Carbon Tax and Energy Intensity: Assessing the Channels of Impact using UK Microdata

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ABSTRACT

Prior empirical studies indicate that carbon taxes have a negative impact on energy intensity, yet, the literature is unable to shed much light on the channels through which a moderate carbon tax reduces industrial energy intensity. Using a two-stage econometric approach, we provide the first comprehensive analysis of the five components of the *energy intensity gain* (EIG) arising from the UK climate change levy (CCL). First, we propose an EIG decomposition based on a stochastic energy cost frontier and a confidential panel of UK manufacturing plants covering 2001–2006. In the second stage, we identify the impact of the CCL on EIG components using an instrumental variable (IV) approach that addresses the endogeneity of the carbon tax rules. Factor substitution and technological progress are the dominant firm responses to the CCL, while energy efficiency is surprisingly the least responsive component. Our findings underscore the challenge arising from overreliance on narrow energy policy objectives such as energy efficiency improvements, suggesting that a broader policy approach aimed at improving overall firm resource allocation might be more appropriate.

Keywords: Climate Change Levy, Stochastic frontier analysis, Energy intensity gain, Firm Behavior, Manufacturing

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1. INTRODUCTION

It is well established from previous studies that climate change mitigation will require substantial abatement of greenhouse emissions from different sectors of the economy (see Pacala and Socolow, 2004). However, because sectors differ in terms of their levels of energy intensity, the abatement effort required across different sectors would vary accordingly.[1] For instance, achieving the much-needed global emissions reduction will require significant emissions abatement in the production technologies of manufacturing plants. This is because manufacturing is a major contributor to worldwide pollution, accounting for around 20% of global greenhouse gas (GHG) emissions (See

1. See for instance, Levinson and Taylor (2008) and Martin, et al. (2014) for analyses and discussions on sectoral heterogeneity in emissions arising from differences in abatement costs and technology.

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IEA, 2010, IPCC, 2014). Similarly, it accounted for around 17% of UK GHG emissions in 2015, mainly dominated by carbon dioxide (CO_2) emissions[2] (MacCarthy et al. 2016).

However, considering that manufacturing output is largely tradable, there are valid concerns that policy instruments aimed at curbing industrial emissions could harm international competitiveness, as well as result in job losses and plant closures (Martin et al., 2014). Consequently, the implicit challenge in designing an optimal industrial climate policy centers on the regulatory dilemma arising from the trade-off between the joint policy objectives of pollution abatement and preserving international competitiveness. This issue underscores the preference of economists for market-based policy instruments[3] in the textbook approach for designing optimal climate change policies.

The most common type of market-based policy instrument is the Pigouvian tax[4] which can be imposed on energy units or carbon content in order to signal the social marginal cost (SMC) of pollution arising from its impact on climate change. While the negative relationship between carbon taxes and energy intensity is well-established in the literature,[5] existing studies are unable to shed much light on the channels through which a moderate carbon tax leads to reductions in energy intensity.[6] As a consequence, important open questions remain about the behavioral components that drive or dominate firm energy intensity reductions: how do firms achieve reductions in their energy intensity when they are faced by a moderate carbon tax liability? How do industrial climate policies place binding constraints on firm behavior? Are the carbon tax-induced changes in actual firm behavior consistent with predicted policy outcomes?

In practice, there exists a range of responses by firms to a moderate tax on carbon. For instance, firms may adjust the input mix within their production technologies in response to changes in the relative price of energy arising from a carbon tax liability. Secondly, they might install new capital with lower energy-using technologies. A third alternative is that firms may pursue low carbon innovation efforts or knowledge through RandD investments that deliver efficiency improvements in existing production technologies. Furthermore, it is also possible that some firms may choose to exploit scale economies in order to absorb the shocks to energy costs due to the carbon tax.

In this paper, we evaluate the components of energy intensity reductions arising from the UK carbon tax, using a panel of 493 manufacturing firms over the period 2001–2006. In the first place, the empirical evaluation of market-based climate policies on manufacturing is scarce, due in part to the lack of suitable microdata (Martin et al., 2014). In particular, the dearth of studies on the impact of UK carbon tax on the components of energy intensity reduction is even more severe, such that the empirical literature is unable to shed any light on the crucial policy discussions above. Using a two-stage econometric approach, we provide the first comprehensive analysis of the five components of industrial energy intensity gain (EIG) due to the UK CCL. In the first stage of our

2. Given that carbon dioxide is the dominant pollutant, it is unsurprisingly the focus of many climate change policy instruments.

3. The general notion about the superiority of market-based instruments such as pollution taxes and emissions trading schemes (ETS) stems from the theoretical arguments that they are more efficient than alternative approaches such as command and control policies (see Pearce, 1991; Bovenberg and Goulder, 2002; for some discussions). More specifically, market-based policy instruments allow for cost-effective allocations of abatement burdens among firms and they provide continuous (dynamic) incentive for technological innovations for pollution abatement (Jaffe and Stavins, 1995; Williams, 2012).

4. In the UK, the single most important market-based instrument is the Climate Change Levy (CCL), which is a carbon tax imposed on industrial sectors' carbon emissions.

5. See for instance, Bjorner and Jensen (2002), Floros and Vlachou (2005), Martin et al. (2014)

6. For instance, Martin et al. (2014) highlighted the importance of gaining a better understanding of how firms achieve reduction in energy intensity in response to the UK CCL.

research design, we propose an energy intensity decomposition based on a stochastic energy cost frontier. In the second stage, we estimate the impact of the carbon tax on the EIG components using an instrumental variables (IV) approach that addresses the endogeneity of the UK CCL rules.

Contrary to the much-touted idea that energy conservation through efficiency improvements is the most effective energy policy approach to tackling global emissions, we find that the dominant firm responses to the UK CCL are factor substitution and technological progress. These findings signal a need for broader energy policy objectives towards improving overall resource allocation, as opposed to the narrow objective of energy efficiency improvements.

The remainder of the paper is organized as follows. In section 2, we provide a background and description of the UK CCL scheme. Section 3 set out our two-stage econometric methodology. In section 4, we describe our estimation strategy with emphasis on how we address the econometric issues arising from the unobserved heterogeneity and endogeneity problems within our specified models. Section 5 describes the data set employed, and section 6 contains the econometric results and study findings. Section 7 concludes.

2. BACKGROUND ON UK CLIMATE CHANGE LEVY (CCL) PACKAGE

During the last 20 years, the reduction of greenhouse emissions from manufacturing has become a top priority of the UK energy and climate policy agenda. In the same vein, it seems that reduction in industrial energy use features prominently in the policy plans towards meeting ambitious carbon reduction targets. For instance, a recent paper by the Committee on Climate Change (CCC) stated inter alia:

> *The CCC recommend the implementation of a stronger policy framework for industrial energy efficiency in order to meet the fifth carbon budget.*
>
> (HM Government, 2016)[7]

However, the reduction in industrial sector energy remains a source of political debate, especially as it mirrors the policymaker's dilemma between low-carbon economy and industrial sector competitiveness or job creation.[8] These considerations are at the core of the CCL package as a climate policy response to the joint objectives of reducing industrial GHG emissions and enhancing industrial competitiveness. The package, which was introduced in 2001, has two components: (i) a carbon tax component namely climate change levy (CCL), which is a tax per unit[9] of industrial fuel[10] purchased and (ii) the Climate Change Agreement (CCA), which is an alternative scheme available to preserve the competitiveness of energy intensive manufacturing plants through a reduced carbon tax liability.

While the CCL is a straightforward tax on energy and carbon content, CCAs[11] entail negotiated energy (or energy intensity) reduction targets between manufacturing firms and the UK

7. For instance, in like manner, the CCL package was projected as the main source of carbon savings (6.6 million tonnes carbon (MtC) towards an overall reduction goal of 20.8 MtC by 2010) under the UK Climate Change Programme (HM Government, 2006).

8. These sentiments are echoed by Hansford, et al. (2004) who argue that the CCL would raise production cost and limit international competitiveness, with little potential to achieve the UK's ambitious carbon reduction targets.

9. Usually per kilowatt hour (kWh) equivalent

10. The fuels taxed under the scheme are electricity, natural gas, coal and non-transport liquefied petroleum gas (LPG). Other low carbon fuels (e.g. electricity generated from renewable energy sources or from combined heat and power) are exempted from the carbon tax.

11. See http://www.cclevy.com/

Environment Agency,[12] in exchange for up to 80% discount on the CCL liability.[13] The negotiated CCAs are undertaken at two levels. Firstly, 'umbrella agreements' on sector-wide energy use or CO_2 emissions targets are agreed between sector/trade associations and the environmental agency. Secondly, at the micro level, plant-level 'underlying agreements' are negotiated between firms and the environmental agency for specific energy reduction targets by the plant.

One critical feature of the CCL package, which raises vital questions in our research design, is the self-selection of firms encountered in typical voluntary emissions abatement schemes such as the CCA. Effectively, plants under the CCL scheme are liable to pay the full carbon tax rates, whereas CCA plants receive discounted tax liabilities in exchange for binding energy reduction or efficiency targets. One the one hand, these targets (if stringent) could influence firm opt-out decisions from the CCA. On the other hand, a further compounding feature of the CCA's design is the non-eligibility of some plants for CCA participation. CCA eligibility is based on polluting activities regulated under the Pollution Prevention and Control (PPC) act of 1999, such that a manufacturing firm is eligible if at least one of its installation is engaged in a PPC activity (e.g. a blast furnace). This implies that, albeit CCA participation is voluntary, not every plant is eligible. This results in a selection endogeneity into the CCA scheme, with the implication that non-eligible plants incur the *full* CCL tax liability by default. In short, the design of the CCL-CCA package design embodies non-random selection[14] of plants into one of the schemes.[15]

Turning now to the CCL component, one of its important features worth mentioning is the non-uniformity of tax rates across fuels. For instance, Martin et al. (2014) demonstrated that the carbon tax rates per unit of energy varied significantly across fuel types, ranging from 6% on coal to 10% on electricity; and approximately 17% on natural gas. These tax rates indicate, for instance, that the carbon contained in gas is on average taxed at more than twice the rate as the equivalent carbon content of coal. The variation in tax rates across fuel types is a second source of endogeneity concern since the effective or overall carbon tax rates per unit of total energy consumed is dependent on firm fuel mix. In this case, coal reliant firm pay lower carbon tax rates whereas the converse is the case for firms with relatively high levels of electricity or gas consumption.

3. LITERATURE REVIEW

There is a substantial body of literature on the impact of carbon taxes in general.[16] However, there is a dearth of studies on the impacts of carbon taxes on industrial sectors despite their widespread adoption across advanced economies. In terms of the UK literature, a small body of

12. Department for Environment, Food, and Rural Affairs (DEFRA)

13. See De Muizon and Glachant (2004) for a detailed description of the agreements and the nature of the commitments under the CCA scheme.

14. This non-random self-selection feature of the CCL/CCA scheme is central to the potential endogeneity of the carbon tax variable within an empirical assessment or policy evaluation, such as the one undertaken here. We address this endogeneity issue in greater detail in Section 4.

15. See De Muizon and Glachant (2004), Martin et al. (2014) for some discussion on CCA eligibility rules. For instance, Martin et al. (2014), provides strong empirical evidence that CCA plants are, on average, larger older and highly energy intensive than CCL plants. These larger dirtier plants are (by default) likely to join the CCA scheme in order to receive substantial tax discount savings since they hitherto use large amounts of energy. A converse argument can be made for smaller plants who are likely to have lower fixed costs and levels of energy consumption and are likely to choose to pay the full tax rate on modest energy use rather than join the CCA scheme.

16. See for instance, Aldy and Stavins (2012) for a survey on the experience and literature pertaining to carbon taxes in developed countries.

literature on the CCL[17] exists, although the micro-econometric evaluation of its impact on industrial sectors is sparse. Agnolucci, et al. (2004) and Ekins and Etheridge (2006) provide empirical evidence on "announcement effect" and "awareness effect" of the CCL. Barker et al. (2007) simulate the impact of CCAs on sectoral output, employment, and energy demand. More recently, Martin et al. (2014) conducted a microeconometric analysis of the impact of the CCL/CCA on a range of outcome variables such as energy intensity, plant exit and employment. Four main challenges exist with the existing studies.

First, most of the studies are based on aggregate, regional and sectoral data which make it impossible to obtain insight on the microeconomic impacts of the CCL package. This is a crucial limitation, given that carbon tax impacts are likely to vary across firms. Secondly, sectoral time series studies suffer from the impossibility of disentangling the impact of the CCL from other aggregate policy shocks. Thirdly, simulation studies are susceptible to the challenges arising from their assumptions about key analytical variables. Because they tend to use simulated trajectories of energy intensity as counterfactual baselines upon which carbon tax effects are estimated, their estimated results can be sensitive to the baseline assumptions. Fourthly, although the more recent micro-econometric evaluation by Martin et al. (2014) mostly alleviates[18] the above three issues above, one major challenge persists. The available literature has been unable to shed light on the channels through which manufacturing plants reduce their energy intensity in response to the CCL.

While the empirical evidence from the sparse body of literature (e.g. Bjorner and Jensen, 2002; Floros and Vlachou, 2005; Martin et al., 2014) demonstrates the significant impact of carbon taxes on industrial energy use and pollution, we know little about how firms achieved the substantial reductions in energy intensity. Unbundling these firm responses to a moderate carbon tax is important for at least two reasons. First, it allows for a comprehensive policy evaluation that presents a more complete picture of the energy intensity adjustments within production technologies, which might be impossible in a typical impact study. Secondly, because most market based environmental policy instruments are usually geared towards stimulating energy efficiency, this study allows us to assess the implicit assumption or widely held notion that climate policy instruments lower energy intensity[19] through energy efficiency improvement.[20]

A recently emerging strand of the literature (e.g. Filippini and Hunt, 2011, 2012; Saunders, 2013) highlights that energy intensity embodies a range of behavioral, economic and technological components, such that it might be misleading to treat EIG and energy efficiency improvements as equivalents. As these studies demonstrate, if energy efficiency is a small component of overall energy intensity reduction, it raises great potential for policy failure in cases where huge public investments are directed towards stimulating efficiency improvements in the face of other dominant components. Therefore, gaps in knowledge about firm responses to climate policy instruments can

17. See Varma (2003) and Fullerton, et al. (2008) for a detailed background and discussions on the CCL.

18. Since their analysis is based on a micro-econometric assessment of the CCL for a panel of UK manufacturing plants, it is devoid of the potentially arbitrary baseline assumptions required in simulation studies, while also exploiting the response of firm performance variables to the CCL both over time and across plants, which is impossible to achieve in a sectoral study.

19. Conventionally, falling energy intensity (represented by the ratio of energy to output: e/y) is often treated as an indicator of energy efficiency improvement by engineers and energy policy makers.

20. This implicit assumption is well established in the academic literature (see Linares and Labandeira, 2010; Gillingham, et al., 2009 for reviews and discussions). Similarly, policymakers and practitioners appear to also anchor most policy objectives on *reducing energy intensity through improved energy efficiency*. For instance, the UK CCL package aims to enhance the efficiency of energy use in the industrial sectors and this objective is echoed by the Committee on Climate Change (CCC) recommendation for the "*implementation of a stronger policy framework for industrial energy efficiency in order to meet the fifth carbon budget*". (see HM Government, 2016).

be costly. In cases of misdirected policy objectives, it becomes crucial to ask if policy instruments are better directed towards stimulating other dominant responses?[21]

4. METHODOLOGY

In this paper, our aim is to evaluate the channels of impact of the UK carbon tax on manufacturing firms' behavior. This objective poses two critical challenges. The first challenge relates to the question of how to unbundle EIG into its components. The second challenge pertains to the endogeneity of the carbon tax variable within our empirical setting. To address these challenges, we adopt a two-stage research design. Firstly, we obtained estimates of the EIG via a decomposition of productive performance using SFA[22] in Stage 1. Secondly, in Stage 2, we explore the relationship between these components and the CCL. Although we are not aware of an empirical study which decomposes the energy cost function as done in this study, the use of productivity decomposition from SFA as part of multi-stage econometric techniques has been explored by previous studies.[23]

4.1 Stage One: Unbundling EIG

In the first stage of our research design, we employ a productivity approach based on the stochastic frontier analysis (SFA). Consider a representative firm with a production24 technology which can be represented by a production function $F(\cdot)$ in which an input vector25 $(\mathbf{x}', e) = (x_1, \ldots, x_K, e)$ is used to make output *y*. Energy input is symbolized by *e* and its market price relative to the numeraire is p_e, so we write the energy input dual cost function or short run energy cost function at time *t* where *t* also represents the state of technology as follows.

$$p_e e^* = c^e\left(p_e, y, \mathbf{x}', t\right) = \min_{e}\left\{p_e e : y = F\left(\mathbf{x}', e, t\right)\right\} \qquad [1]$$

The expression in [1] is increasing and concave in p_e, homogeneous of degree +1 in p_e and increasing in *y*. The $(x_1, \ldots, x_K)$ are treated as quasi-fixed inputs. It is embedded in the standard stochastic frontier analysis with the multiplicative error terms $u > 0$ representing the one-sided asymmetric inefficiency and *v* representing the two-sided zero mean idiosyncratic error, capturing measurement, sampling and specification error. Actual cost on energy by the cross-section observation $i = 1, \ldots I$ at time $t = 1, \ldots, T$ is:

$$C_{it}^e = \left(p_e e\right)_{it} = c^e\left(p_e, y, \mathbf{x}', t\right)_{it} exp\left(u_{it} + v_{it}\right) \qquad [2]$$

21. Even if we made a strong behavioral assumption that energy efficiency improvement has a proportional impact on energy intensity, another strand of the literature (e.g. Saunders, 2013; Adetutu et al., 2016) highlights second-round behavioral failures in which the impact of energy efficiency improvement on reducing energy intensity might be partially or entirely offset through the so called "rebound effect". These second-round effects provide further motivation for an assessment of other behavioral responses to climate policy instruments.

22. Examples of SFA studies applied to energy and emissions include Boyd (2008)

23. For instance, previous studies such as Adetutu et al (2015, 2016) employ a two-stage econometric approach to investigating issues relating to pollution and energy rebound effects using productivity measures from a first stage SFA. Some other studies in the banking literature (e.g. Cipollini and Fiordelisi, 2012; Duygun et al., 2015) also employ first stage SFA measures as part of a broad range of multi-stage analysis.

24. We study this issue using the production-theoretical decomposition analysis (PDA) technique. Within a production theory framework, PDA examines CO_2 emission changes from the perspective of productive efficiency. See Wang, et al. (2018) for an application.

25. Throughout this paper we denote the input vector as $\mathbf{x}'$.

Subsequently, we make use of the log derivative of this expression to measure the rate of change over time, using the general notation:

$$\Delta \log z \approx d \log z / dt \equiv (1/z)(dz/dt) \equiv \dot{z} \quad [3]$$

By suppressing the observational subscripts for the moment to minimize notation and assuming the time derivative of the idiosyncratic error is zero, we obtain:

$$\dot{C}^e = \dot{p}_e + \dot{e} = \varepsilon_p \dot{p}_e + \varepsilon_y \dot{y} + \boldsymbol{\varepsilon}'_{\mathbf{x}} \dot{\mathbf{x}} + \varepsilon_t + (du/dt) \quad [4]$$

The functions: $\varepsilon_p, \varepsilon_y, \boldsymbol{\varepsilon}_{\mathbf{x}}, \varepsilon_t$ are respectively the cost elasticity (i.e.log cost derivatives) functions for the price of energy, the output produced, the quasi-fixed inputs used and the passage of time or changes in technology. By rearranging this expression, we obtain an exact relationship between the conventional energy intensity indicator and the concept of economic energy efficiency embodied in the production technology:

$$\dot{y} - \dot{e} = (1-\varepsilon_p)\dot{p}_e + (1-\varepsilon_y)\dot{y} - \boldsymbol{\varepsilon}'_{\mathbf{x}} \dot{\mathbf{x}} - \varepsilon_t - (du/dt) \quad [5]$$

The left-hand side of the expression in [5] is the rate of improvement in the energy intensity, i.e. the rate at which the chosen measure of economic activity increases faster than the rate of energy consumption, which we designated earlier as the energy-intensity-gain (EIG). It is also a measure of factor (energy) productivity change. The first term on the right-hand side represents allocative efficiency change (AEC). We see immediately that it is equivalent to the failure of the homogeneity assumption. Failure of the homogeneity postulate when this energy price elasticity of the energy cost function differs from one reflects allocative inefficiency. The second term is the scale efficiency change with respect to the chosen measure of economic activity, (SEC). The third represents the impact of exogenous other input change, (OIC). The fourth term is the rate of technological change (TC) and the final term is the rate of economic efficiency change (EEFC). Therefore, we can summarize the arguments of our method as:

$$EIG = AEC + SEC + OIC + TC + EEFC \quad [6]$$

4.1.1 Model Specification and Estimation

We propose the estimation of the energy cost function in [2] above with two major considerations in mind: homogeneity and the functional form of our model. As we stated above, using Shephard's lemma (Shephard, 1953), the homogeneity property in this case of an energy cost function corresponds to the assumption of allocative efficiency. Therefore, a test of the homogeneity property and a test of allocative efficiency amount to the same thing and both correspond to testing whether the energy price elasticity of the energy cost function differs from one in value. Using vector notation for the logs of inputs, i.e. $\mathbf{lx}' = (\ln x_1, \ldots, \ln x_K)$, we have the translog function:

$$\begin{aligned}\ln C^e_{it} &= \alpha_0 + \alpha_1 \ln p_{eit} + \frac{1}{2}\alpha_{11}(\ln p_{eit})^2 + \alpha_y (\ln p_{eit})(\ln y_{it}) + \boldsymbol{\alpha}'_{\mathbf{x}}(\ln p_{eit})(\mathbf{lx}_{it}) \\ &+ \beta_1 \ln y_{it} + \frac{1}{2}\beta_{11}(\ln y_{it})^2 + \beta_y (\ln y_{it})\mathbf{lx}_{it} + \boldsymbol{\gamma}'\mathbf{lx}_{it} + \mathbf{lx}'_{it}\boldsymbol{\Gamma}\mathbf{lx}_{it} + \delta_1 t \\ &+ \frac{1}{2}\delta_2 t^2 + \boldsymbol{\mu}'(\mathbf{lx}_{it})t + u_{it} + v_{it} \quad [7]\end{aligned}$$

The elasticities are critical for the energy intensity decomposition and in this translog case the elasticity functions are given by the linear-in-log functions:

$$\begin{bmatrix} \varepsilon_p \\ \varepsilon_y \\ \boldsymbol{\varepsilon}_{\mathbf{x}} \\ \varepsilon_t \end{bmatrix} = \begin{bmatrix} \alpha_1 & \alpha_{11} & \alpha_y & \boldsymbol{\alpha}'_{\mathbf{x}} & 0 \\ \beta_1 & \alpha_y & \beta_y & \boldsymbol{\beta}'_{\mathbf{x}} & 0 \\ \boldsymbol{\gamma} & \boldsymbol{\alpha}_{\mathbf{x}} & \boldsymbol{\beta}_{\mathbf{x}} & \boldsymbol{\Gamma} & \boldsymbol{\mu} \\ \delta_1 & 0 & 0 & \boldsymbol{\mu}' & \delta_2 \end{bmatrix} \begin{bmatrix} 1 \\ \ln p_{eit} \\ \ln y_{it} \\ \mathbf{lx}_{it} \\ t \end{bmatrix} \quad [8]$$

4.1.2 Stage 1: EIG Decomposition

The primary aim of the first stage of our research design is the decomposition in [6], which is dependent on the elasticity function estimates in eqn. [8], and from the sample, we can use Tornqvist indices to obtain the EIG components as follows:

$$AEC = \left(1-\varepsilon_p\right)\dot{p}_e \approx \frac{1}{2}\left[\left(1-\varepsilon_{pit}\right)+\left(1-\varepsilon_{pit-1}\right)\right]\left[\ln p_{eit} - \ln p_{eit-1}\right] \quad [9a]$$

$$SEC = \left(1-\varepsilon_y\right)\dot{y} \approx \frac{1}{2}\left[\left(1-\varepsilon_{yit}\right)+\left(1-\varepsilon_{yit-1}\right)\right]\left[\ln y_{it} - \ln y_{it-1}\right] \quad [9b]$$

$$OIC = -\sum_{k=1}^{K}\left(\varepsilon_k\right)\dot{x}_k \approx -\frac{1}{2}\sum_{k=1}^{K}\left(\left[\left(\varepsilon_{kit}\right)+\left(\varepsilon_{kit-1}\right)\right]\left[\ln x_{kit} - \ln x_{kit-1}\right]\right) \quad [9c]$$

$$TC = -\varepsilon_t \approx -\frac{1}{2}\left(\varepsilon_{it} + \varepsilon_{it-1}\right) \quad [9d]$$

$$EEFC = -du/dt \approx \ln\left(CE_{it}/CE_{it-1}\right) \quad [9e]$$

4.1.3 Stage Two: Estimating CCL Impact Channels

Having obtained the EIG components in stage 1 above, we then focus on evaluating the impact of the CCL on each of the unbundled components, which we express in a vector of response variables, $\boldsymbol{Q}_{it}$:

$$\boldsymbol{Q}_{it} = (AEC_{it}, SEC_{it}, OIC_{it}, TC_{it}, EEFC_{it}) \quad [10]$$

We seek to estimate the changes in the elements of $\boldsymbol{Q}_{it}$ as a function of the carbon tax:

$$\boldsymbol{Q}_{it} = \boldsymbol{\pi}_1 CCL_{it} + \boldsymbol{\vartheta}_1 PET_{it} + \theta_i + \xi_t + \epsilon_{it} \quad [11]$$

where $\boldsymbol{\pi}_1,\ldots,\boldsymbol{\pi}_5$ are 5×1 vectors of regression parameters that capture the relationships between $\boldsymbol{Q}_{it}$ and CCL_{it}. $\boldsymbol{\vartheta}_1,\ldots,\boldsymbol{\vartheta}_5$ are 5×1 vectors of regression parameters that capture the impact of energy prices (excluding the CCL tax). θ_i is a 5×1 vector of fixed firm effects to account for heterogeneity in the EIG components between firms, ξ_t is a vector of time fixed effects to control for certain unobserved time trends that affect the EIG components, over and above the effect the carbon tax. ϵ_{it} is a vector of idiosyncratic error terms.

4.2 Estimation Issues

The classic econometric problem in the estimation of [11] is the potential endogeneity of the carbon tax variable CCL_{it}. In the first place, we think of θ_i as capturing fixed unobserved heterogeneity, which might include persistent factors that are approximately fixed over the time frame where we observe a plant in our data sample. Because the CCL tax liability is largely driven by time-invariant factors such as plant size,26 in practice the CCA/CCL participation will be non-random, so that θ_i is potentially correlated with CCL_{it}.

Secondly, while the theoretical construction of our model in [11] intuitively leads us to expect that firm EIG components are driven by the carbon tax, an issue that is allied to the selection endogeneity discussed above is the potential for reverse-causality. Plants with improvements in their EIG components (this could be due to RandD activities which may further improve productivity performance in the near future) may choose not to enter into a CCA because the potential tax savings to be generated over the remaining lifetime of their installed technology are lower than the fixed cost commitment required under the CCA. In this case, some plant may choose to pay the full CCL tax rates rather than join a CCA. Hence, EIG performance may also influence firm participation choices, and by extension, the carbon tax liabilities that they incur. Therefore ϵ_{it} is potentially correlated with CCL_{it}.

Thirdly, ϵ_{it} includes other random shocks which may explain the variations in a firm's tax rate. For instance, as we highlighted previously, the carbon contained in gas and electricity is taxed at almost twice the rate as carbon contained in coal. Given this situation, the effective carbon tax rates would clearly vary according to the fuel mix across plants: specifically, firms with greater electricity and gas shares invariably pay higher CCL tax rates. This further confounds the non-random selection issues documented above, since variation in the tax rates emanate from the omitted firm-level differences in the fuel mix. Consequently, CCL_{it} is potentially correlated with the fuel mix distribution embedded in ϵ_{it} .

Given the fundamental issues discussed above, estimating [11] under the assumption of orthogonality of the regressors is not likely to produce consistent estimates of $\boldsymbol{\pi}_1$. Hence, estimating the model parameters of [11] by ordinary least squares (OLS) method will produce biased estimate of $\boldsymbol{\pi}_1$ since θ_i and ϵ_{it} are important factors in explaining $\boldsymbol{Q}_{it}$. To address this endogeneity problem and to estimate $\boldsymbol{\pi}_1$ consistently, we adopt an instrumental variables (IV) approach.

4.2.1 Instrumental Variables (IV) Approach

One of the main aims of this paper is to assess the relationship between the UK carbon tax and the EIG components using microdata. However, a common problem when estimating this type of relationship is the lack or limited availability of conventional instrumental variables (IV) for the carbon tax. Even when such instruments exist, there can be doubts on whether they satisfy the exclusion restriction. To overcome these challenges, we adopt an identification strategy where we identify the impact of the carbon tax using firm age as an instrument, augmented by an internal instrument constructed following Lewbel (2012).

Our identifying assumption is that older plants are more likely to belong to larger firms who sign up to a CCA with a view to enjoying the tax savings available through the allied tax

26. As we discussed in Section 2 large older energy-intensive plants under the PPC act are likely to sign-up or self-select into the CCA discount scheme, meaning that they incur lower carbon tax liabilities. Therefore, plants paying higher CCL tax rates are likely to be smaller plants that may not be incentivized to join the CCA, but rather choose to pay the full tax rates.

discount (see Martin et al, 2014, p. 4). Hence, firm age and carbon taxes should be negatively correlated.[27] Besides meeting the relevance/correlation criterion, a strong case can be made for the exogeneity of the firm age variable, especially given that almost all of the firms in the data sample (491 out of 493), were established before the beginning of the sample period in 2001 (which is also the beginning of the CCL package).

In order to be able to test the overidentifying restriction, we include a second instrument, which we derived using the observable heteroskedasticity procedure proposed by Lewbel (2012). Baum et al. (2012) demonstrate that this approach is useful when no external instruments are available; or, alternatively, it can be used to supplement external instruments in order to test over identifying restriction; which in our case would be impossible, due to the exactly identified model with the firm age variable only. Secondly, the approach is also relevant in cases where limited external instruments are supplemented to improve the efficiency of the IV regression.

Specifically, in a single equation context, the first stage regression may be employed to provide the components for Lewbel's propositions, by generating instruments from the residuals of the first stage regression, multiplied by the mean-adjusted values of each of the included exogenous variables:

$$Z_j = \left(X_j - \bar{X}\right) \cdot \epsilon \qquad [12]$$

Where ϵ is the vector of residuals from the first-stage regression of the endogenous tax variable on the exogenous regressors and the vector of constants. Millimet and Roy (2016) provide a relevant empirical example of the Lewbel procedure in their analysis of the pollution haven hypothesis in the presence of endogenous environmental regulation, using state-level US data.

5. DATA

Our model estimations and analysis are based on a unique dataset, which we constructed from the most comprehensive restricted-use business microdata on UK manufacturing firms. Particularly, our data construction required collection and matching of information across two different confidential firm-level datasets held by the Office for National Statistics (ONS), which we obtained through the secure access program offered by the UK Data Service. These two surveys are the Quarterly Fuels Inquiry (QFI) SN: 6898 and the Annual Respondents Database (ARD) SN: 6644. The QFI is a quarterly survey of over 1000 UK manufacturing plants, containing information on energy consumption, expenditures and CCL payments. The ARD on the other hand is an annual production survey spanning 10,000 UK manufacturing plants.

Our sample period covers the years since the UK CCL/CCA package was introduced up to 2006. Our data set ends in 2006 for two main reasons. First, roughly around 800 plants have consistent QFI data across all the periods since the introduction of the CCL in 2001 up to around 2006. Consistent quarterly data are required to derive annual data, which are then matched with the ARD data. Second, our matching scheme indicates a drastic fall in the number of plants with consistent data after 2006, with the number of plants with continuous data falling from around 500 plants to under 200 plants after 2006. Further, when matched with the ARD, the number of plants with consistent data shrinks considerably to around 100 plants. This is not surprising given the random sampling in the ARD, which means that we do not have ARD data for all QFI plants.

27. We confirm this negative correlation in the first stage regression presented in Table A3 in the appendix

Table 1: Summary Statistics

Variables	Mean	SD
Energy cost (£)	111785.1	722326.1
Energy consumption (toe)	96972.41	362312.5
Output (£ '000)	27376.37	60176.94
Capital stock (£ '000)	3644.323	13311.69
Labour (employee headcount)	487.338	737.39
Energy price (£)	0.859	0.909
Climate change levy (CCL) (£ per unit of energy)	0.549	0.892
Firm age (years)	24.48	7.51
Observations	**2307**	**2307**

The ARD contains core production function variables such as capital stock, K, number of employees (our measure of labour, L) and value added, which we employed as our measure of output Y. Other core variables in this study are energy consumption (e) which is measured in kilowatt-hour (kWh) equivalent, and energy price (p) which is the price per kilowatt-hour equivalent (£/kWh). Both variables are used to compute the total energy cost $C_{it}^{e} = \left(p_e \times e\right)_{it}$. Another key variable in our analysis is the CCL, given by a unit tax measure which we derived as the ratio of total CCL payments (£) to total energy consumed (kWh). All the variables expressed in monetary values are deflated using the producer price indices, normalised to 2001=100. Table 1 displays the descriptive statistics28 on the variables in our data sample, which contains information for 493 firms and 2307 observations.

6. EMPIRICAL RESULTS

6.1 Parameter Estimates from Stage 1 Energy Cost Function

One key issue in the analysis of regulatory instruments such as the carbon tax is how to address the presence of time-invariant effects arising from inter-firm heterogeneity or variation in performance across firms, which do not change over time. There is a consensus in the productivity measurement literature that productive efficiency of a firm embodies two critical components: a persistent and a transient part (Filippini and Greene, 2016) and failure to capture the persistence effect results in unobserved heterogeneity bias (Filippini and Hunt, 2015). Hence, we propose a specification for the energy cost function that allows for error components that distinguish between latent heterogeneity, idiosyncratic error and inefficiency. In the context of panel data, models that allow for these three critical elements are proposed by Greene (2005a and 2005b) who extended the SFA model by adding a fixed effect in the model in order to obtain time-varying inefficiency, time-invariant (firm) fixed effects and an idiosyncratic error. We estimate a translog[29] energy cost function following Greene's *true fixed effects model* (TFE) by MLE:

$$\ln C_{it}^{e} = \alpha_i + TL\left(p_e, y, \mathbf{x}', t\right)_{it} + u_{it} + v_{it} \qquad [13]$$

where $TL\left(p_e, y, \mathbf{x}', t\right)_{it}$ is the translog approximation to the energy cost function containing energy price, output, other inputs and the technology parameter, respectively. u_{it} is the inefficiency component of the disturbance error; v_{it} captures the traditional idiosyncratic error term which contains

28. See Table A1 in the appendix for a summary of the variables employed, along with their definitions and sources.

29. As part of our preliminary analysis, we test for the appropriate functional form by comparing the Cobb-Douglas formulation with the Translog form. The resulting LR test (df=20) is 331.7 rejects the Cobb-Douglas restriction at the 1% level.

sampling error, measurement error and specification error. The TFE cost function in [13] uses firm dummy variables α_i in the MLE model to capture latent heterogeneity or time-invariant (firm) fixed effects.30

In addition to addressing the issue of heterogeneity or persistence across sampled firms, we also deal with the problem of heteroscedasticity in SFA models, a very important issue for applied parametric efficiency research. Studies such as Reifschneider and Stevenson (1991) and Battese and Coelli (1995) demonstrated how SFA models can address this issue of heteroscedasticity in the composed errors by proposing frontier models where the specific parameters of the inefficiency density function for u_{it} are modelled as functions of time-varying exogenous variables (i.e. conditional heteroscedasticity). There are two broad approaches to introducing exogenous variables into the inefficiency term.

Under the first approach, which follows the proposal by Battese and Coelli (1995), observable characteristics of the firm are introduced into the location of the distribution of inefficiency so that u_{it} is assumed to follow the truncated normal distribution with a mean μ_{it} specific to each observation $u_{it} \sim \mathcal{N}^+\left(\mu_{it}, \sigma_{it}^2\right)$. Here the mean of the inefficiency term is modelled as a function of observable firm-specific factors F_{it}: $\mu_{it} = \boldsymbol{\varphi}' \boldsymbol{F}_{it}$. Under the second approach, the observable firm-specific effects are introduced into the inefficiency term by scaling its distribution (i.e. the assumption of constant variance of the truncated normal distribution is relaxed). In this case the variance is a function of the firm-specific variables31 and it permits heteroscedasticity in u_{it} such that $u_{it} \sim \mathcal{N}^+(0, \sigma_{u_{it}}^2)$ where $\sigma_{u_{it}}^2 = \exp\left(\boldsymbol{\gamma}' \boldsymbol{F}_{it}\right)$.

In this study, the latter is adopted for a range of reasons. First, the scaling property of this approach is desirable when evaluating the impact of firm-specific effect on inefficiency. Alvarez et al. (2006) provide a detailed technical explanation of the practical advantages and the desirability of the scaling property. Notably, they show that the property implies that changes in the firm-specific factors affect/determine the scale and not the shape of the distribution of u_i, unlike under the previous approach where the F's enter the mean efficiency and alter the shape of its distribution.32 Secondly, scaling offers an intuitive economic interpretation in that u_{it} is taken as a firm's (random) base level of efficiency which captures its natural abilities, so that the extent to which these natural abilities or skills are exploited depends on the operating environment which is captured by exogenous influences, F_{it}. Thirdly, and more importantly, the scaling property allows for a straightforward interpretation of the parameter $\boldsymbol{\gamma}$.

Scaling functions, such as the exponential function yield coefficients that are derivatives of the log of inefficiency w.r.t the exogenous variables: $\gamma = \partial \ln\left(u_{it}\right) / \partial F_{it}$ for $u_{it} = \exp\left(F_{it}, \gamma\right) \cdot u_{it}^*$. This is a highly desirable property, as it permits the interpretation of the coefficients as the quantitative effects of changes in exogenous variables on inefficiency. This is not the case with the Battese and Coelli (1995) specification which has no quantitative interpretation in terms of the magnitude of the parameters of F_{it}. Given the foregoing, we introduce heteroscedasticity into the TFE model using

30. In our preliminary analysis, we estimated Eq. (13) using classical fixed effects and random effects models. The Hausman specification test yields a test statistic $\chi^2 = 159.7$ which confirmed the presence of the unobserved heterogeneity bias, and by extension the need for controlling for fixed effects.

31. The impact of exogenous variables on the variance of inefficiency is particularly crucial since the variance parameters of the model are the key devices in the estimation of inefficiencies.

32. Under the heteroscedastic model where $u_{it}\left(F_{it}, \gamma\right) = h\left(F_{it}, \gamma\right) \cdot u_{it}^*$ changes in F_{it} change the scale but not the shape of the distribution of inefficiency, u_{it}. As Alvarez et al. (2006) demonstrate, because the shape of the inefficiency is determined by the basic random distribution u_{it}^*, which does not depend on F_{it} , whereas the scaling function $h\left(F_{it}, \gamma\right)$ determines the scale of the estimates.

the Normal-Exponential stochastic energy cost frontier model so that the composed error terms can be expressed as:

$$v_{it} \sim \mathcal{N}(0,1) \quad [14]$$

$$u_{it} \sim \mathcal{F}(\sigma_{uit}) \quad [15]$$

$$\sigma_{uit} = exp\left[0.5(2 + 1 \times Fu_{it})\right] \quad [16]$$

where the inefficiency error scale parameter is now a function of a constant term and an exogenous covariate (Fu_{it}), which in our case is an RandD variable.

The coefficients of the fitted heteroscedastic TFE-UHET model, along with other alternative specifications are presented in table 2. This model (last column of table 2) yields sensible coefficients that have the right signs and are all statistically significant at the sample mean, so that it is taken as our preferred model33 upon which our subsequent analyses are based. Given that our data are expressed as deviations from the overall sample mean, the first order terms are also the cost function elasticities at the sample mean. The estimation results show that the elasticity of cost with respect to output and each of the input prices are positive. The output elasticity is 1.005, lending some support to the homogeneity postulate. We test the homogeneity postulate restriction (i.e. $\varepsilon_p = 1$), and we are unable to reject this restriction at conventional levels of significance given chi2(1) =0.20 (prob = 0.6572). By confirming the homogeneity assumption, we can conclude that, since the only cost measure in our model is energy cost, then the share of energy and the price elasticity are exactly one in value. We proceed to retrieving the EIG components from our preferred model.

6.2 Energy Intensity Decomposition Results

Our next exercise pertains to the unbundling of energy intensity components described in equations 9a–9e using the matrix Eq. [8] and estimates from the model in Table 2, which we estimated with a high degree of precision and statistical significance. We present the decomposition results (at the sample mean) in table 3. The numerical impacts are expressed as percentage contributions to the rate of annual EIG change.

A first glance at table 3 will reveal that EIG is negative for most of the years under consideration, apart from the last year in our study sample. Nonetheless, the EIG at the sample mean was generally rising over the sample period. Also, these results indicate that EIG have been positively stimulated by scale efficiency change (SEC) and other input change (OIC).34 We also find limited contributions from technological change (TC) and efficiency change (EEFC). One essential point from the estimates is that economic energy efficiency EEEF had a strong negative impact on EIG in the first three years of our sampling period, but this turned positive in the last two years. The EEFC estimates speak to two contrasting viewpoints. On the one hand, when interpreted in the context of the dominant energy policy approach of reducing energy intensity via efficiency improvements,

33. This approach is underpinned by the LR test of a homoscedastic error TFE model as a restricted form of the heteroscedastic formulation. The LR test statistic of 41.87 (prob=0.0000) indicates that the homoscedastic formulation is rejected by the data in favor of the heteroscedastic approach.

34. There might be concerns that the input change component of the decomposition might be driven by the cost function formulation which does not include a material variable, due to the lack of a direct material input measure. Hence, we conduct a robustness test using a material input proxy: expenditure on goods for own use. The re-estimated decomposition is given in the appendix, and it shows that the results are quite similar. We thank an anonymous referee for making this point.

Table 2: Estimated translog energy cost function

Dep. Var.: lced	Pooled model	TFE model	TFE-UHET model
Energy Price	0.761*** (0.046)	1.183*** (0.024)	1.005*** (0.011)
Output	0.437*** (0.047)	0.051*** (0.007)	0.150*** (0.004)
Capital	0.318*** (0.025)	-0.003*** (0.009)	0.035*** (0.004)
Labour	0.022 (0.056)	0.442*** (0.008)	0.257*** (0.005)
Energy Price^2	-0.005 (0.044)	-0.062*** (0.013)	-0.010*** (0.000)
Output^2	0.031*** (0.003)	0.003*** (0.000)	0.010*** (0.000)
Energy price*Output	-0.012 (0.018)	0.004*** (0.000)	-0.002*** (0.000)
Capital^2	0.027*** (0.002)	0.001 (0.001)	0.002*** (0.000)
Labour^2	0.001 (0.005)	0.036*** (0.001)	0.021*** (0.000)
Capital*labour	-0.010*** (0.003)	-0.004*** (0.001)	-0.003*** (0.000)
Energy price*capital	0.007 (0.010)	-0.005** (0.002)	-0.009*** (0.001)
Energy price*labour	-0.009 (0.017)	0.003 (0.003)	0.007*** (0.000)
Output*capital	-0.010*** (0.003)	-0.001*** (0.000)	-0.004*** (0.000)
Output*labour	-0.008** (0.005)	-0.011*** (0.001)	-0.008*** (0.000)
Time	0.066*** (0.018)	0.010*** (0.015)	0.009*** (0.003)
Time^2	-0.013 (0.012)	-0.012*** (0.000)	-0.011*** (0.002)
Capital*time	-0.008 (0.005)	0.001 (0.001)	0.0001 (0.000)
Labour*time	0.004 (0.007)	0.002*** (0.001)	0.001*** (0.000)
Parameters in the one-sided error			
Constant			-1.991*** (0.063)
RandD			-0.351*** (0.084)
Time			0.150*** (0.028)
Variance parameters for the compound error			
Sigma	2.813*** (0.198)	0.338*** (0.084)	
Lambda	0.959*** (0.155)	1.919*** (0.007)	
N	2307	2307	2307

***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. A full description of econometric model specifications is given in the appendix

Table 3: EIG decomposition and its components

Average annual rate of change (%)	AEC	SEC	OIC	TC	EEFC	EIG
2002	-0.08	**18.39**	-0.32	-5.25	-20.63	-7.88
2003	0.19	**18.88**	**2.42**	-3.01	-35.43	-16.94
2004	0.70	**16.78**	-1.31	-0.77	-24.91	-9.52
2005	-0.09	-11.16	**2.35**	**1.51**	**4.47**	-2.84
2006	-0.09	**26.59**	0.81	**3.71**	0.36	31.38

Notes: positive contributions shaded grey; dominant positive in bold text. AEC: allocative efficiency change; SEC: scale efficiency change; OIC: other input change; TC: technical change; EEFC: economic energy efficiency change

then over-reliance on energy efficiency policies might not yield the intended reductions in energy intensity. On the other hand, we note that the wider interpretation of this results might be mitigated by the limited scope of our data, which although captures some efficiency contributions to EIG, might not fully capture more recent efficiency improvements in industrial production technologies.

More specifically, because we find scale, other inputs and technology to be the main drivers of EIG, it is intuitive to think that energy intensity reductions across sampled UK manufacturing firms during the period under consideration appeared to have come from scale economies, high levels of factor substitution and shifts in the cost frontier/introduction of new technologies, respectively. Overall, the variations in the estimated EIG components indicate that, rather than focus on narrow policy objectives, energy and climate policies might be better directed at achieving other objectives such as overall resource allocation and innovation efforts that improve industrial technologies.

6.3 Stage 2: Impact of CCL Taxes on EIG Components

Having identified the main components of EIG, we now turn our attention to answering the headline research question pertaining the impact of the CCL on each of the components from stage 1 of our analysis. Given the previously documented endogeneity concerns about the carbon tax variable, we begin our stage 2 analyses by testing if OLS estimates of Equation [11] are consistent or whether IV methods are required to estimate the equations. To achieve this, we implement the C test, an equivalent to the Durbin-Wu-Hausman (DWH) test of the endogeneity of regressors. This test compares IV and OLS estimates under the null hypothesis of exogeneity of our tax variable.

By regressing energy intensity on the tax variable, we obtain a C test statistic of 6.565 with $\chi^2(1)$=0.0104, which rejects the null hypothesis that the CCL tax variable can be treated as exogenous at the conventional 5% level. Hence, we explore an alternative instrumental variables approach. Although, we attempt to instrument for the carbon tax within the limits of the available data, we recognize that the full alleviation of the endogeneity posed by the tax variable is a challenge. This challenge mainly stems from the difficulty in finding instruments that are both truly exogenous and valid in the econometric sense (Stock et al., 2002; Davis and Kilian, 2011). Consequently, as we discussed previously, we rely on Lewbel's (2012) approach.

A first a sensible step is to check that the instruments are properly excluded from the second-stage regression using the Hansen *J*-test, although the test provides little specific information on the individual validity of each instrument. We present the EIG regression results in table 4. For each of the components, we present OLS and IV estimates of the carbon tax impact on the respective components. The Hansen J statistics in Table 4 appear to suggest that the instruments are correctly excluded, and the Cragg-Donald F-test of 373.91 (versus the 10% maximal test value of 16.38), also suggests that the problem of weak instrumentation is mitigated within the model. Furthermore, the relative importance of controlling for the CCL tax endogeneity is evident as the point estimates from the IV regressions are quantitatively larger than the OLS estimates, which appear to be downward biased. This bias plausibly reflects that the OLS model does not account for the eligibility and self-selection issues arising from the design of the CCL package.

Notice that the coefficients of the CCL on allocative efficiency (AEC), scale efficiency (SEC) and energy efficiency (EEFC) are not statistically significant for both the OLS and IV regressions. Given the dominance of scale efficiency in EIG, this finding suggests that there is no statistically significant evidence that the UK carbon tax influences firm energy intensity reduction through its most dominant component. However, the IV estimates of the tax impact on the "other input" and technological change components are positive and statistically significant at the 10% and 5%-level, respectively. These results potentially suggest that the UK CCL stimulated energy intensity reduction across sampled plants via two of the three dominant channels: OIC and TC.

Table 4: Stage 2 regressions, impact of CCL on EIG components

	AEC		SEC		OIC		TC		EEFC	
	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
$\ln(CCL_{it} / E_{it})$	–0.0001	–0.001	0.077	0.087	**0.005***	**0.055***	0.0001	**0.004*****	–12.452	–0.039
	(0.000)	(0.001)	(0.062)	(0.034)	(0.003)	(0.049)	(0.000)	(0.001)	(10.064)	(0.074)
$\ln(PET_{it} / E_{it})$	–0.003	–0.002*	–0.001	0.003	0.001	0.004	0.002	0.001***	0.004	–0.006
	(0.004)	(0.001)	(0.001)	(0.005)	0.001	(0.004)	(0.003)	(0.000)	(0.007)	(0.000)
Hansen		3.362		4.718		3.735		5.021		3.963
		(0.34)		(0.19)		(0.29)		(0.10)		(0.30)
Cragg-Donald F-stat		373.91		373.91		373.91		373.91		373.91
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1649	1578	1649	1578	1649	1578	1649	1578	1649	1578

Notes: Robust standard errors in parentheses are clustered at the firm level. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Hansen test statistic of the over-identifying restrictions is asymptotically chi-square distributed under the null of instrument validity: p-values are reported in parentheses.

In particular, the CCL impact on the OI component is consistent with Martin et al. (2014) who found evidence of UK manufacturing plants substituting labor for energy in response to higher energy prices. This production flexibility demonstrated by the ease of factor substitution, potentially indicates that sampled firms were able to absorb the impact of the CCL by replacing energy with labor inputs. Our technology (TC) result is similar to the findings provided by Aghion et al. (2016) which demonstrate that manufacturing firms tend to innovate more in clean energy technologies when they face higher carbon tax-induced energy prices. On the other hand, the limited contribution of energy efficiency (EEFC) to EIG supports the results in Filippini and Hunt (2011) that changes in energy intensity are not necessarily equivalent to changes in energy efficiency.

Overall, the combined effect of the components yield negative EIG estimates for most of the periods before 2006. We note that the positive EIG estimate for 2006, rather than the negative estimates in the previous periods is more consistent with the more recent reality that manufacturing industries across OECD countries are rapidly 'cleaning up' their production technologies.35 Due to data limitations (i.e. because our data ends in 2006), we are unable to further capture these clean-up effects. However, it is more than plausible that the positive result for 2006 has continued beyond the sample period, given the introduction of the EU-ETS in 2005/6.

35. See for instance Levinson (2009) for the US and Brunel (2014) for the EU. We thank an anonymous referee whose comments helped to further clarify this point.

What can we conclude from these findings? First it might be too simplistic to associate changes in energy intensity with improved energy efficiency. The data indicate that changes in the energy intensity measure arise from a wide range of factors, only one of which can be treated as energy efficiency improvements. Second, by identifying the different component channels of the changes in energy intensity including the channel of energy efficiency improvement but also allowing for allocative, scale and technology change and the impact of other inputs, we have been able to relate each to the impact of the climate change levy, while attempting to address the endogeneity arising from the design of the policy instruments. Several lessons stand out. During the period under consideration, energy efficiency was a less important factor in changing energy intensity than scale efficiency change and was rivalled in magnitude of impact by technical change and the role of other inputs. In our second stage modelling, we are able to relate the components of the changes in energy intensity to the impact of the climate change levy. Its statistically significant impacts are on the way that firms choose other inputs in relation to the use of energy in minimizing energy cost and on the role of technical progress, i.e. innovation in reducing energy cost. Our findings suggest that, during the period under consideration, declining energy intensity was driven by other dominant firm responses, such as factor substitution and technological progress, as is the case in our sample. These findings are underpinned by the results from regressing the log of energy intensity on the EIG components (see appendix).

6.4 Robustness Checks

We undertake robustness checks on our findings using two different strategies. First, we run sub-sample regressions to unravel the sensitivity of our results to the impact of sample heterogeneity. This could also provide checks on endogeneity concerns about the tax variable. Secondly, we re-estimate the EIG regressions using a balanced sample in order to address the potential problems arising from unbalanced panels where results could be driven by outliers in discontinuous data, as well as variation in sample composition over time, as opposed to the impact of the CCL. We now take these checks in turn.

6.4.1 Subset and balanced sample regressions

Heterogeneity between high-intensity and low intensity (or between big and small), as well as domestically owned versus foreign-owned plants might fuel concerns that our results might be driven by these fundamental differences. These concerns could also amplify the endogeneity problem within our models, since for instance, plant size and energy intensity levels are front and center in the endogeneity arising from firm selection decisions into a CCA versus paying the full CCL tax rates. Therefore, we verify the robustness of our results by re-estimating the IV regressions using sub-samples of firms that are similar in terms of their size, energy intensity and domestic-foreign ownership categories. The results obtained for the subset samples are reported in Table 5.

Although the point estimates from the subset IV regressions are different in numerical terms, our main findings remain qualitatively intact. For instance, similar to the full sample case, the coefficient of the CCL on AEC remains largely statistically insignificant across all the estimated sub-sample regressions, apart from the sample for large firms. The balanced sample yields a negative coefficient that is statistically significant at the 10% level. The qualitative implication is that the carbon tax does not strongly improve the level of firm allocative efficiency embodied in an EIG.

For the scale change SEC, the lack of statistical significance remains the case across all the re-estimated IV regressions, with all the sub-sample coefficients remaining negative. Again, the sub-sample SEC results are intuitively similar to the full sample results. For the OIC regressions, the coefficients remain positive across the board, but the estimates for the size regressions lose statistical significance. However, the regressions for energy intensity and ownership criteria, along with the balanced sample regressions are statistically significant. For the technological change regressions, the carbon tax coefficients largely retain their positive sign and statistical significance, except for the small-sized and low-intensity firms for which both coefficients are not significant while the former turns negative.

Table 5: Impact of Log (CCL) on EIG components, subset and balanced IV regressions

	Size		Energy Intensity		Ownership		
	Small	**Large**	**Low**	**High**	**Domestic**	**Foreign**	**Balanced Panel**
AEC	0.001	0.001*	0.001	0.002	0.001	0.001	–0.001*
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
Hansen	10.73	1.20	0.83	4.10	3.36	1.43	2.36
p-value	0.07	0.75	0.84	0.25	0.34	0.23	0.50
Cragg-Donald	356.32	162.66	313.33	47.86	373.91	19.46	295.68
SEC	–0.010	–0.003	–0.059	–0.361	–0.005	–0.201	–0.032
	(0.028)	(0.052)	(0.057)	(0.373)	(0.034)	(0.279)	(0.056)
Hansen	4.11	3.25	2.11	5.28	4.718	0.48	2.80
p-value	0.25	0.35	0.55	0.15	0.19	0.50	0.42
Cragg-Donald	356.32	162.66	313.33	47.96	373.91	19.46	295.68
OIC	0.032	0.014	0.005	0.044**	0.010	0.023	0.003
	(0.051)	(0.015)	(0.022)	(0.021)	(0.020)	(0.024)	(0.004)
Hansen	2.31	1.96	1.94	2.76	3.74	0.011	7.20
p-value	0.51	0.58	0.58	0.43	0.29	0.92	0.07
Cragg-Donald	356.32	162.66	313.33	47.96	373.91	19.46	295.68
TC	0.002	0.004**	0.004***	0.005	0.004***	0.001	0.005***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)
Hansen	42.82	2.78	4.38	18.56	3.72	1.16	0.81
p-value	0.00	0.26	0.16	0.01	0.24	0.28	0.19
Cragg-Donald	356.32	162.66	313.33	47.96	373.91	19.46	295.68
EEFC	0.006	0111	0.061	–0.046	0.040	1.063	0.020
	(0.021)	(0.157)	(0.111)	(0.041)	(0.074)	(0.665)	(0.021)
Hansen	2.03	3.26	3.55	0.38	3.70	0.26	1.48
p-value	0.56	0.35	0.31	0.94	0.29	0.61	0.68
Cragg-Donald	356.32	162.66	313.33	47.96	373.91	19.46	295.68
Year FE	Y	Y	Y	Y	Y	Y	Y
N	476	644	796	324	920	309	748

Notes: Robust standard errors in parentheses are clustered at the firm level. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Size: "Large" are firms with 250 employees or more and "Small" otherwise. Energy intensity samples are split according to the sample median. Firm ownership is based on codes for "ultimate owner" of the enterprise in the Inter-Departmental Business Register (IDBR), available from the ARD dataset.

Finally, for the energy efficiency component, the CCL coefficients in the sub-sample regressions are largely positive, as opposed to the negative sign on in the full sample regression. However, these sub-sample coefficients all lack statistical significance across the board, so that the implication remains that, firm energy efficiency component of EIG may not be attributed to the CCL. Finally, it is worth reiterating the, apart from the difference in sign for the tax impact on the energy efficiency component, all the balanced sample regressions are consistent with the full sample regressions.

7. CONCLUDING REMARKS

In this paper, we have tried to do two things: first, to understand the components in the observed changes in energy intensity reduction in UK manufacturing, and, second, to investigate whether any or all of these components are driven by the climate change levy. It is often simplistically assumed that changes in energy intensity of economic activity are synonymous with changes in energy efficiency. Using a model of the dual energy cost function, we have shown that this is not the case, as we have derived a range of components of EIG that includes as well as energy efficiency change, the role of allocative, scale and technical change and the choice of other inputs in production. We have done this by deriving a factor productivity relationship for EIG that decomposes a stochastic frontier analysis of the energy cost function.

We learned that, contrary to a common perception, energy efficiency change derived from our specified stochastic energy cost frontier is a relatively small part of the overall changes in energy intensity. Following from this decomposition, we used an instrumental variable estimation to relate each of our components to the impact of the main policy instrument, the climate change levy. Again, the results are counter to the common perceptions of energy and environmental policy. The chief impact of the climate change levy is on the adjustment between energy and the use of other inputs and on the rate of technological change. Both results lead us to conclude that firm investments and RandD expenditure are important channels of the impact of environmental policy on reducing the ratio of energy usage to economic activity levels.

A strong policy implication follows from these findings. Much of the discussion of energy and environmental policy equates the long-term overall objective of decreasing the energy intensity of production—the de-carbonization agenda—with a supposed unexploited reservoir of energy efficiency. Our findings cast doubt on the idea that there is a large reservoir of energy efficiency changes or 'unnoticed dollar bills on the sidewalk' waiting to be picked up if only firms and consumers made the effort. This notion still characterizes much of the popular debate on decarbonizing the economy. Our findings suggest that "massive potential gains" in energy intensity are not readily available without effortful policy innovation, and policy is better directed at the everyday decisions to invest in new technologies and to innovate in the relative use of different inputs. Rather than targeting hypothetical and ephemeral energy efficiency improvements, policy may be more effective if it is directed towards improvements in the overall allocation of resources including the incentivization of investment and RandD. Certainly the current policy instrument, the climate change levy, works most effectively in this way.

While our study constitutes the first comprehensive analysis of the channels of the carbon tax impact on firm energy intensity, we recognize that the findings of this study may not apply to firm behavior in other economies. This might be due to differences in political economy, market and industrial structure. Given the increasing availability of business microdata, it is hoped that future studies will aim to understand the dominant components of energy intensity in other country samples. Furthermore, other policy interventions have taken place since the CCL package was introduced in 2001 (e.g. the European Union Emissions Trading Scheme (EU ETS) was introduced in 2005), such that, as more detailed UK data become available, future research may extend or test the validity of our research findings in the face of these additional interventions. Similarly, we note that results from studies relying on data sets covering more recent years may differ in terms of the energy productivity performance of manufacturing industries. Finally, it would be interesting to place our results in the context of future research relying on alternative methods. In the long run, this would contribute to the evolution of a rich array of identification strategies for evaluating firm responses to market-based climate policy instruments.

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APPENDIX

Table A1: Definition of Variables and Sources

Variable	Definition	Source
Carbon emissions	Total CO_2 emissions (in thousands of tonnes)	QFI
Carbon tax levy	CCL payment per thousand tonnes of carbon (£)	QFI
Carbon tax rate	Percentage of CCL payment to total energy expenditure (%)	QFI
Output	Gross value added at market prices (£ '000)	ARD
Capital	Net capital stock (£ '000)	ARD
Labour	Total employment, year average (head count)	ARD
RandD	Dummy (1 if engaged RandD activities or investment, 0 otherwise)	ARD
Size	Big dummy (1 if employees >250, 0 otherwise)	ARD
Ownership	Domestic dummy (1 if UK-owned, 0 otherwise)	ARD
Export	Goods and services sold to foreign clients (£ '000)	ARD
Firm age	Years since firm's date of birth	ARD

Table A2: Econometric specifications of the stochastic cost frontier

Model	Specification	Description
Greene (2005) TFE	$u_{it} \sim \mathcal{N}^+(0,\sigma_u^2)$ $v_{it} \sim \mathcal{N}^+(0,\sigma_v^2)$ $\alpha_i,\ i=1\ldots n$	Panel, time varying inefficiency estimated by MLE with normal-half normal errors and firm-specific intercept
Greene (2005) TFE-UHET	$v_{it} \sim \mathcal{N}(0,1)$ $u_{it} \sim \mathcal{F}(\sigma_{uit})$ $\sigma_{uit} = exp\left[0.5\left(2+1\times Fu_{it}\right)\right]$	Panel, time-varying inefficiency, firm-specific intercept and conditional heteroscedasticity in *u*
Pooled model	$v_{it} \sim \mathcal{N}^+(0,\sigma_v^2)$ $u_{it} \sim \mathcal{N}^+(0,\sigma_{u_{it}}^2)$	Panel, time-varying inefficiency, no firm-specific effect and homoscedasticity in *u*

Table A3: Instrument relevance: Relationship between CCL and age

Dep var: $\ln(CCL_{it}/E_{it})$	Coefficient
Age_{it}	–0.931**
	(0.432)
Constant	3.744***
	(1.423)
Cragg-Donald statistic (Stock and Yogo, 2005)	32.59
R^2	0.024
N	2307
Year FE	Y
Firm FE	Y

Notes: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Robust standard errors in parentheses. F-test of the joint significance of the instruments (p-value in parenthesis).

Table A4: EIG decomposition with material input proxy

Average annual rate of change (%)	AEC	SEC	OIC	TC	EEFC	EIG
2002	–0.238	**19.41**	2.09	–6.91	–20.33	–5.978
2003	–0.501	**19.78**	**–0.57**	–4.22	–32.24	–17.751
2004	0.384	**16.73**	0.86	–1.49	–22.34	–5.856
2005	0.210	–16.15	**–2.29**	**1.24**	**5.78**	–6.57
2006	–0.275	**27.01**	2.14	**3.87**	1.70	34.445

Table A5: Log of intensity on EIG components

Dep var: $\ln(Cn_{it} / Y_{it})$	
AEC	0.942
	(1.263)
SEC	–0.010**
	(0.005)
OIC	–0.470***
	(0.158)
TC	–0.947
	(0.761)
EEFC	–0.357
	(0.682)
F-test	6.83
Prob	(0.000)
R^2	0.23
N	1649
Year FE	Y
Firm FE	Y

Notes: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Robust standard errors in parenthesis. F-test of the joint significance of EIG components (p-value in parenthesis).