Industrial characteristics and air emissions

Long-term determinants in UK manufacturing

Paolo Agnolucci & Theodoros Arvanitopoulos
University College London, Institute for Sustainable Resources
p.agnolucci@ucl.ac.uk & t.arvanitopoulos@ucl.ac.uk

Abstract

We assess long-term relationship between industrial process and air emissions by building on an existing empirical framework. 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.

Introduction

Air pollution affects negatively health, the economy and ecosystems in various ways. Although the manufacturing sector is one of the major air polluters (ONS, 2016), not many studies have responded to the task highlighted by Cole et al (2005) who were the first to assess empirically the relationship between industrial activity and air pollution outside of the US. This apparent lack of investigative effort is preventing a rigorous understanding of the historical determinants of emissions from the manufacturing sector. Building on Cole et al (2005), we investigate the long-term determinants of emissions from the industrial sector while we assess the extent to which unobserved common factors through cross section dependence (CSD) affect our results.

Emissions and manufacturing

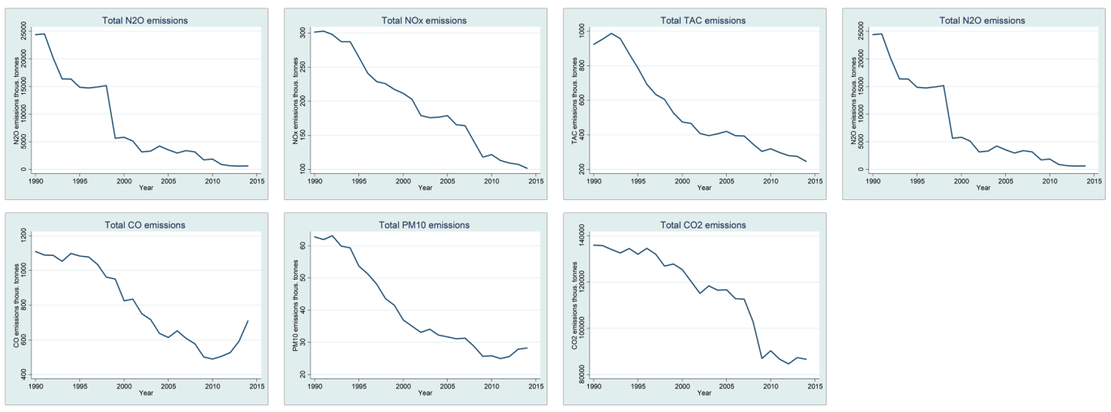

Figure 1: Total UK manufacturing emissions per emissions pollutant

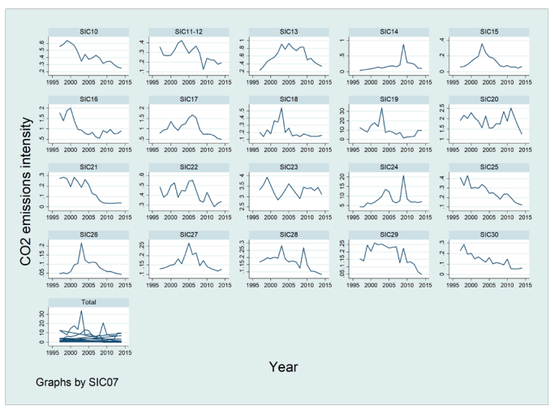

Figure 2: CO_2 emissions intensities per subsector

The UK has experienced a significant reduction in the overall level of atmospheric emissions from the manufacturing sector in the last 25 years (Figure 1). Between 1990 and 2014 CO_2 emissions have fallen by 35%, N_2O emissions by 97%, NO_x by 66% and SO_2 emissions by 90%. The most emissions intensive sectors (Figure 2) are "wood and products of wood and cork" (SIC 16), "paper and paper products" (SIC 17), "coke and refined products" (SIC 19), "chemical and chemical products" (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 intensity (Figure 2) therefore making an investigation focused on industry-specific determinants a sensible approach.

Econometric modelling

Our investigation centers on emissions intensity 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 Cole et al (2005), but also by the fact that the time pattern of emissions is driven by intensive factors rather than the level of production.

$$E_{it} = \alpha_i + \beta_1 EN_{it} + \beta_2 GAS_{it} + \beta_3 HCI_{it} + \beta_4 PCI_{it} + \beta_5 SIZE_{it} + \beta_6 TFP_{it} + \beta_7 HHI_{it} + \beta_8 HHI_{it}^2 + \beta_9 CAP_{it} + \epsilon_{it} \quad (1)$$

We estimate Equation 1 for $i = 1, .., 20$ industrial sectors and $t = 1, .., 18$ years (timespan 1997-2014), where the effect on emissions intensity (E_{it}) is estimated separately for each emissions pollutant (Table 1). Table 2 shows the independent variables used in Equation 1. All variables used in Equation 1 are expressed in real values and in logarithmic form.

SO_2	=	sulphur dioxide	NO_x	=	nitrogen oxides
TAC	=	total acid precursors	CO	=	carbon monoxide
PM_{10}	=	particular matter	CO_2	=	carbon dioxide
N_2O	=	dinitrogen monoxide			

Table 1: Dependent variables used in Equation 1

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 independent variables and the values of the estimated coefficients. Application of the Common Correlated Pooled Group estimator (CCEP - Pesaran, 2006) tackles CSD and enables us to point at statistically significant coefficients as robust determinants of industrial emissions across the pollutants assessed in this study.

EN_{it}	=	energy intensity	=>	total fossil fuel use intensity
GAS_{it}	=	fuel substitution	=>	substitution from dirtier to cleaner fuels
HCI_{it}	=	human capital intensity	=>	value added per skilled worker
PCI_{it}	=	physical capital intensity	=>	non-wage value added per worker
$SIZE_{it}$	=	size of the average firm	=>	effect of intra-sectoral economies of scale
TFP_{it}	=	total factor productivity	=>	output not explained by used production inputs
HHI_{it}	=	Herfindhal-Hirschman index	=>	intra-sectoral market concentration index
CAP_{it}	=	capital expenditure intensity	=>	investment intensity

Table 2: Independent variables used in Equation 1

Results

Our results in Table 3 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 total factor productivity cannot be relied upon to produce certain environmental benefits from policies aimed at changing any of these factors.

	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)	(0.71)	(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)	(0.95)	(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	0.27	0.78	-0.03	-1.44	0.16	-0.92
CD *p*-value	(x)	(0.788)	(0.435)	(0.972)	(0.151)	(0.87)	(0.359)
HHI F-test	3.71	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 HHI F-test indicates that market concentration effect is significant.

Table 3: Results from the estimation of Equation 1 from the CCEP estimator

Our results in Figure 3 are strikingly similar to Aghion et al (2005) which assesses the relationship between competition and innovation. Following Aghion et al (2005) argument, firms in highly competitive markets are "prevented" from innovating and therefore abating emissions intensities due to low 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 margins.

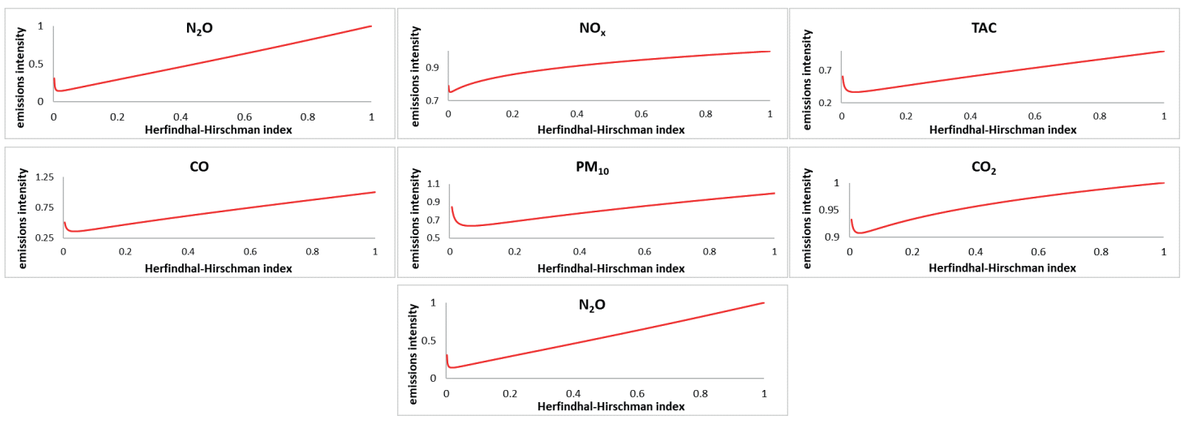

Figure 3: Emissions intensities and market concentration (HHI)

Conclusions

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. Reflecting results from Aghion et al (2005) on the relationship between market concentration and innovation we estimate a non-linear relationship between market concentration and emissions intensities therefore contributing to an area of environmental economics which appear surprisingly under-researched.

References

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