also negatively influenced by regional population density, prosecution activity and regional age of population and positively by unemployment. This study responds to the task highlighted by CES (2005) on establishing an empirically grounded understanding of the relationship between emissions and industrial activity, with a focus on the UK manufacturing subsectors. The United Kingdom is chosen due to our easy access to subsector specific data (as well as datasets required to build potential explanatory variables) but also for the ability to compare our results to those in CES (2005) in a similar fashion to the replication study performed by Karakaya et al. (2017) on CO_2 emissions. Lacking an established and generally accepted theoretical framework, the best way to analyse the extent to which emissions from the manufacturing sector are related to the characteristics of the production process is to assess the robustness of established findings in the literature such as those in CES (2005).

This study investigates the long-term determinants of emissions from the industrial sector by assessing the robustness of the results in CES (2005) in three ways. First of all, we adopt a specification as close as possible to the one CES (2005) estimated on a 1990–1998 sample, which we re-estimate on our sample, from 1997 to 2014. If results from CES (2005) are reflective of long-term determinants of emissions, we would expect our results to be fairly similar to those in CES (2005), with some changes in the value of the coefficients maybe due to the possibility of time-varying parameters in the data generation process or missing variables. Secondly, we estimate a model augmented by two factors which might have an impact on emissions from the manufacturing sector, fuel substitution and market concentration. As emissions intensities vary across different fuels, fuel substitution seems an obvious candidate as explanatory factor. Building on the results in Aghion et al. (2005) introducing market concentration might help to consider the impact of innovation on emissions, therefore tackling lack of R&D data at the subsectoral level. Again, if results from CES (2005) are reflective of long-term determinants of emissions, we would expect changes from introducing two explanatory variables to be limited, especially in cases where correlation between the explanatory variables is low. Thirdly, as our requirements for long-term determinants of emissions are not met by most of the variables in CES (2005), we assess the extent to which unobserved common factors (through cross section dependence – CSD – see Chudik et al. (2011)) affect our results. Our choice of focusing on CSD is motivated by the fact that industrial subsectors in the same country are likely to be affected, to some extent, by a common set of unobserved factors, e.g. either through the impact of spillovers or common shocks, such as technological progress and regulatory pressure, as confirmed by the statistical tests we ran. Not taking CSD into account is a serious shortcoming, as it may impact both the statistical significance of explanatory variables and the values of the estimated coefficients, as discussed below. Application of the Common Correlated Pooled Group estimator (Pesaran, 2006) tackling CSD enables us to point at energy intensity, fuel substitution, and capital expenditure intensity as robust determinants of industrial emissions across the pollutants assessed in this study. Reflecting results from Aghion et al. (2005) on the relationship between market concentration and innovation, our results point at a robust U-shaped relationship between market concentration and emissions intensities, therefore contributing to an area of environmental economics which appear surprisingly under-researched. We also conclude that factors such as production inputs i.e. labour and capital, total factor productivity and size of typical firm are not robust determinants of emissions from industrial sector, at least in the timespan assessed in this study, based on our definition of the variables, and the level of aggregation at which our analysis is conducted.

The remainder of the paper is structured as follows: Section 2 briefly describes the trend in the emissions from the industrial sector and discusses potential emissions determinants we consider in this study. Section 3 introduces our econometric methodology with most of the discussion focusing on CSD and estimators able to take it as our contribution represents our example of tackling CSD in the environmental economics literature. Section 4 presents our results which are further discussed in Section 5. Section 6 concludes.

2. Atmospheric emissions and their determinants

The UK has experienced a significant reduction in the overall level of atmospheric emissions from the manufacturing sector in the last 25 years. Between 1990 and 2014 CO_2 emissions have fallen by 32%, N_2O emissions by 96%, NO_X by 64% and SO_2 emissions by 84% (Brown et al., 2016, p.108–111), with the great majority of the reductions additional to those assessed in CES (2005) which are related only to the 1990–1998 time period (see Fig. A1). As one can see in Table 1, there is considerable variation in the average emissions intensity across manufacturing subsectors in our sample (1997–2014) so that one can notice a handful of emissions intensive sectors, such as “wood and products of wood and cork” (SIC 16), “paper and paper products” (SIC 17), “coke and refined products” (SIC 19), “chemical and chemical product's” (SIC 20), “non-metallic minerals” (SIC 23) and “basic metals” (SIC 24). Although the overall emissions have significantly decreased, industrial subsectors have continued to experience disparate trends in emissions intensities documented in CES (2005) - as one can see in Fig. A3 for CO_2[3] . Agnolucci et al. (2017) also reveals the existence of considerable heterogeneity across UK industrial subsectors when it comes to the long-run impact of economic activity on energy consumption. Therefore, it seems sensible to implement an investigation focused on industry-specific determinants, like the one pursued in CES (2005).

Our investigation centres on emissions intensities rather than the level of emissions, a choice motivated by our aim of identifying long-term industrial characteristics related to industrial emissions by assessing the robustness of results in CES (2005), but also by the fact that the time pattern of emissions is driven by intensive factors rather than the level of production, as one can appreciate from comparing the time pattern of emissions (Fig. A1) and emissions intensity (Fig. A2). The variables used in our study include most of those used in CES (2005), with only R&D excluded due to data limitations.[4] As our interest is on the relationship between emissions and characteristics of the production process, we dropped regional variables discussed in CES (2005), a decision which does not affect our comparison with CES (2005) as their results were robust to the absence of regional variables. Moreover, results in Cole et al. (2013) cast doubts on the importance of these factors, or maybe the extent to which available data enable a precise estimation, as none of the four regional variables used in Cole et al. (2013) were found statistically significant in any of the estimated models. In addition to the variables in CES (2005) we include two factors which might affect emissions intensity, i.e. fuel substitution and market concentration, as discussed below. As emissions are compiled on the basis of Standard Industrial Classification 2007 (SIC07), we use

[3] Figure A3shows only CO_2 emissions intensity per SIC07 manufacturing sectors due to space constrains, nevertheless, graphs of the rest emissions intensities are available upon request.

[4] The ONS Business Enterprise R&D development dataset reports R&D expenditure data for “product groups” which is an industrial classification that classifies sectors on a more aggregated level than SIC07 two-digit classification, i.e. SIC 10–11-12 are aggregated on one product group., the same applies to 13–14-15 and 16–17-18. R&D expenditure data by product group are not directly comparable to R&D data by industrial sector according to ONS (2014) while R&D expenditure data by industrial sector has started to be reported by the ONS Business Enterprise R&D development dataset only after 2010 and onwards.

Table 1
Average emissions intensities per UK manufacturing subsector for 1997–2014.

SIC07	Manufacturing industry	SO_2	NO_x	Tot. acid	CO	PM_{10}	CO_2	N_2O
10	Food products	2.88E-04	9.56E-04	1.34E-03	1.21E-03	1.01E-04	4.25E-01	4.52E-03
11–12	Beverages and Tobacco products	2.27E-04	5.81E-04	8.19E-04	8.28E-04	4.25E-05	2.84E-01	1.49E-03
13	Textiles	6.24E-04	1.10E-03	1.73E-03	2.66E-03	1.78E-04	6.03E-01	3.19E-03
14	Wearing apparel	1.36E-04	3.35E-04	4.67E-04	8.32E-04	3.76E-05	1.92E-01	7.44E-04
15	Leather and related products	2.95E-05	2.17E-04	2.61E-04	3.57E-04	3.58E-05	1.26E-01	4.32E-04
16	Wood and products of wood and cork[a]	3.88E-04	**2.24E-03**	**2.95E-03**	**2.79E-02**	**1.14E-03**	**1.05E+00**	**9.08E-03**
17	Paper and paper products	**1.08E-03**	1.60E-03	2.69E-03	2.44E-03	2.09E-04	1.01E+00	5.59E-03
18	Printing and reproduction of recorded material	5.78E-05	3.36E-04	4.01E-04	6.70E-04	2.32E-05	2.12E-01	1.11E-03
19	Coke and refined petroleum	**4.10E-02**	**1.15E-02**	**5.27E-02**	**2.21E-02**	**1.44E-03**	**9.80E+00**	**1.86E-02**
20	Chemical and chemical products	**2.63E-03**	**2.54E-03**	**5.90E-03**	**7.96E-03**	**3.51E-04**	**1.90E+00**	**4.04E-01**
21	Pharmaceutical products	1.17E-04	1.90E-04	3.09E-04	4.90E-04	1.47E-05	1.52E-01	4.92E-04
22	Rubber and Plastic	8.76E-04	9.84E-04	1.87E-03	2.05E-03	2.03E-04	4.17E-01	3.46E-03
23	Non-metallic minerals	**6.70E-03**	**6.50E-03**	**1.35E-02**	**9.65E-03**	**1.24E-03**	**3.32E+00**	**1.45E-02**
24	Basic metals	**1.89E-02**	**7.22E-03**	**2.61E-02**	**1.17E-01**	**2.48E-03**	**8.18E+00**	**1.90E-02**
25	Fabricated products[b]	1.06E-04	5.07E-04	6.19E-04	1.07E-03	1.45E-04	2.61E-01	1.54E-03
26	Computer, electronic and optical products	4.07E-05	2.09E-04	2.57E-04	4.47E-04	3.12E-05	8.21E-02	1.21E-03
27	Electrical equipment	4.36E-05	3.75E-04	4.26E-04	8.35E-04	7.72E-05	1.61E-01	1.61E-03
28	Machinery and equipment	4.62E-05	4.37E-04	4.89E-04	9.99E-04	9.64E-05	1.69E-01	1.23E-03
29	Motor vehicles, trailer and semi-trailers	1.88E-04	3.20E-04	5.11E-04	6.91E-04	1.67E-04	1.81E-01	1.07E-03
30	Transport equipment	1.06E-04	2.96E-04	4.09E-04	3.97E-04	7.21E-05	1.36E-01	5.86E-04

Notes: Emissions intensities are measured as thousand tonnes per million pounds sterling of real GVA. For each column, the five highest emitting industries are highlighted in bold. We use SIC07 industrial classification.
[a] Except furniture.
[b] Except machinery and equipment.

the same industrial taxonomy to build the variables in our study which are mainly based on the ONS Input-Output Supply and Use tables - available for the 1997–2014 time-period (ONS, 2015), therefore limiting the overlap between our sample and the sample used in CES (2005) to 2 years only, i.e. 1997 and 1998. This is not a limitation for our study as our analysis of the long-term relationships between industrial emissions and their determinants is not expected to be impaired by limited overlap between the sample in our study and the one used in CES (2005).

Following CES (2005), we focus on carbon dioxide (CO_2), nitrogen oxides (NO_x), sulphur dioxide (SO_2), total acid precursor emissions[5] (TAC), particular matter (PM_{10}) and carbon monoxide (CO). We also add another GHG to the set in CES (2005), i.e. Nitrogen Monoxide (N_2O), data for which is available in ONS (2016a). All abovementioned pollutants are divided by the level of real GVA, which we obtain from Input-Output Supply and Use tables - for more information see ONS (2016c) - for 20 UK manufacturing subsectors to compute emissions intensities. In addition to energy intensity, an obvious determinant of emissions intensity[6] (we expect a positive relationship between emissions and energy intensities), we consider two other factor intensities, i.e. Physical Capital Intensity (PCI) and Human capital intensity (HCI). The use of PCI and HCI when studying emissions intensity is related to the relationship between production inputs, including energy and therefore emissions, and the associated debate on the substitution or complementarity in the so-called KLE (Capital, Labour and Energy) literature, e.g. Thompson (2006) and Koetse et al. (2014). While results from Antweiler et al. (2001) and Cole and Elliott (2003) suggest that higher emissions are related to higher physical capital intensities, perhaps due to higher abatement costs, it is not entirely clear whether this empirical relationship would hold between emissions intensity and physical capital intensity, especially after controlling for energy intensity, a factor which is not included in neither Antweiler et al. (2001) nor Cole and Elliott (2003). After all, if higher abatement costs manifest themselves through demand for energy, so that it is more difficult for these firms to reduce emissions by substituting away from energy, a statistically significant relationship between physical capital and emissions intensity might not hold after energy intensity use is controlled for. CES (2005) argues that certain complex industrial processes which tend to be physical capital intensive might generate more emissions per unit of energy than less capital-intensive processes. CES (2005) also argues that that human capital-intensive sectors are likely to be more efficient and hence less energy intensive and therefore relatively clean (CES 2005) but again, it is not clear whether this plausible relationship would hold after one controls for energy intensity. CES (2005) eventually finds a statistically significant positive relationship between HCI and emissions intensities (after controlling for energy intensity), a result contradicting their reasoning above. We conclude that there does not seem to be very strong theoretical reasons for expecting statistically significant relationships between physical and human capital intensities, on one side, and emissions intensities, on the other, especially after controlling for energy intensity.

We include among emissions intensity determinants, the capital expenditure intensity, measured based on Gross Fixed Capital Formation, a measure of investment intensity slightly different from the one used in CES (2005). CES (2005) argues that capital expenditure intensity can be used as a measure of the vintage of production processes, under the assumption that the higher this expenditure, the more modern the equipment and machinery are likely to be, and the lower the emissions from the production process. Results in CES (2005) contradict their argument, as the estimated coefficients are positive for all emissions intensities although non-statistically significant. We also consider Total Factor Productivity (TFP) to take into account the output not explained by the amount of inputs used in the production (Hulten, 2000). According to CES (2005), emissions are expected to be negatively correlated with TFP, as a more productive firm tend to be better managed, more resource efficient, produce less waste per unit of output and able to respond relatively quickly to any change in pollution control incentives. While more efficient firms are likely to produce a lower level of emissions, it is however not clear whether this hold after energy intensity is controlled for. Cui et al. (2015) found a negative relationship between a simplified measure of TFP[7] and emissions intensities.

[5] Total acid precursor emissions (TAC) are the weighted sum of SO_2, NO_x and NH_3 (ammonia) produced by industrial processes and direct fuel use at the point of release.

[6] In fact, in the case of Chinese industrial sectors Qi et al. (2016) provide evidence that CO_2 emissions have been mainly reduced by the reduction in energy intensity per output while Li et al. (2017) prove that economic scale effect and energy intensity are the major factors driving regional differences in CO_2 emissions.

[7] TFP is estimated as a simple firm and industry-specific fixed effect in a linear production function comprising labour, an industry fixed effect, an industry-specific time effect and a firm and industry-specific fixed effect taken to measure TFP.

A similarly negative relationship has been estimated in CES (2005) which, unlike Cui et al. (2015), control for energy intensity.

We also include size among our explanatory variables. CES (2005) discusses the hypothesis of a positive relationship between a firm's total output and emissions, although diminishing at the margin, so that emissions intensities decline as output increases, due to economies of scale in resource use and in pollution abatement. Engineering evidence supporting lower unitary abatement costs as size of the plant increases is briefly discussed in Andreoni and Levinson (2001) but analysis of detailed US factories reveals a great diversity with regard to marginal abatement cots, i.e. some marginal costs rising with the scale of abatement, while others falling. Similarly, for some sectors and some pollutants, marginal abatement costs decline across time while for others they rise across time (Hartman et al., 1997). Impact of firm size on emissions intensities in Cole et al. (2013) and Gray and Shadbegian (2007) is negative although not always statistically significant.[8] However, none of these studies control for energy intensity when estimating the impact of firm size on emissions intensities. Impact of size is negative but statistically significant only in half of the selected final models in CES (2005).

As emissions intensity vary across fuels, fuel substitution seems an obvious driver of emissions intensities, especially bearing in mind that part of the emissions is calculated in ONS (2016a) by applying sector- and fuel-specific emissions coefficients. According to Liaskas et al. (2000) fuel substitution from conventional fuels to natural gas in the industrial sector has resulted in the reduction of CO_2 emissions in most of the EU countries while Dachraoui and Harchaoui (2006) find that a reduction in Canadian CO_2 emissions intensities has been the outcome of a combination of energy intensity and substitution effect. The fact that fuel substitution is not controlled for in CES (2005) and in any of the other contributions estimating the relative importance of the determinants of emissions intensity, e.g. Cole et al. (2013), Cui et al. (2015) and Gray and Shadbegian (2007), is a shortcoming maybe related to the overall low profile of fuel substitution in the EKC literature.[9] We test the extent to which fuel substitution is an important factor in determining emissions intensities by using the gas share, as a proxy for substitution from dirtier to cleaner fuels. One would therefore expect a negative relationship between gas share and emissions intensities. Statistically significant substitution effects between coal and gas for the UK manufacturing sectors are discussed in Steinbucks (2012). The impact of switching from coal to gas on the level of CO2 emissions is one of the generally acknowledged facts in the literature assessing the EU ETS, e.g. Chevallier (2012), while, similarly, low coal and carbon prices is one of the causes of the low demand for gas in Europe (Stern, 2017).

Market structure and concentration[10] have received considerable attention in the literature focused on the optimal choice of policy instruments aimed at maximising social welfare in presence of externalities (Harberger, 1954; Buchanan, 1969; Oates and Strassman, 1984; Baumol and Oates, 1975). Textbook environmental economics conclude that reduction in the level of externalities is related to the reduction in economic activity brought about by any degree of market power, an established relationship which does not seem to cast much light on the relationship between emissions intensity, i.e. level of emissions given the level of economic activity, and its determinants. The empirical relationship between observed emissions and market structure or concentration is however a surprisingly little researched topic with very few exceptions in the electricity market. Mansur (2007) finds that exercise of market power in the Pennsylvania, New Jersey and Maryland Interconnection (PJM), i.e. the world's largest restructured wholesale electricity market, resulted in the reduction of SO_2, NO_x and CO_2 emissions, a result further supported by Chaton and Guillerminet (2013) with regard to CO_2 emissions although it is not clear what the effect would have been on emissions intensity. On one hand, Asane-Otoo (2016) found that the degree of vertical integration in OECD electricity markets was positively correlated to emissions intensity while on the other hand, market concentration was found to be positively related to air emissions abatement control costs (per unit of economic activity) although the effect is not statistically significant (Farber and Martin, 1986). Similarly, Barrows and Ollivier (2018) show that increased competition, which one would expect from decreased concentration, decreases aggregate emission intensity through increases in aggregate productivity. As there is no established consensus, it is worth exploring the historical relationship between market concentration and emissions intensity. We do so while accounting for energy intensity and fuel substitution effects and to this end, we incorporate in our study (see Section 3) the logarithm of HHI and the square of the logarithm of HHI in order to incorporate evidence of non-linear effects of market concentration on innovation discussed by Aghion et al. (2005)[11] in the UK manufacturing sector.

3. Econometric modelling

We start by re-estimating as closely as possible the model implemented in CES (2005), i.e.

$$E_{it} = \alpha_i + \delta_t + \beta_1 EN_{it} + \beta_2 HCI_{it} + \beta_3 PCI_{it} + \beta_4 SIZE_{it} + \beta_5 TFP_{it} + \beta_6 CAP_{it} + \varepsilon_{it} \quad (1)$$

for $i = 1, \ldots, 20$ industrial sectors and $t = 1, \ldots, 18$ years where the independent variable E_{it} is emissions intensity, i.e. atmospheric emissions divided by real GVA. Eq. (1) is estimated separately for sulphur dioxide (SO_2), nitrogen oxides (NO_x), total acid precursor emissions (TAC), carbon monoxide (CO), particular matter (PM_{10}), carbon dioxide (CO_2) and dinitrogen monoxide (N_2O) emissions intensities. Independent variables in Eq. (1) include energy intensity (EN_{it}), human capital intensity (HCI_{it}), physical capital intensity (PCI_{it}), size of the average firm in the manufacturing subsector ($SIZE_{it}$), total factor productivity (TFP_{it}), and capital expenditure intensity (CAP_{it}). We take the logarithms of all variables, so that the estimated coefficients can be interpreted as elasticities like in CES (2005). When estimating Eq. (1) we choose between fixed effects (FE) and random effects (RE) estimators using the Hausman test and we use a F-test to determine the existence of time-effects, i.e. introducing time dummies if the null of the F-test is rejected. From the estimation, we obtain a benchmark model for comparison with results from CES (2005). We then introduce in Eq. (2) gas share (GAS_{it}) and the Herfindhal-Hirschman index (HHI_{it}), with the latter both in levels and squares to incorporate the possibly non-linear impact of market concentration on emissions intensity.

$$E_{it} = \alpha_i + \delta_t + \beta_1 EN_{it} + \beta_2 GAS_{it} + \beta_3 HCI_{it} + \beta_4 PCI_{it} + \beta_5 SIZE_{it} + \beta_6 TFP_{it} + \beta_7 HHI_{it} + \beta_8 HHI_{it}^2 + \beta_9 CAP_{it} + \varepsilon_{it} \quad (2)$$

We continue by testing for the existence of CSD in the dataset which may arise from unobserved common processes or "factors" affecting both the variables and the error term, possibly to a different extent. The factors can be either strong or weak, the former representing shocks

[8] When using categorical size variables, Cole et al. (2013) finds that only two of the three size variables are statistically significant. Similarly, Gray and Shadbegian (2007) finds that the continuous size variable used in their study is not statistically significant in the two models explaining PM emissions.

[9] Fuel substitution is mentioned only once, as part of the technological changes associated with the production process, in a survey of EKC (Dinda, 2004) and estimated to have a relatively overall minor impact in a number of influential articles, i.e. Stern (2002) and Stern (2004).

[10] Although conceptually distinct, market structure and concentration are naturally interlinked, with the conventional understanding, e.g. Bikker and Haaf (2002), being that the greater the market share of a firm, the more concentrated an industry is and the smaller the level of competition in that industry.

[11] Correa (2012) argues that a structural break in the early 1980s makes Aghion et al. (2005) competition-innovation relationship unstable as he finds a positive relationship between the examined variables for 1973–1982 and no relationship for 1983–1994.

Table 2
Results from the estimation of Eq. (1) from the Fixed or Random Effects estimator, as selected by the Hausman test.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	RE	FE	FE	RE	FE	FE
Energy Intensity	0.766***	0.787***	0.727***	0.677***	0.785***	0.904***	0.568***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	−0.098*	−0.066***	−0.053***	0.01	−0.078***	−0.004	−0.049*
	(0.086)	(0.000)	(0.005)	(0.719)	(0.001)	(0.565)	(0.076)
Human capital intensity	−0.062	−0.045***	−0.052*	−0.054	−0.107***	−0.01	−0.135***
	(0.468)	(0.000)	(0.080)	(0.203)	(0.000)	(0.326)	(0.004)
Size	0.128***	0.022**	0.041***	−0.053**	0.063***	−0.015***	−0.006
	(0.003)	(0.020)	(0.007)	(0.015)	(0.003)	(0.004)	(0.804)
TFP	−0.013	0.125***	0.039	−0.162	−0.101	−0.077***	−0.389***
	(0.949)	(0.006)	(0.570)	(0.104)	(0.318)	(0.002)	(0.001)
Capital expenditure int.	−0.087	0.018	0.047	0.044	−0.038	0.038**	0.093
	(0.588)	(0.575)	(0.392)	(0.571)	(0.569)	(0.050)	(0.202)
Constant	−6.880***	−6.139***	−5.418***	−4.435***	−8.044***	0.995***	−4.445***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
CD test	X	−2.45**	−2.62***	−2.89***	−1.85*	3.23***	3.06***
CD *p*-value	(x)	(0.014)	(0.009)	(0.004)	(0.064)	(0.001)	(0.002)
R^2 between	0.807	0.935	0.947	0.862	0.766	0.963	0.559
R^2 within	0.513	0.948	0.863	0.713	0.707	0.98	0.576
R^2 overall	0.772	0.929	0.923	0.845	0.741	0.966	0.576
Hausman χ^2	31.4***	8.997	41.903***	46.009***	2.466	52.46***	11.982*
Hausman *p*-value	(0.000)	(0.174)	(0.000)	(0.000)	(0.872)	(0.000)	(0.062)
Time dummy F-test	6.024***	174.7***	9.612***	6.141***	25.88*	1.486*	0.6491
F-test *p*-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.077)	(0.099)	(0.850)
Time dummies	YES	YES	YES	YES	YES	YES	NO

Notes: Values in parenthesis are *p*-values of coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE and RE stand for fixed effects and random effects estimators, respectively. Hausman test indicates use of either FE or RE estimator where under null hypothesis RE is chosen. Rejection of null hypothesis of time dummy F-test indicates use of times dummies.

affecting all panel units, while the latter representing spillovers across panel units with strength of the dependence declining as some notion of distance, suitably measured, between panel components increases (Chudik et al., 2011; Smith and Fuertes, 2016). Estimators not taking CSD into account, like the FE and RE above, produce biased and inconsistent estimates when both disturbance and regressors share a common factor (Andrews, 2005; Phillips and Sul, 2003, 2007; and Sarafidis and Robertson, 2009). We use the CD test (Pesaran, 2004) to assess the existence of CSD, our choice motivated by the CD test being robust to structural breaks, and having good small sample properties even when *T* is small relative to *N* which might be an important feature bearing in mind the structure of our panel dataset. We use the Common Correlated Effects (CCE) estimator (Pesaran, 2006; Kapetanios et al., 2011) to account for the presence of CSD in our sample. This estimator can be algebraically derived from a multifactor error structure such as:

$$
\begin{aligned}
y_{it} &= \varphi_i y_{it-1} + \beta_i^{'} x_{it} + u_{it}, \\
u_{it} &= c_{yi} + \gamma_i^{'} f_t + \epsilon_{it}, \\
x_{it} &= c_{xi} + \Gamma_i^{'} f_t + \varepsilon_{it}
\end{aligned} \tag{3}
$$

where $c_i = (c_{yi}, c_{xi})$ is the individual specific effects, $f_t = (f_{1t}, f_{2t}, \ldots, f_{mt})$ is a $m \times 1$ vector of unobserved common factors affecting both error terms u_{it} and variables with Γ_i' and γ_i' being two $m \times 1$ vectors of factor loadings of the independent variables and the error term, respectively, and γ_i' a $m \times 1$ vector of factor loadings for the dependent variable. The terms ϵ_{it} and ε_{it} are idiosyncratic errors with $E(\epsilon_{it}) = 0$, $E(\varepsilon_{it}) = 0$, $E(\epsilon_{it}^2) = \sigma_i^2$, and $E(\varepsilon_{it}^2) = \sigma_i^2$, while the covariance of error u_{it} is determined by factor loadings Γ_i' and γ_i'. If unobserved factors f_t are correlated with the vector of the independent variables x_{it} (which is common in the economic literature) omitting f_t will result in biased and inconsistent β_i' estimates, as the resulting omitted factor will then be incorporated in u_{it}. The CCE Pooled (CCEP), which has good small sample properties (Pesaran, 2006) in the model above even with small *T* relative to *N*, can be implemented by estimating:

$$
y_{it} = \alpha_i + \beta_i x_{it} + \delta_{xi} \overline{x}_t + \delta_{yi} \overline{y}_t + u_{it}, \tag{4}
$$

where $\beta_i = \beta$ and $\sigma_i^2 = \sigma^2$ for all *i*. The CCEP estimator allows for unobserved effects to have heterogeneous impact on individual units and arbitrarily correlated to the individual-specific regressors (Eberhardt and Teal, 2010). f_t is treated as nuisance parameter while CSD is removed from the model by including $\overline{y}_t$ and $\overline{x}_t$ which are the cross-section averages of the independent (y_{it}) and the dependent variables (x_{it}), respectively. The CCE estimator remains consistent with good small sample properties when f_t is non-stationary and by extent when x_{it} is non-stationary (Kapetanios et al., 2011).

4. Estimation results

We start the presentation of our results from the estimation of Eq. (1) with a Random or Fixed Effects estimator which should produce results close to results in CES (2005), if underlying data generation process is structurally stable across time and if CSD does not affect the estimation. As it can be seen in Table 2, the RE estimator is selected by the Hausman test in the case of NOx, PM_{10} while for the remaining emissions intensities the FE estimator is preferred, a departure from CES (2005) where FE model was preferred in all cases by the Hausman test.[12] Confirming results in CES (2005), all models in Table 2 include time dummies, with the exception of the model for N_2O (not included in CES 2005). The sign of the time dummies matches results from CES

[12] It is worth pointing out that in our case, contrary to evidence presented in CES (2005), the choice between FE and RE estimator does not affect the results from the estimation, as values of the coefficients and their statistical significance are fairly similar – see Table A3 and Table A4 in the Appendix.

(2005) with the exception of CO_2 where time dummies are negative in CES (2005) but overall positive in the model presented in Table 2. As shown in Fig. A4 in the Appendix, time dummies in the models for NO_x and TAC have overall downward trends while one can see that CO_2 dummies display an upward trend. The values for SO_2, CO and PM_{10} are U-shaped, with a downward trend up to around 2005 which becomes slightly upward for SO_2 and is completely reversed by 2014 for CO and PM_{10}. A similarity between the time pattern of the dummies (Fig. A4) and the time pattern of emissions intensities (Fig. A2) can be observed in the case of NO_x and TAC. In the case of SO_2, CO and PM_{10} the rebound we observed in the time dummies does not materialise itself in the time pattern of SO_2, CO and PM_{10} intensities. Finally, emissions intensity is downward sloping in the case of CO_2 even though pattern of time dummies is upward sloping.

With regards to the determinants of emissions intensity, energy intensity is always positive and highly significant with values of the coefficients in the models in Table 2 close to those in CES (2005) for SO_2, NO_x, TAC, PM_{10} and CO_2, i.e. difference between the estimates in this paper and CES (2005) being at most 0.18, with the exception of CO where our estimated value is 2 times larger than the value in CES (2005). With regard to the other determinants, we find stronger evidence for statistical significance of PCI than CES (2005), even though in our case coefficients are mostly negative, contradicting findings from CES (2005). Contradictory results are also obtained in the case of HCI (positive impact in CES (2005) but negative in Table 2) and the size (impact being negative in CES (2005) but not showing clear direction in Table 2). The statistically significant impact of TFP is negative in two instances, CO_2 and N_2O, and positive the case of NO_x. This is also a departure from CES (2005) which reports all coefficients being negative and statistically significant. Finally, our results agree with those in CES (2005) with regards to the difficulty in estimating statistically significant impact of capital expenditure intensity.

The next step in our strategy consists in estimating Eq. (2), i.e. the specification in CES (2005) with additional variables taking into account fuel substitution and market concentration. Although our estimation followed exactly the same procedure we implemented for Eq. (1), a number of changes can be observed by comparing the results in Table 3 and Table 2. Based on the Hausman test, RE model is now selected in five of the seven intensities, i.e. all cases except CO and CO_2, a striking change from the results in CES (2005) and to a less extent those in Table 2. Five out of the seven models in Table 3, i.e. those for SO_2, NO_x, TAC, CO and N_2O incorporate time dummies. Time dummies were included in six models in Table 2 i.e. those for SO_2, NO_x, TAC, CO, PM_{10} and CO_2 and in all models in CES (2005). One can notice some changes with regard to the pattern of time dummies that are included in models in Table 3 (see Fig. A5), compared to those in the models in Table 2 (see Fig. A4). With regard to the determinants of emissions intensity, we can see in Table 3 that energy intensity remains always positive and statistically significant for all emissions intensities. A considerable change in its coefficient occurs in the case of SO_2, TAC and N_2O, with SO_2 increasing from 0.77 to 1.31, TAC from 0.72 to 1.03 and N_2O from 0.56 to 1.24. We find evidence that gas share is a negative

Table 3
Results from the estimation of Eq. (2) from the Fixed or Random Effects estimator, as selected by the Hausman test.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RE	RE	RE	FE	RE	FE	RE
Energy Intensity	1.317***	0.888***	1.033***	0.678***	0.638***	0.879***	1.240***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas share	−0.326***	0.007	−0.238***	0.06	−0.604***	−0.029	0.610***
	(0.000)	(0.860)	(0.000)	(0.505)	(0.000)	(0.168)	(0.000)
Physical capital intensity	−0.011	−0.169***	−0.097***	0.009	−0.017	0.0004	−0.185***
	(0.810)	(0.000)	(0.000)	(0.746)	(0.342)	(0.937)	(0.000)
Human capital intensity	0.043***	−0.040***	−0.026***	−0.055	−0.088***	0.002	−0.086***
	(0.008)	(0.000)	(0.000)	(0.226)	(0.000)	(0.878)	(0.000)
Size	0.084	0.086**	0.101***	−0.081*	0.016	−0.039***	0.467***
	(0.317)	(0.011)	(0.005)	(0.065)	(0.539)	(0.000)	(0.000)
TFP	0.651**	0.463***	0.458***	−0.143	−0.207***	−0.067***	−0.248
	(0.012)	(0.000)	(0.000)	(0.158)	(0.004)	(0.005)	(0.388)
HHI	0.018	−0.006	−0.016	0.036	0.002	0.020**	−0.389***
	(0.829)	(0.857)	(0.638)	(0.365)	(0.930)	(0.020)	(0.000)
HHI^2	−0.043	−0.032	−0.018	0.036	−0.016	−0.007	−0.181***
	(0.410)	(0.134)	(0.440)	(0.195)	(0.423)	(0.312)	(0.002)
Capital expenditure int.	−0.109	−0.110***	−0.063*	0.036	0.067	0.028*	0.279***
	(0.208)	(0.002)	(0.092)	(0.645)	(0.146)	(0.075)	(0.003)
Constant	−6.467***	−7.299***	−6.258***	−4.240***	−8.033***	1.094***	−5.893***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
CD test	X	−2.61***	−2.19**	−2.81***	1.6	0.43	−1.23
CD p-value	(x)	(0.009)	(0.029)	(0.005)	(0.109)	(0.667)	(0.219)
R^2 between	0.927	0.95	0.97	0.866	0.758	0.953	0.802
R^2 within	0.477	0.906	0.843	0.716	0.765	0.979	0.368
R^2 overall	0.875	0.94	0.954	0.84	0.75	0.96	0.737
Hausman χ^2	−61.93	10.88	13.36	25.17***	−2.199	19.82**	7.64
Hausman p-value	(1.000)	(0.284)	(0.147)	(0.003)	(1.000)	(0.019)	(0.570)
Time dummy F-test	52.65***	31.68**	46.2***	6.1764***	8.12	1.1311	26.16*
F-test p-value	(0.000)	(0.016)	(0.000)	(0.000)	(0.964)	(0.324)	(0.072)
Time dummies	YES	YES	YES	YES	NO	NO	YES
HHI F-test	0.860	2.280	0.684	1.29	0.650	3.23**	24.085***
HHI F-test p-value	(0.650)	(0.319)	(0.710)	(0.276)	(0.722)	(0.041)	(0.000)
HHI vertex	0.05	0.04	0.03	0.02	0.04	0.17	0.01

Notes: Values in the parenthesis are p-values of the coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests the regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE and RE stand for fixed effects and random effects estimators, respectively. Hausman test indicates the use of either FE or RE estimator where under the null hypothesis RE is chosen. Rejection of null hypothesis of time dummy F-test indicates use of times dummies while rejection of null hypothesis of HHI F-test indicates that market concentration effect is significant.

Table 4
Results from the estimation of Eq. (1) from the CCEP estimator.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP
Energy Intensity	0.505***	0.787***	0.792***	0.557***	0.578***	0.946***	0.562***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	0.028	−0.025**	0	−0.008	−0.023	0	−0.044
	(0.629)	(0.027)	(0.995)	(0.724)	(0.235)	(0.933)	(0.166)
Human capital intensity	0.058	−0.041**	−0.014	−0.032	−0.063**	0.005	−0.111**
	(0.467)	(0.014)	(0.601)	(0.331)	(0.034)	(0.495)	(0.037)
Size	−0.13	0.004	0.012	−0.002	−0.072*	−0.003	−0.05
	(0.222)	(0.864)	(0.762)	(0.966)	(0.099)	(0.781)	(0.448)
TFP	0.147	0.128	0.088	0.099	0.176	0.038	−0.027
	(0.706)	(0.137)	(0.527)	(0.578)	(0.263)	(0.371)	(0.914)
Capital expenditure int.	0.399**	0.064*	0.140**	0.321***	0.123*	0.032**	0.293***
	(0.012)	(0.068)	(0.014)	(0.000)	(0.056)	(0.042)	(0.001)
Constant	1.957	−0.247	0.058	−1.072	−0.091	0.379	−3.323
	(0.784)	(0.904)	(0.987)	(0.798)	(0.986)	(0.588)	(0.517)
Panel groups	20	20	20	20	20	20	20
Observations	286	300	300	300	300	300	300
CD test	X	−0.5	−1.71*	−1.35	−1.09	1.79*	1.41
CD *p*-value	(x)	(0.616)	(0.087)	(0.177)	(0.276)	(0.074)	(0.158)

Notes: Values in parenthesis are *p*-values of coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. CCEP stands for Common Correlated Effect Pooled estimator.

and significant determinant of SO_2, TAC, and PM_{10} and N_2O but, surprisingly, it is not significant in the models for the other intensities. Regarding the other determinants, PCI remains statistically significant and negative for NO_x and TAC, as it occurred in Table 2, while it becomes positive and significant in the case of N_2O, positive but non-statistically significant for SO_2 and negative but non-statistically significant in the case of PM_{10}. The size variable remains positive and statistically significant for NO_x and TAC, negative and significant for CO and CO_2, while it becomes significant in the case of N_2O but non-statistically significant for SO_2 and PM_{10}. HCI is almost always negative and significant with the exception of SO_2. TFP becomes significant in all cases except CO and N_2O although its impact is positive in the case of SO_2, NO_x and TAC. The coefficient on the linear term of market concentration is significant in two cases (CO_2 and N_2O) while the quadratic coefficient is significant only for N_2O. Joint significance of the two terms for market concentration using an F-test (see Table 3) reveals that market concentration has a statistically significant inverted-U relationship for CO_2 and N_2O (see Fig. A6). Interestingly a similarly shaped relationship, although non-statistically significant, occurs also in the case of SO_2, NO_X, TAC and PM_{10}, while in the case of CO the curve is U-shaped. In all cases one can notice that this non-linear relationship is highly skewed so that the global maximum or minimum is very close to the case of no market concentration (or perfect competition). Lastly, capital expenditure intensity becomes significant and negative for NO_x and TAC while significant and positive for CO_2 and N_2O.

Results related to the CSD among the variables incorporated in this study (see Table A5) cast doubts on the results presented so far. One can also notice that CSD is left in all but three residuals of the models presented in Table 2 and Table 3.[13] In fact, results from the re-estimation of Eq. (1) and Eq. (2) using the CCEP estimator cast an entirely new light on the determinants of the emissions intensities. Results in Table 4 shows that accounting for CSD does not affect the statistical significance of energy intensity although it implies on average reduction in the coefficients, with those in Table 2 in the models for SO_2 and PM_{10} particularly affected while the coefficient in the model for NO_x virtually unaffected. Our results differ considerably from those in CES (2005) with regard to the coefficient for energy intensity in the SO_2 and CO models, with our estimate being 0.44 units smaller and 0.31 units larger, respectively.[14] Strikingly, capital expenditure intensity becomes statistically significant for all emissions intensities (it was significant only for CO_2 in Table 2). The remaining coefficients in Table 4 have overwhelmingly lost their statistical significance in contrast to the selected models in Table 2.[15] Overall, energy intensity and capital expenditure intensity are the prevalent determinants of UK demand for manufacturing emissions in Table 4 once we account for CSD. The robustness of the results produced by CCEP estimator is backed up by the fact that almost all residuals in Table 4 are cross section independent except TAC and CO_2.[16]

Results from the CCEP estimator in Table 4 are robust to the introduction of variables taking into account fuel substitution and market concentration (see Table 5). Energy intensity remains positive and highly significant in all cases while capital expenditure intensity remains positive and statistically significant in all cases but PM_{10}. Changes in the value of the coefficients are limited, at most by 0.11 units for CO with only exception SO_2 that increases by 0.35 units, while the average elasticity is virtually identical. Elasticity of natural gas share in Table 5 become statistically significant for all emissions intensities except N_2O, with considerable change in the values compared to those in Table 3, with the biggest changes observed in the case of SO_2 and TAC - a change of 1.42 and 0.96 units respectively. The average impact (in absolute value) of fuel substitution across emissions intensities increases by an order of magnitude, from −0.07 in Table 3 to −0.79 in Table 5. Fuel substitution affects more severely SO_2 emissions intensity as its elasticity is equal to −1.758, and given that SO_2 emissions are highly related to the level of sulphur used in the manufacturing process, this result reflects the fact that coal and oil contain high levels of sulphur while gas contains only negligible quantities (Brown et al., 2017; Wakeling et al.,

[13] The CD test is unable to produce results for panel regression residuals in column 1 due to missing observations for SO_2 emissions.

[14] Coefficients in Table 4 are mostly higher in absolute value than those in CES (2005) with the exception of the coefficient on the SO_2 and PM_{10} models. The average difference between the coefficients in Table 4 and Table 2 is similar in absolute terms to the average difference between coefficients in CES (2005) and those in Table 2.

[15] The impact of size is mostly negative but non-statistically significant in all cases except PM_{10} while the impact of TFP is mostly positive, but non-statistically significant in all cases. HCI however remains significant in three instances, i.e. NO_x, PM_{10} and N_2O, with estimated values in the case of PM_{10} and N_2O being almost by 50% and 33% higher, respectively than those in Table 2, while the value in the case of NO_x remains approximately the same. PCI remains significant only for NO_x and its estimated value increases by more than 50%.

[16] As mentioned in Section 3, the CCEP estimator is robust to shocks affecting some or all panel units such as the 2008 economic crisis or perhaps the impact of the business cycle, the dynamics of which may very different across industrial subsectors.

Table 5
Results from the estimation of Eq. (2) from the CCEP estimator.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP
Energy Intensity	0.855***	0.816***	0.944***	0.662***	0.662***	0.966***	0.378***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas share	−1.758***	−0.582***	−1.201***	−0.687***	−0.916***	−0.203***	−0.261
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.201)
Physical capital intensity	0.024	−0.023**	−0.008	−0.027	−0.046**	0.004	−0.062**
	(0.731)	(0.042)	(0.679)	(0.158)	(0.037)	(0.174)	(0.024)
Human capital intensity	−0.076	−0.036**	−0.01	−0.013	−0.02	0.012***	−0.046
	(0.424)	(0.016)	(0.681)	(0.622)	(0.503)	(0.002)	(0.379)
Size	−0.003	−0.038	0.067	−0.015	0.029	0.011	−0.137*
	(0.982)	(0.202)	(0.124)	(0.751)	(0.588)	(0.103)	(0.051)
TFP	−0.567	0.034	−0.330**	−0.159	−0.176	−0.019	−0.101
	(0.252)	(0.710)	(0.024)	(0.328)	(0.338)	(0.395)	(0.632)
HHI	0.042	0.041	−0.013	0.014	−0.06	0.004	0.195***
	(0.752)	(0.102)	(0.743)	(0.734)	(0.196)	(0.521)	(0.000)
HHI^2	0.185*	0.011	0.100***	0.093***	0.061	0.008*	0.117**
	(0.068)	(0.559)	(0.001)	(0.006)	(0.106)	(0.089)	(0.013)
Capital expenditure int.	0.476**	0.063*	0.200***	0.200***	0.106	0.034***	0.270***
	(0.017)	(0.075)	(0.001)	(0.002)	(0.178)	(0.000)	(0.002)
Constant	−20.486	1.027	−0.599	1.113	−7.875	0.162	0.825
	(0.177)	(0.892)	(0.950)	(0.738)	(0.365)	(0.704)	(0.856)
Panel groups	20	20	20	20	20	20	20
Observations	283	300	300	300	300	300	300
CD test	X	−1.5	−0.81	0.19	1.28	2.73***	−0.88
CD *p*-value	(x)	(0.134)	(0.419)	(0.853)	(0.2)	(0.006)	(0.379)
HHI F-test	3.710	3.096	11.56***	7.48**	4.502	3.095	20.286***
HHI F-test *p*-value	(0.156)	(0.213)	(0.003)	(0.024)	(0.105)	(0.213)	(0.000)
HHI vertex	0.04	0.01	0.04	0.04	0.07	0.03	0.02

Notes: Values in parenthesis are *p*-values of coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests the regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. CCEP stands for Common Correlated Effect Pooled estimator. Rejection of null hypothesis of time dummy F-test indicates use of times dummies while rejection of null hypothesis of HHI F-test indicates that market concentration effect is significant.

2017). Fuel substitution is non-statistically significant for N_2O which confirms the fact that the main historical sources of N_2O emissions reduction have been the closure of adipic acid manufacturing plants (reflected in the time pattern of emissions intensities in Fig. A2) and the installation of abatement technologies in the largest remaining plants (Brown et al., 2017). The negative and significant impact of PCI and size elasticities for N_2O supports the findings from Brown et al. (2017) with regard to the installation of abatement technology in large plants. Similarly, to Table 4, we observe in Table 5 that most of the remaining coefficients are non-statistically significant once we account for CSD. PCI is statistically significant in the cases of NO_x, PM_{10}, and N_2O (as just mentioned), while HCI is significant only for NO_x and CO_2, although the impact is negative in the former and positive in the latter. Size remains non-statistically significant in all cases except N_2O in Table 5 (which matches evidence discussed above). As suggested by both CES (2005) and Cui et al. (2015), TFP becomes mostly negative but remains non-statistically significant in all cases but for TAC. Coefficient on the linear term of the market concentration variable in Table 5 remains significant only for N_2O but the coefficient on the squared term becomes significant in 5 out of 7 cases - SO_2, NO_x, TAC, CO_2 and N_2O – with the relationship taking the shape of an upwards parabola in all cases – see Fig. A7. An F-test on both the linear and quadratic coefficients of market concentration (see Table 5) reveals the existence of a statistically significant relationship between concentration and intensities in 3 out of 7 cases, namely NO_x, TAC, and N_2O. Again, this nonlinear relationship (see Fig. A7) is greatly skewed towards zero market concentration (or perfect competition) with the highest value of the vertex being a bare 0.07. In other words, accounting for CSD, implies a change in the relationship between market concentration and emission intensities - from downward to upward parabola (see Fig. A6 and Fig. A7) with three of these relationships being statistically significant. The robustness of our results presented in Table 5 is supported by the fact that the residuals of all emissions intensities but for CO_2 are now cross section independent in contrast to those is Table 4 where TAC and CO_2 still suffered from CSD. Since both Table 5 and Table 4 use the CCEP estimator taking into account CSD, the cross section independence of almost all residuals in Table 5 indicates that the introduction of gas share and market concentration in Eq. (2) allows us to accurately identify the long-run effect of industrial characteristics on emissions intensities which has not been possible with the use of CES (2005) specification (see Eq. (1)).

5. Discussion

We are able to draw a number of insights related to the long-term determinants of emissions intensity in the manufacturing sector from our analysis which is based on the methodology in CES (2005), augmented by taking into consideration fuel substitution, market concentration and unobserved common factors through CSD. From our analysis, we see that energy intensity elasticities remain consistently positive and statistically significant for all emissions intensities, confirming the robustness of results from CES (2005). Variation in the value of the elasticities in Table 2 - Table 5 is fairly limited with variation highest for SO_2 (0.8 points) and lowest for CO_2, i.e. 0.09 points at most. Estimated coefficients when re-estimating the model in CES (2005) are very similar to those in CES (2005), with the difference between coefficients in Table 2 and those in CES (2005) being at most 0.18 units (CO being an exception with the difference equal to 0.43 units), a considerable similarity bearing in mind the difference between the two samples. Our results and the similarity with CES (2005) results confirms that energy intensity is a positive long-term and statistically significant determinant of emissions intensity, as we expected based on the fact that emissions data are obtained, at least in part, from energy consumption data, therefore validating the econometric approach used in this study.

The conclusions from our results for physical and human capital intensities, size and total factor productivity are however starkly different.

First of all, one can notice that the size of elasticities is considerably lower, than those we estimated for energy intensity. The highest value of the estimated elasticities, in absolute value, is 0.18, with an average of 0.03 for physical capital intensity, and 0.13 for human capital intensity, across specifications and emission intensities. Our re-estimation of the approach in CES (2005) produced considerably different results both in terms of the number of statistically significant coefficients and their sign. Physical (PCI) and Human Capital intensities (HCI) increase emissions intensities in CES (2005) but take a negative coefficient in Table 2, strongly contradicting results in CES (2005). Size and Total Factor Productivity (TFP) have a negative impact on emission intensities in CES (2005) but our results are inconclusive with respect to the direction of the impact (when statistically significant) as one can see in Table 2, again contradicting results from CES (2005). Considerable changes with regard to statistical significance of the variables can be observed when introducing gas share and market concentration.[17] We interpret these results as evidence of an instable relationship between emissions on one side and PCI, HCI, size and TFP on the other, pointing out that these relationships are spurious or at least unstable based on the dataset used by CES (2005) and ourselves. Further doubts are related to the presence of CSD in the residuals of the estimated models, implying that standard errors and estimated coefficients might be biased. Our concerns about the possible spurious nature of the relationship between emissions intensity and physical and human capital intensity, size and TFP are increased by the fact that statistical significance almost completely disappears after taking into account unobserved factors, fuel substitution and market concentration, with the exception of very few instances, i.e. PCI in NO_x, PM_{10}, and N_2O, HCI in NO_X and CO_2, size in N_2O and TFP in TAC. Our analysis leads us to conclude that elasticities of emissions with respect to PCI, HCI, size and TFP are small, and mostly non-statistically significant, especially when implementing more comprehensive econometric approaches. This implies that relationship between capital, labour and emissions cannot be relied upon to produce certain environmental benefits from policies changing either the labour or the capital intensity of an industry, trying to increase total factor productivity or size of the manufacturing sector.

Our results point at fuel substitution being an important factor in reducing emissions from UK manufacturing, with the exception of N_2O. This finding which echoes results from energy demand and ETS literature (Chevallier, 2012; Steinbucks, 2012) has surprisingly not been explored before in the literature on the determinants of emissions intensities (CES, 2005; Cole et al., 2013; Cui et al., 2016; Gray and Shadbegian, 2007). Value of elasticities and statistically significance are considerably influenced by taking unobserved factors into account, as one can conclude by comparing results in Table 3 and Table 5, a sign that these unobserved factors are correlated to the time pattern of the gas share. In Table 5, elasticities are all negative, as one would expect based on natural gas being a cleaner fuel than oil and coal. The plausibility of this finding is further supported by the fact that the coefficient with the highest absolute value is observed in the case of SO_2 emissions, i.e. the emissions for which natural gas delivers the highest savings (Wakeling et al., 2017; Brown et al., 2017). The non-statistically significant impact of fuel substitution on N_2O is reflective of the fact that historical reductions in N_2O emissions has been mainly delivered by the closure of adipic acid manufacturing plants and the installation of abatement technologies (Brown et al., 2017).

Our re-estimation of the approach in CES (2005) produced results similar to theirs for capital expenditure intensity, confirming their difficulty of estimating a statistically significant impact and the direction of the impact, which in both studies is mainly positive. The impact remains positive and become statistically significant after unobserved factors are taken into account. Including fuel substitution and market concentration affect the size but not the direction and statistically significance of the impact, with the only exception of PM_{10}. The similarity of our results from fixed and random effect models to those in CES (2005) is taken as evidence of capital expenditure being a long-term of emissions intensity while the fact that its impact becomes statistically significant only after controlling for unobserved factors shows the importance of adopting a comprehensive and robust econometric approach. With regard to market concentration, our results point at a quadratic functional relationship between this variable and emissions. The shape of this relationship changes from a downwards, when implementing fixed and random effect models – see Fig. A6, to an upwards parabola when taking into account unobserved factors through CSD – see Fig. A7, an outcome that shows once again the importance of adopting a comprehensive and robust econometric approach. In the latter case, market concentration impacts emissions intensities through an initial dip and then a steady increase up to the maximum level of emissions observed in the case of monopoly. As TAC is the weighted sum of SO_2, NO_x and NH_3 emissions, our findings indicate the existence of a statistically significant relationship between market concentration and acid rain precursors, in addition, to market concentration being statistically significant in the case of case of CO and N_2O. In all cases, regardless of the statistically significance, a similar non-linear shape of the functional relationship between market concentration and emissions intensities can be observed, confirming the robustness of our findings, so that it is greatly skewed towards perfect competition. This implies that increased concentration in the market increases emission intensity with the exception of very low level of market concentration, at which reduction in competition delivers increasing environmental benefits. Our finding might be explained by increased productivity, or CSR performance. In fact, Fernández-Kranz and Santaló (2010) shows that a number of market concentration proxies and widely used CSR measures are inversely related so that an increase in concentration deteriorates the CSR performance of firms to an extent that firms in more competitive environments have a superior environmental performance, measured by firm pollution levels. Considering that we have already accounted for both energy intensity and fuel substitution effects, a superior performance of firms in more competitive environments can be the reflection of superior innovation performance, if innovations tends to be emissions savings, an assumption which is supported by the results in CES (2005). In fact, our results are strikingly similar to Aghion et al. (2005) which assesses the relationship between competition and innovation. Their estimated inverted-U relationship between market competition and innovation is greatly skewed towards perfect competition. Following the argument of Aghion et al. (2005), firms in highly competitive markets are "prevented" from innovating, and therefore abating emissions intensities, due to low profit margins. Reduction of competition allows firms to increase their margins, innovate to be ahead of the curve and eventually increase the abatement of emissions although this incentive decreases as market concentration increases above a certain threshold due to market power guaranteeing profit margins. In both our case and the one discussed by Aghion et al. (2005), the vertex of this relationship is fairly close to the case of perfect competition – value of 0.95 in the case of Aghion et al. (2005) with perfect competition in Aghion et al. (2005) being equal to one. As far we are aware there is no published empirical evidence on the impact of increasing competition on emissions in the UK. On the other hand, related research reveals that increased consolidation in the UK defence sector has been accompanied by sharp fall in R&D funds (Hall and James, 2009) which implies increased emissions assuming a positive correlation between R&D budget and environmental performance.

6. Conclusions

Lacking an established and generally accepted theoretical framework on the relationship between emissions and characteristics of the production process in the manufacturing sector, this study has

[17] The number of instances in which coefficients are statistically significant changes from 5 to 3 in the case of physical capital intensity, from 4 to 5 in the case of human capital intensity, from 6 to 5 in the case of size variable and from 2 to 5 in the case of TFP, as one can see by comparing Table 2 and Table 3.

investigated the long-term determinants of emissions by assessing the robustness of established findings in the literature such as those in Cole et al. (CES) (2005). Our strategy implied re-estimating a specification as close as possible to CES (2005), originally estimated on the 1990–1998 sample, using observations between 1997 and 2014, and adding two factors which might have an impact on emissions from the manufacturing sector, fuel substitution and market concentration. We expect long-term determinants of emissions to be reasonably robust to changes in the estimation sample and the addition of a limited number of explanatory variables. We then explored the impact of unobserved factors through cross sectional dependence (CSD) on the difference between our results and those in CES (2005). As expected, we find that energy consumption is positive and significant determinant for all emissions intensities, with values of estimated elasticities similar to those in CES (2005). However, once we account for CSD, physical and human capital, size and total factor productivity (TFP) become overwhelmingly non-statistically significant for most of the emissions assessed in this study.

Our results indicate that factors such as production inputs i.e. labour and capital, total factor productivity and size of typical firm are not robust determinants of emissions from industrial sector but on the other hand, energy intensity, fuel substitution, capital expenditure intensity and market concentration are long-term determinants of industrial emissions across the pollutants assessed in this study. This implies that the relationship between emissions on one side and physical and human capital, size of the typical firm and TFP cannot be relied upon to produce certain environmental benefits from policies aimed at changing any of these factors. A sustained reduction in emissions from the manufacturing sector needs to be delivered through the leverages of reduced energy consumption and increased adoption of cleaner fuels, therefore indicating the crucial role of energy efficiency policies and those facilitating adoption of cleaner fuels, e.g. the Climate Change Levy, in reducing emissions. On the other hand, increases in capital expenditure intensity brought about by policies facilitating investments, for example to increase productivity, have an adverse impact on emissions, therefore pointing at a trade-off between economic growth and environmental quality. Investing in new capital equipment and machinery should not per se be considered equivalent to investing in cleaner technologies, therefore contradicting the assumption in CES (2005). The fact that we find evidence that capital expenditure intensity has increased all emissions of all pollutants except PM_{10} indicates the importance of redirecting capital investment towards "green" industrial technologies. On the other hand, changing level of competition through a change in market concentration delivers emissions savings probably through an increasing level of innovations documented in Aghion et al. (2005). This implies that reduction of entry barriers for firms in the manufacturing sector delivers environmental benefits which are consistent across emissions assessed in this study perhaps through stimulating rate of innovation in the sector.

From an academic perspective, it would be interesting to explore the extent to which our results on the limited importance of physical and human capital, size and total factor productivity are robust across time, countries and regulation environments. One would also want to assess whether our estimated relationships are confirmed when using microdata rather than observations aggregated to industrial subsector. By matching patent and emissions datasets observed at firm level one would be able to test our conjecture that innovation processes directed towards reducing emissions are responsible for the hump-shaped relationship between market concentrations and emissions. From an environmental policy perspective, industrial policy planning in the short-term should continue to encourage fuel switching from carbon fuels to cleaner fuels and reduce energy consumption. As possibilities of switching to low carbon fuels and energy efficiency might be limited after sustained efforts in this direction are undertaken by the manufacturing sector, long-run industrial policy planning should focus on development and adoption of technologies minimising emissions so as to counteract increases brought about by the scale of economic activity and capital expenditure. Our results pointing at environmental benefits arising from increased competition in the market place highlight potential synergies between policies focused on industrial strategy, market completion and environmental welfare. Reduced emissions observed in presence on increased competition is likely to be due to the pressure to innovate taking place in competitive markets so that adoption of and development of emissions saving technologies can reduce abatement cost, and achieve positive brand recognition and a competitive advantage in the supply chain. The relationship between emissions abatement and market concentration through innovation is likely to become more and more important in delivering reduction in industrial emissions, especially because estimated autonomous technological change (measured through a time effect) only rarely shows a distinct trend towards reducing emissions.

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Appendix A. Appendix

In order to produce the dataset that used in our empirical analysis, we use a combination of publicly available datasets (National Atmospheric Emissions Inventory, ONS Environmental Accounts, ONS Gross Fixed Capital Formation chain volume measure, ONS Input-Output Supply and Use tables, ONS Labour Force Survey – see Table A1). We also use the ONS (2018) Annual Business Survey (ABS) and ONS (2012) Annual Respondents Database (ARD) which can be accessed only by ONS Accredited Researchers under the Statistics and Registration Services Act of 2007.[18] Although the security agreement that we have signed with UK Data Service does not allow us to publicly share the final dataset that has been used in the present analysis, the syntax file accompanying this paper contains all the necessary information to produce the variables below from the ONS ABS and ARD, as well the steps required to produce the tables and figures presented in this paper. Our description is particularly detailed in the case of the variables obtained from the ABS and ARD, due to limited accessibility to the dataset and the several steps required to build variables.

(Direct) Emissions Intensity (emissions / real GVA). Direct atmospheric emissions for the UK industrial sectors are computed by the National Atmospheric Emissions Inventory (NAEI) and compiled by AEA Energy & Environment on behalf of the Department for Environment, Food & Rural Affairs (DEFRA) (Wakeling et al., 2016; Brown et al., 2016). As direct emissions are produced by industrial processes and direct fuel use at the point of release, including generation of electricity from primary fuels for their own use (Wakeling et al., 2016; Brown et al., 2016), the dataset, which we derive from ONS Environmental

[18] One can access the abovementioned Controlled Data via the UK Data Service Secure Lab on the condition that they fulfil specific requirements (for more information please check the UK Data Service webpage – see https://www.ukdataservice.ac.uk/get-data/how-to-access/accesssecurelab). UK Data Service (UKDS) Secure Lab provides access to ABS and ARD databases only to accredited researchers that have successfully completed the Safe Researcher or Safe User of Research data Environments (SURE) training course.

Accounts (ONS, 2016a), is essentially obtained by multiplying direct fuel use by emission factors and subsequently adding emissions unrelated to fuel consumption. Following CES (2005), we focus on carbon dioxide (CO_2), acid rain precursors such as nitrogen oxides (NO_x), sulphur dioxide (SO_2), and total acid precursor emissions[19] (TAC), as well as other pollutants such as particular matter (PM_{10}) and carbon monoxide (CO). We also add another GHG to the set in CES (2005), i.e. Nitrogen Monoxide (N_2O), data for which is also available in the Defra dataset. All abovementioned pollutants are divided by the level of real GVA, which we obtain from Input-Output Supply and Use tables - for more information see ONS (2016c) - to compute emissions intensities.

(fossil fuel) Energy intensity (fossil fuels energy consumption / real GVA). We obtain this variable, denominated energy use intensity in CES (2005), by dividing total fossil fuels consumption, obtained from ONS (2016a) by the level of real GVA, obtained from Input-Output Supply and Use tables (ONS, 2016c), with fossil fuels consumption, which we derive from ONS Environmental Accounts (ONS, 2016a), measuring the direct use of primary fossil fuels in the industrial process as well as some secondary fuels, e.g. from coke. Following CES (2005), our measure of energy intensity excludes consumption of electricity and hydrogen since consumption of these secondary fuels does not influence the levels of direct emissions from firms in the industrial sector. We expect a positive relationship between emissions and energy intensity, as the higher the amount of combusted fossil fuels per unit of GVA the higher the direct emissions intensities.

Factor intensities, i.e. Physical Capital Intensity (PCI) (*nonwage value added per worker*) and **Human capital intensity (HCI)** ((*total real payroll* – unskilled real wage times *employment*) / real GVA). Total real payroll and GVA were obtained from ONS Input-Output Supply and Use tables (ONS, 2016c), employment from ONS Labour Force Survey – for more information see ONS (2016d), unskilled real wage was produced by dividing real payroll by employment,[20] nonwage value added per worker was built by subtracting a real measure for total real payroll from real GVA (ONS, 2016c). With regard to the actual measurement of capital and labour intensities, while the capital-labour ratio is probably the most common measure of capital-intensity, e.g. Cole et al. (2013), Ma et al. (2014), Löschel et al. (2015), other measures, such as the value added per worker (Lim, 1976) or nonwage value added per worker, are adopted especially when reliable data on capital stock are not immediately available (Banerji, 1978).[21] Other measures used in the academic literature and statistical offices include the ratio between real capital stock and total value added, e.g. Ciccone and Papaioannou (2009) and ONS (2016b). With regard to human capital, data on the length of time spent in formal education, education enrolment rates, share of population (or employees) with a certain education level or share of hours worked by those with a certain education level are normally used in empirical studies covering countries or economic sectors (Ciccone and Papaioannou, 2009; Kottaridi and Stengos, 2014, and Wood and Ridao-Cano, 1999). While we are aware of the potential shortcomings in the definition of the variables used in CES (2005),[22] maybe dictated by the dataset they had available, we include their definition of variables in our studyin order to facilitate comparison to their results.

Capital expenditure intensity (Gross Fixed Capital Formation chain volume measure (GFCF CVM)/real GVA). Gross Fixed Capital Formation (Nolan and Field, 2014) captures the annual business investment which is defined as the cost of acquisitions less proceeds from disposals of assets used in the production process. We decided to adopt a slightly different definition of this variable from CES (2005), as Gross Fixed Capital Formation in chain volume measure is the most comprehensive deflated measure of UK capital expenditure for the industrial sectors (Nolan, 2013). It is worth mentioning that results from CES (2005) points at no statistically significance for the impact of this variable on emissions intensities.

Total factor productivity (TFP). We estimated TFP for each sector using the empirical approach developed by Olley and Pakes (1996) and, subsequently, we calculate TFP (or aggregate industry productivity) using real turnover as a firm-specific weight (Beveren, 2012).[23] Our choice is not likely to influence our findings, as CES (2005) reports little effect on the estimated coefficient on TFP when TFP data were estimated using a number of different production function specifications. As ABS and ARD datasets are provided by UK Data Service Secure lab on an annual basis, we append all ABS and ARD annual datasets from 1997 to 2015 and keep only the variables required for our research and related to the firms that are part of the manufacturing sector i.e. SIC07 industrial classification 10 to 30. Thus, we namely use the variables "wq550" (total turnover), "wq450" (total employment costs), "wq523" (total net capital expenditure) and "wq499" (total purchases of energy, goods, materials services) (see ONS, 2015). More information on the construction of TFP can be found in the attached with this paper syntax file – see section called "BUILD TOTAL FACTOR PRODUCTIVITY (TFP) USING PRODEST".

Size (Gross value added per firm). The average firm size within an industrial sector is obtained by dividing the total number of firms, the number of which is obtained by the ONS (2018) Annual Business Survey (time-span 2009–2014) and the ONS (2012) Annual Respondents Database (time-span 1998–2008), to the sector's real GVA (ONS, 2016c). This variable indicates the effect of intra-sectoral economies of scale on the emissions intensities.

Fuel substitution (gas share out of total fossil fuels consumption). We obtain this variable by dividing gas consumption by total fossil fuels consumption, both of which are obtained from the Environmental Accounts (ONS, 2016a). Gas share declares the ratio of gas to the total fossil fuels used in industrial processes and works as a proxy for fuel substitution from dirtier fuels to cleaner ones e.g. coal and gas, respectively.

Level of Concentration (Herfindahl-Hirschman index – HHI). Market structure and associated level of concentration in the industrial sectors can be proxied by the **Herfindahl-Hirschman index** (HHI), which is probably the most widely used concentration index in the industrial literature. HHI is equal to the sum of squares of the market share of the firms in an industrial sector, with firms having a high market share influencing more than proportionally the level of the index (Ginevičius and Stasys, 2007). HHI takes values from 0 to 1, where 0 represents perfect competition and 1 monopoly. In order to estimate the HHI we use the variable "wq550" (total turnover variable) from ONS ABS and ARD (see ONS, 2015). More information on the construction of HHI can be found in the attached with this paper syntax file – see section called "BUILD HERFINDHAL-HIRSCHMAN CONCENTRATION INDEX".

[19] Total acid precursor emissions (TAC) are the weighted sum of SO_2, NO_x and NH_3 (ammonia) produced by industrial processes and direct fuel use at the point of release.

[20] CES (2005) defines unskilled real wage using as a proxy the real wage of the "Wood and products of wood and cork" (SIC 16) sector, a strategy that we also follow as the industrial sector with the lowest real average real wage happens to be the "Wood and products of wood and cork" (SIC 16) industrial sector.

[21] It is important to bear in mind that differences in the nonwage value added per employee will reflect, apart from any real difference in the sectoral PCI it is supposed to proxy for, presence of factors such as imperfections and monopoly (for which we account for using the HHI - see Eq. (2)), differences in tax and credit policies, degree of excess capacity are likely to influence the level of nonwage value added per employee given a certain level of capital intensity, as discussed in Banerji (1978).

[22] We notice that the variable to proxy for human capital in CES (2005) includes real wage obtained by skilled and unskilled workers, i.e. total real payroll – (unskilled real wage times employment), so that factors related to relative scarcity of these two groups and factors such as imperfections and monopoly, differences in tax and credit policies, etc. mentioned above.

[23] TFP (or aggregate industry productivity) is equal to $\widehat{TFP}_{it} = \sum_{i=1}^{N_t} s_{jt}\hat{\Omega}_{jt}$ (for industrial sector i and year *t*) where $\hat{\Omega}_{jt}$ is the firm-specific TFP residual and $s_{jt} = S_{jt}/\sum_j S_{jt}$ is the firm-specific weight where S_{jt} is firm's *j* turnover for year *t*. All productions inputs and turnover used are expressed in real terms, as they are deflated with the use of the ONS producer price inflation index for each industrial sector at the two-digit SIC07 level classification, and transformed in their logarithmic equivalents.

Table A1
Variables definitions and data sources.

Variables	Description
Emissions intensity	Direct atmospheric emissions (source: National Atmospheric Emissions Inventory) divided by real GVA (source: see below). Thousand tonnes of emissions per million pounds sterling.
Energy intensity	Total fossil fuels consumption. (Source: ONS Environmental Accounts) divided by real GVA (source: see below). Thousand tonnes of fossil fuels per million pounds sterling.
GVA	Gross value added in real terms (Source: ONS Input-Output Supply and Use tables). Millions of pounds sterling (2006 base year).
Gas share	Ratio of gas to total fossil fuels consumption (source: ONS Environmental Accounts). Thousand tonnes of gas per thousand tonnes of fossil fuels.
PCI	Physical capital intensity = (real GVA-real payroll)/employment. GVA (source: see above), payroll (source: ONS Input-Output Supply and Use tables), and employment (source: ONS Labour Force Survey).
HCI	Human capital intensity = (real payroll-(real unskilled wage*employment))/real GVA (source: as above).
Size	Real GVA per firm (source: ONS (2018) Annual Business Survey and ONS (2012) Annual Respondents Database).
TFP	Total factor productivity (Olley and Pakes, 1996; Beveren, 2012) estimated using data from ONS (2018) Annual Business Survey and ONS (2012) Annual Respondents Database.
HHI	Herfindhal-Hirschman index estimated using data from ONS (2018) Annual Business Survey and ONS (2012) Annual Respondents Database.
Capital expenditure intensity	Capital expenditure (source: ONS Gross Fixed Capital Formation chain volume measure) divided by real GVA (source: see above). Million pounds of capital expenditure per million pounds sterling.

Table A2
Descriptive statistics.

Variables in levels							
Variables	Obs.	Mean	St. Dev.	Min	Max	Skewness	Kurtosis
SO_2 emissions intensity	330	0.004	0.012	8.05E-06	0.118	5.202	37.177
NO_x emissions intensity	360	0.002	0.004	4.83E-05	0.037	4.612	34.183
TAC emissions intensity	360	0.006	0.015	8.36E-05	0.156	5.317	39.989
CO emissions intensity	360	0.010	0.028	1.38E-04	0.284	5.006	34.803
PM_{10} emissions intensity	360	4.04E-04	0.001	8.19E-06	0.007	3.643	22.590
CO_2 emissions intensity	360	1.433	3.221	0.034	33.742	4.941	37.365
N_2O emissions intensity	360	0.025	0.125	1.74E-04	1.569	9.126	99.287
Energy intensity	360	0.595	1.679	0.014	19.108	6.212	53.544
Gas share	360	0.583	0.233	0.018	0.974	−0.813	2.886
Physical Capital Intensity	360	0.033	0.084	−0.110	1.111	7.568	83.333
Human Capital Intensity	360	0.290	0.228	−0.428	2.348	2.811	23.618
Size	354	88.723	274.207	0.227	3727.647	8.197	94.566
Total Factor Productivity	351	4.949	1.025	2.081	8.621	0.577	3.742
HHI	352	0.085	0.135	0.005	0.763	3.175	13.641
Capital expenditure int.	342	0.198	0.494	0.010	9.067	17.018	305.879
Variables in logs							
Variables	Obs.	Mean	St. Dev.	Min	Max	Skewness	Kurtosis
SO_2 emissions intensity	330	−7.934	2.135	−11.730	−2.137	0.670	2.647
NO_x emissions intensity	360	−7.198	1.306	−9.938	−3.291	0.513	2.711
TAC emissions intensity	360	−6.732	1.613	−9.390	−1.860	0.796	2.935
CO emissions intensity	360	−6.347	1.655	−8.886	−1.259	0.924	3.250
PM_{10} emissions intensity	360	−8.953	1.503	−11.713	−4.992	0.348	2.406
CO_2 emissions intensity	360	−0.872	1.446	−3.375	3.519	0.720	2.860
N_2O emissions intensity	360	−5.916	1.624	−8.658	0.451	1.138	4.839
Energy intensity	360	−1.847	1.409	−4.272	2.950	0.903	3.582
Gas share	360	−0.703	0.719	−4.007	−0.027	−2.183	7.448
Physical Capital Intensity	340	−4.155	1.170	−9.696	0.106	0.097	5.611
Human Capital Intensity	341	−1.787	2.852	−19.816	0.854	−5.450	32.449
Size	354	3.195	1.419	−1.484	8.224	0.364	4.943
Total Factor Productivity	351	1.578	0.207	0.733	2.154	−0.152	3.521
HHI	352	−3.219	1.172	−5.362	−0.271	0.471	2.572
HHI^2	352	0.698	1.026	2.09E-07	6.401	2.545	10.594
Capital expenditure int.	342	−1.942	0.687	−4.637	2.205	0.211	7.286

Table A3
Results from estimation of Eq. (1) when using a Fixed Effects estimator.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Energy intensity	0.766***	0.724***	0.727***	0.677***	0.702***	0.904***	0.525***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	−0.098*	−0.058***	−0.053***	0.01	−0.066***	−0.004	−0.036
	(0.086)	(0.000)	(0.005)	(0.719)	(0.004)	(0.565)	(0.252)

(continued on next page)

Table A3 (*continued*)

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Human capital intensity	−0.062	−0.042**	−0.052*	−0.054	−0.098***	−0.01	−0.126**
	(0.468)	(0.019)	(0.080)	(0.203)	(0.007)	(0.326)	(0.013)
Size	0.128***	0.013	0.041***	−0.053**	0.052***	−0.015***	−0.017
	(0.003)	(0.145)	(0.007)	(0.015)	(0.004)	(0.004)	(0.495)
TFP	−0.013	0.093**	0.039	−0.162	−0.201**	−0.077***	−0.353***
	(0.949)	(0.023)	(0.570)	(0.104)	(0.016)	(0.002)	(0.003)
Capital expenditure int.	−0.087	0.072**	0.047	0.044	−0.064	0.038**	0.107
	(0.588)	(0.028)	(0.392)	(0.571)	(0.331)	(0.050)	(0.247)
Constant	−6.880***	−6.034***	−5.418***	−4.435***	−7.964***	0.995***	−4.448***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
R^2 between	0.807	0.931	0.947	0.862	0.755	0.963	0.562
R^2 within	0.513	0.95	0.863	0.713	0.711	0.98	0.593
R^2 overall	0.772	0.923	0.923	0.845	0.731	0.966	0.575
CD test	X	−2.51**	−2.62***	−2.89***	−2.27**	3.23***	1.28
CD *p*-value	(x)	(0.012)	(0.009)	(0.004)	(0.023)	(0.001)	(0.199)

Notes: Values in parenthesis are *p*-values of the coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE stands for Fixed Effects estimator, respectively. Time dummies are included in all regressions.

Table A4
Results from estimation of Eq. (1) when using a Random Effects estimator.

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RE	RE	RE	RE	RE	RE	RE
Energy intensity	0.923***	0.787***	0.842***	0.920***	0.785***	0.919***	0.566***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	−0.072	−0.066***	−0.045**	−0.036	−0.078***	−0.008	−0.028
	(0.172)	(0.000)	(0.012)	(0.170)	(0.001)	(0.212)	(0.349)
Human capital intensity	0.01	−0.045***	−0.033*	−0.147***	−0.107***	−0.028***	−0.100**
	(0.857)	(0.000)	(0.057)	(0.000)	(0.000)	(0.000)	(0.012)
Size	0.140***	0.022**	0.053***	−0.029	0.063***	−0.011**	−0.014
	(0.001)	(0.020)	(0.000)	(0.234)	(0.003)	(0.038)	(0.588)
TFP	0.047	0.125***	0.09	0.052	−0.101	−0.067***	−0.342***
	(0.812)	(0.006)	(0.211)	(0.661)	(0.318)	(0.008)	(0.003)
Capital expenditure int.	−0.133	0.018	−0.002	−0.078	−0.038	0.027	0.104
	(0.375)	(0.575)	(0.974)	(0.244)	(0.569)	(0.162)	(0.245)
Constant	−6.610***	−6.139***	−5.343***	−5.002***	−8.044***	0.923***	−4.377***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
R^2 between	0.908	0.935	0.962	0.904	0.766	0.973	0.622
R^2 within	0.509	0.948	0.86	0.692	0.707	0.98	0.593
R^2 overall	0.842	0.929	0.939	0.88	0.741	0.971	0.617
CD test	X	−2.45**	−2.66***	−2.76***	−1.85*	3.84***	1.36
CD *p*-value	(x)	(0.014)	(0.008)	(0.006)	(0.064)	(0.000)	0.173

Notes: values in the parenthesis are *p*-values of coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. RE stand for Random Effects estimator, respectively. Time dummies are included in all regressions.

Table A5
CD test for regressors specified in Eq. (1) and Eq. (2).

Variables	CD test	*p*-Value	Variables	CD test	*p*-Value
SO_2 emissions intensity	X	(X)	Gas share	2.73***	(0.00)
NO_x emissions intensity	27.97***	(0.00)	Physical Capital Intensity	8.03***	(0.00)
TAC emissions intensity	24.65***	(0.00)	Human Capital Intensity	6.88***	(0.00)
CO emissions intensity	9.95***	(0.00)	Size	1.03	(0.301)
PM_{10} emissions intensity	12.01***	(0.00)	Total Factor Productivity	6.26***	(0.00)
CO_2 emissions intensity	15.94***	(0.00)	HHI	4.87***	(0.00)
N_2O emissions intensity	15.36***	(0.00)	HHI^2	3.08***	(0.002)
Energy intensity	17.53***	(0.00)	Capital expenditure int.	15.26***	(0.00)

CD test (Pesaran, 2004) tests regressors for cross section dependence and assumes null of cross section independence. CD test cannot produce result for SO_2 emission intensity because of missing values. Values in the parenthesis are *p*-values of CD test statistics. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively.

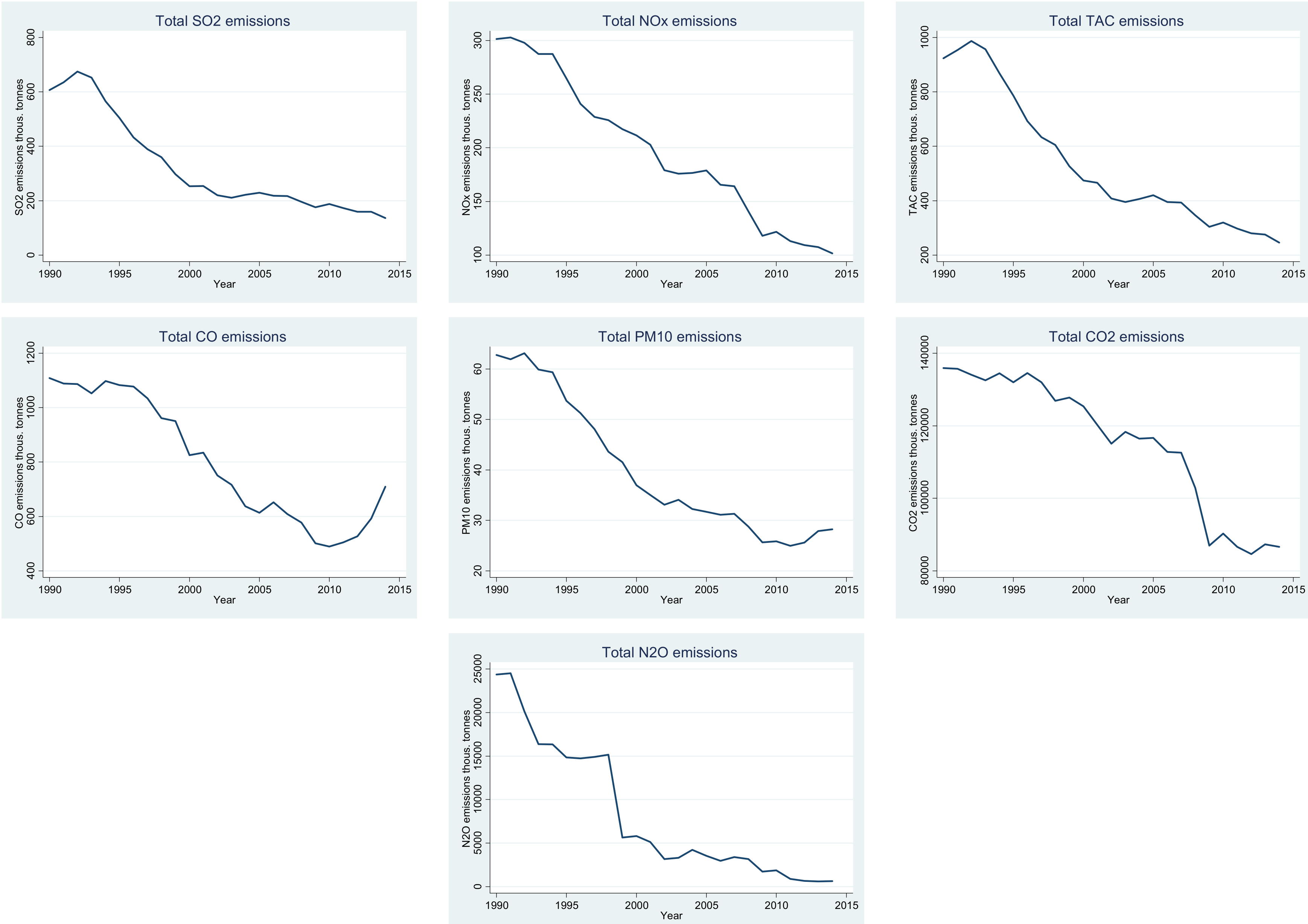

Fig. A1. Total emissions for all industrial sectors expressed in thousand tonnes

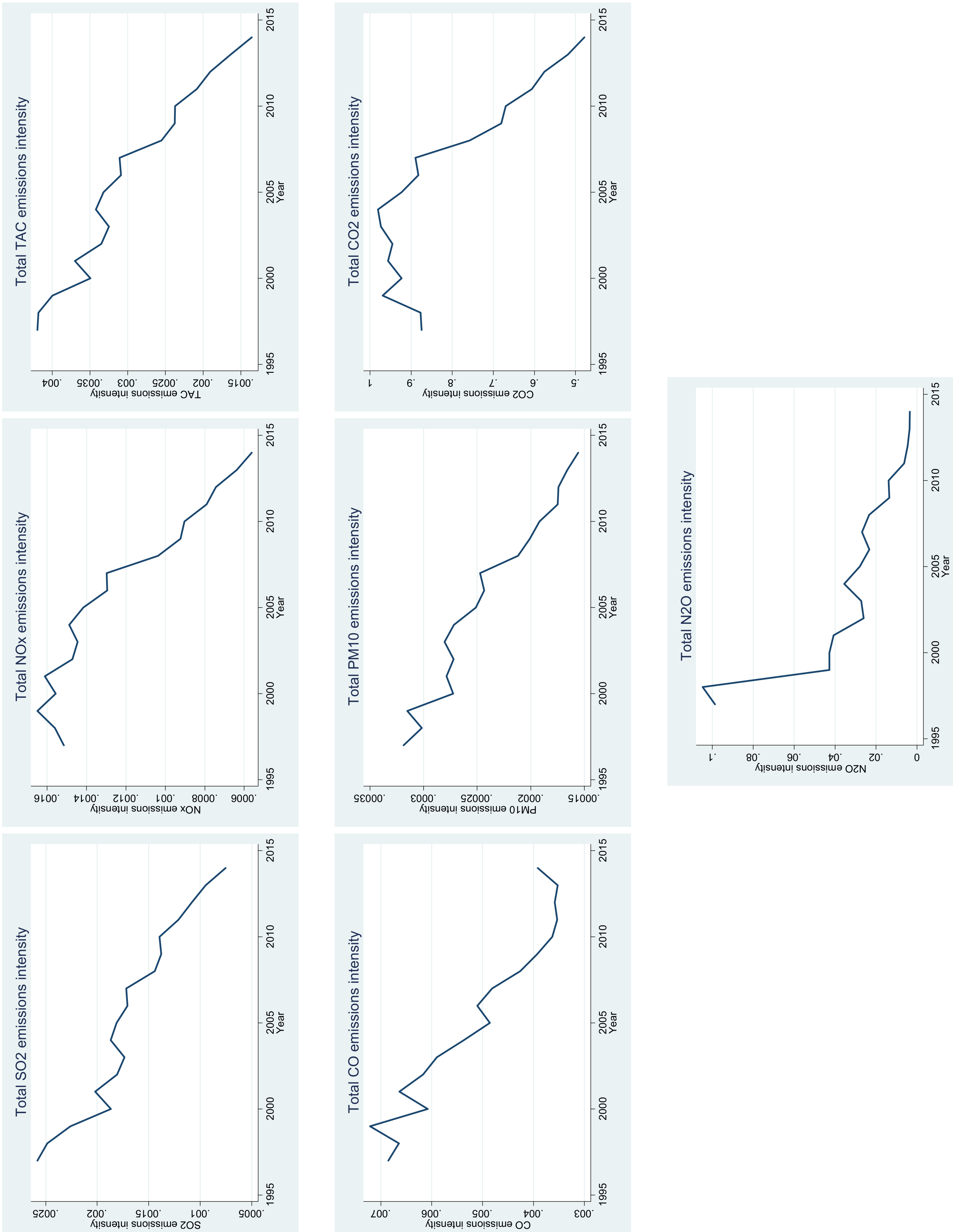

Fig. A2. Total emissions intensities for all industrial sectors

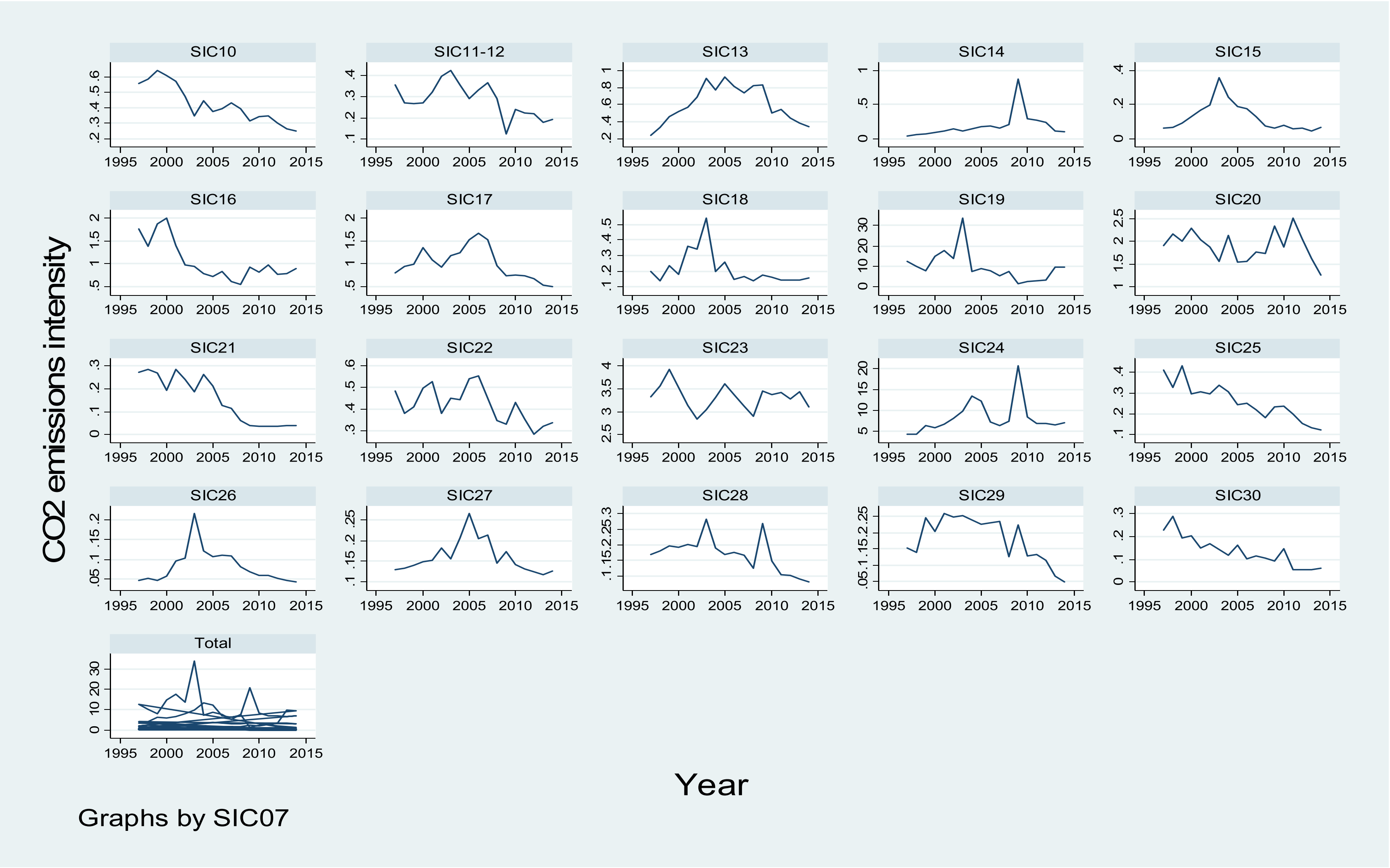

Fig. A3. CO_2 emissions intensity per industrial sector - variable scaling across sectors

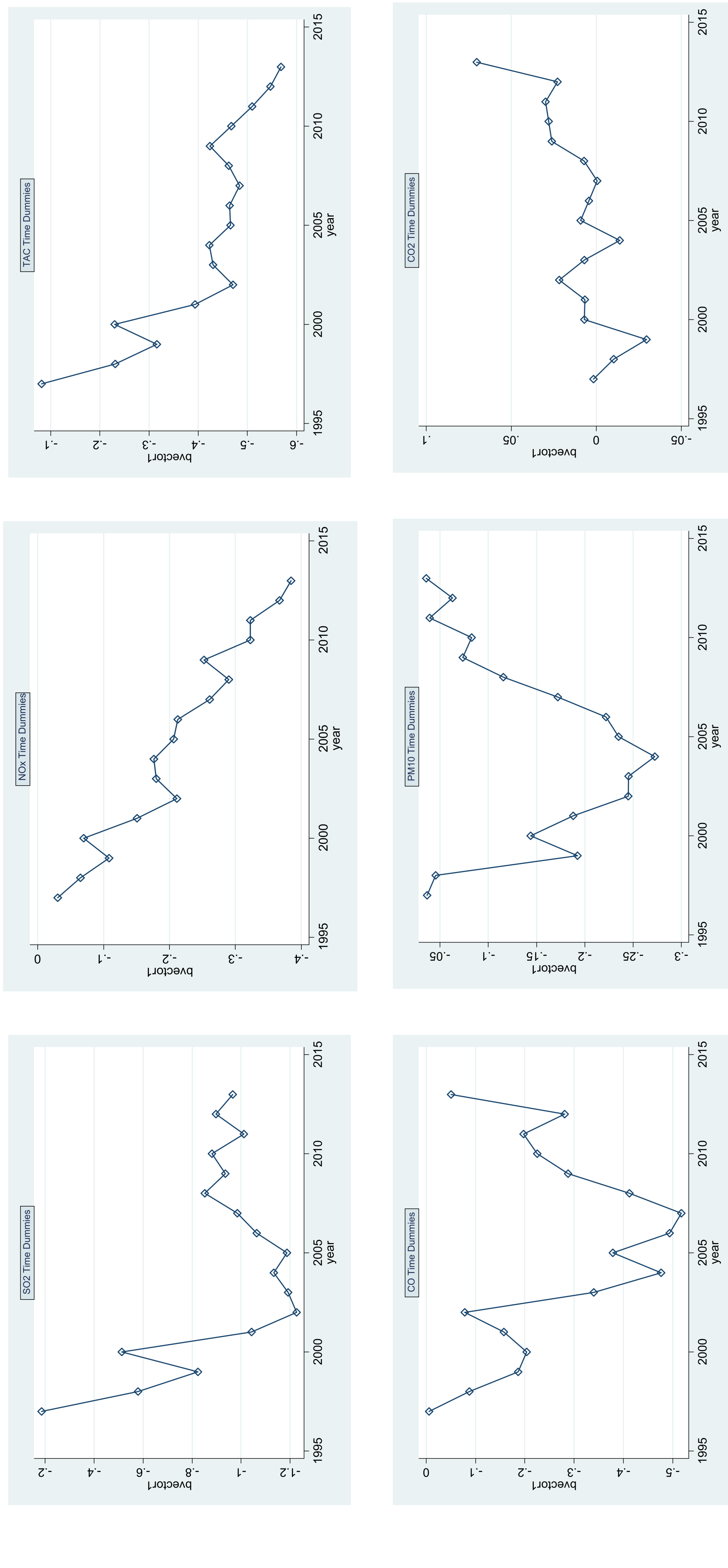

Fig. A4. Time effects from models presented in Table 2

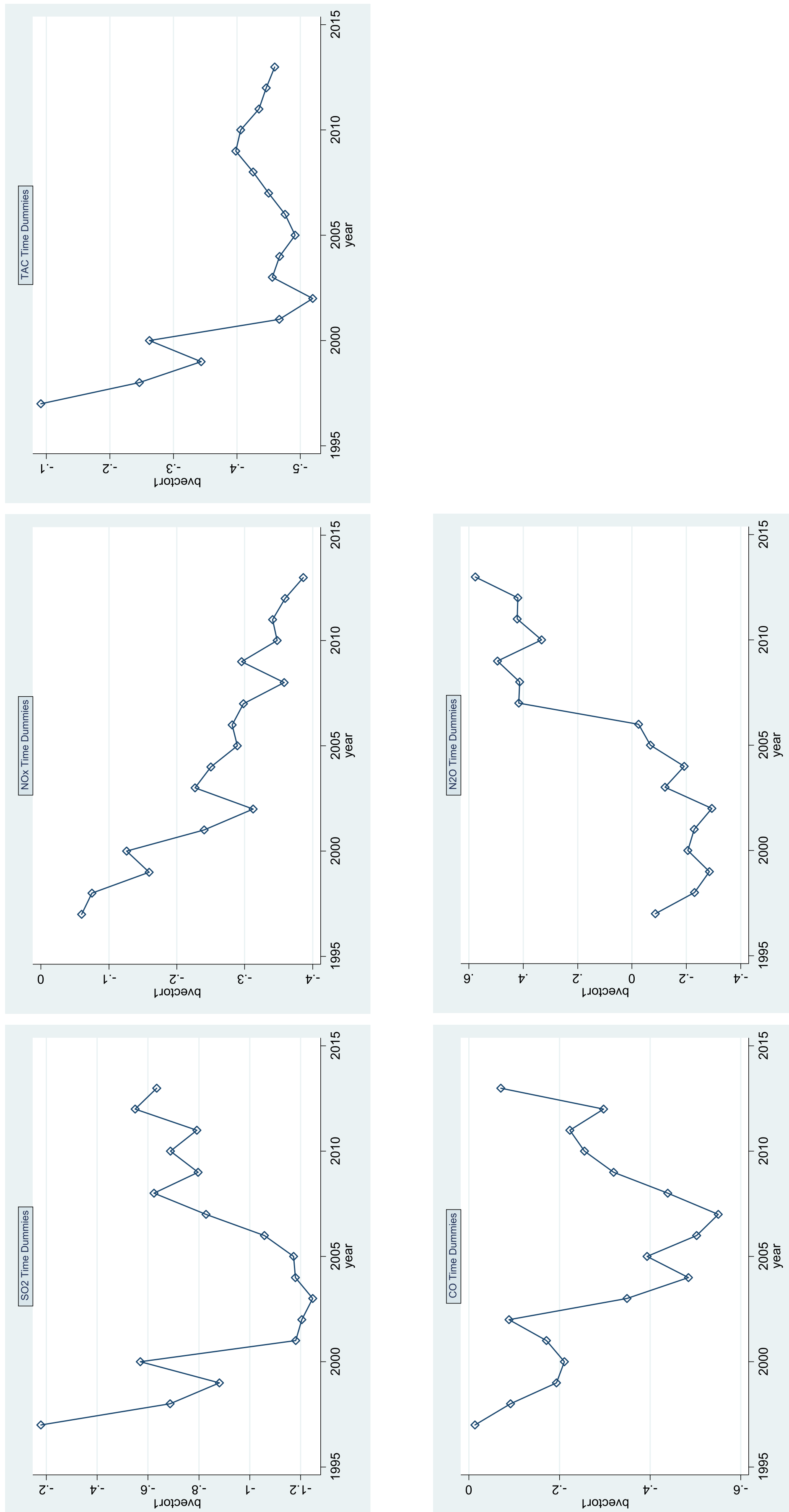

Fig. A5. Time effects from models presented in Table 3

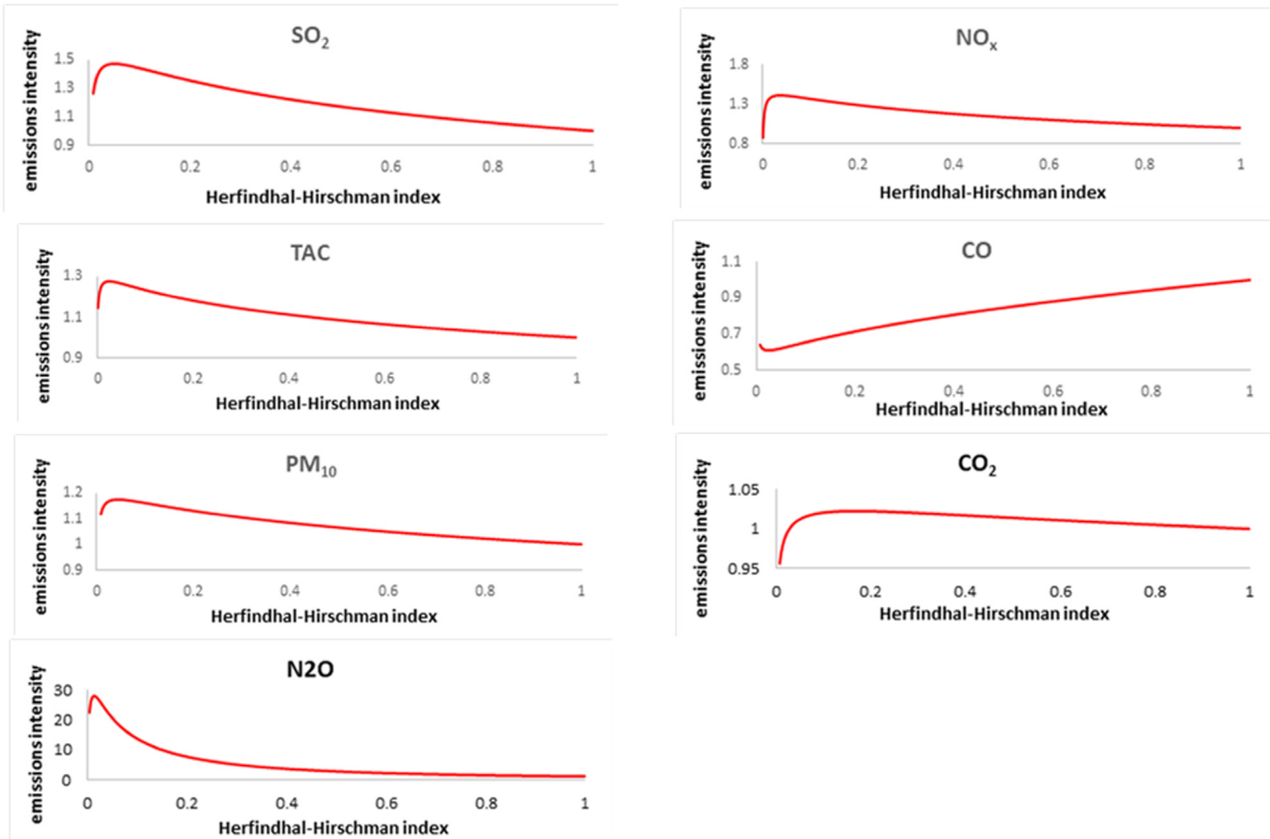

Fig. A6. Relationship between market concentration and emissions intensities based on the estimated models in Table 3. Emission intensity under perfect competition can be seen in correspondence of HHI = 0 while emission intensity under monopoly can be seen in correspondence of HHI = 1

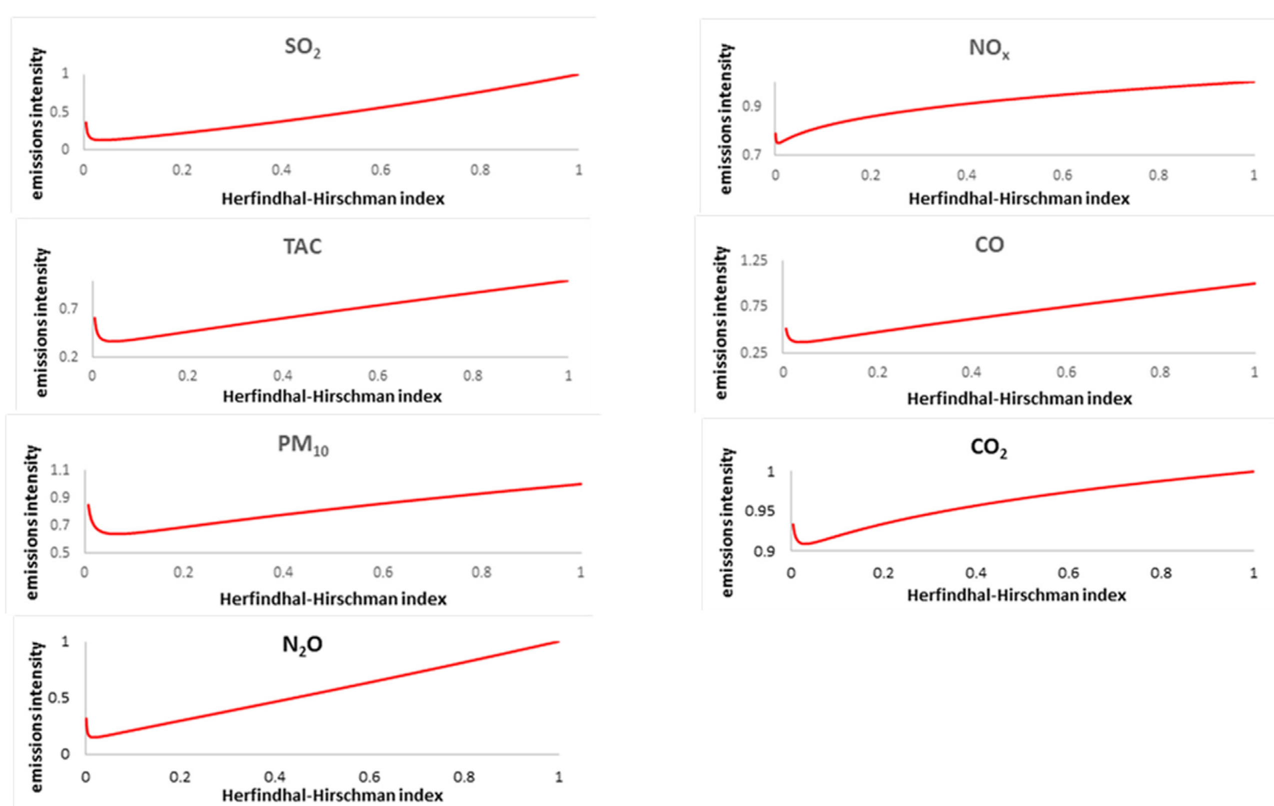

Fig. A7. Relationship between market concentration and emissions intensity based on the estimated models in Table 5. Emission intensity under perfect competition can be seen in correspondence of HHI = 0 while emission intensity under monopoly can be seen in correspondence of HHI = 1

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.12.005.

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