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# Firm-level Estimates of Fuel Substitution: an Application to Carbon Pricing

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# Firm-level estimates of fuel substitution: an application to carbon pricing *

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**Abstract**

We estimate partial- and total-fuel substitution elasticities between electricity, gas and oil, using firm-level data. We find that, based on the partial elasticity measure, electricity is the least-responsive fuel to changes in its own price and in the price of other fuels. The total elasticity measure, which adjusts the partial elasticity for changes in aggregate energy demand induced by individual fuel price changes, reveals that the demand for electricity is much more price responsive than the partial elasticity suggests. Our results illustrate the importance of accounting for the feedback effect between interfactor and interfuel substitution elasticities when considering the effectiveness of environmental taxation. We use the estimated elasticities to simulate the impact of a €15/t$CO_2$ carbon tax on average energy-related $CO_2$ emissions. The carbon tax results in a small reduction in $CO_2$ emissions from oil and gas use, but this reduction is partially offset by an increase in emissions due to increased electricity consumption by some firms.

**Keywords:** fuel substitution, firm-level data, environmental taxation

**JEL Classification: D24, Q38, Q41, Q48, Q58**

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# 1 Introduction

The ability of firms to substitute between energy inputs is key when considering both the effectiveness and the costliness of climate policy. Stern (2012) highlights that the more difficult it is for firms to substitute between clean and dirty fuels, the more expensive climate-change mitigation will be. The macroeconomic implications of fuel switching are highlighted by Acemoglu et al. (2012), who show that if clean and dirty inputs are substitutable in production, emission-reduction targets can be achieved without sacrificing long-term economic growth. Papageorgiou et al. (2013) note that the innovations in clean technologies needed to achieve significant reductions in $CO_2$ emissions will only occur if the right incentives are in place for firms to switch from dirty to clean production. The authors state that this depends on both economic policy and on the structure of the economy. Thus, to get a sense of the extent to which fuel switching is possible, as well as to provide guidance on the most appropriate policy instruments, estimates of fuel substitution at the firm level are crucial.

In this paper we analyse the ability of Irish manufacturing firms to switch between different fuels, by estimating partial and total fuel substitution elasticities. This allows us to evaluate the likely effectiveness of carbon pricing in achieving a reduction in industrial, energy-related $CO_2$ emissions. Ireland represents an interesting case study in this respect. Much of the literature to date has focused on larger economies, such as the US, however, these elasticities may not be applicable to smaller countries with less energy-intensive industrial sectors. Indeed our results do point to the fact that there are some differences in fuel-price elasticities for firms operating in more energy-intensive sectors. The Irish manufacturing sector is dominated by high-tech manufacturing and pharmaceutical companies, and thus is characterised by very low-levels of energy intensity. Fuel substitution elasticities for Ireland will be of interest to other countries similarly characterised by low levels of energy intensity.[1]

We contribute to the literature on fuel substitution and environmental taxation in a number of important ways. First, we estimate elasticities of fuel substitution at the firm level; thus avoiding the aggregation bias present in studies at industry or country level. Second, unlike most other studies, in addition to partial elasticities we calculate total elasticities of substitution. These take into account the feedback effects from individual fuel price changes to aggregate energy use. Finally, we demonstrate how these elasticities can be used to evaluate, ex-ante, the likely effectiveness of certain environmental policies. We do so by simulating the impact of a carbon tax on industrial emissions.

Most studies of interfuel substitution find that electricity is the least price-responsive energy

[1] According to data from The World Bank (2012), of EU countries, Ireland has the lowest level of energy use per unit of output, but other countries with similarly low levels include Switzerland, Denmark, Portugal and Cyprus.

source, this is true for estimations at state, region and firm level. Furthermore, most research suggests that energy inputs are substitutable (as opposed to complementary) in the production process, although the extent of this substitutability varies significantly between studies. Our estimated elasticities are broadly in line with previous estimates. Our results show that, according to partial price elasticities, electricity is the least price-responsive energy source. However, in contrast to the partial elasticities, the total fuel elasticities (which take account of decreases in aggregate energy demand in response to individual fuel price increases) indicate a higher sensitivity of electricity demand to price changes. While our results show that all fuels are substitutes according to the partial elasticity measure, the total elasticities reveal that, for some firms, electricity and oil are complementary inputs. This is good news if the aim of energy taxes is to decrease aggregate energy usage, but indicates that incentivising firms to switch from oil to electricity use may not be possible using price instruments alone.[2]

Results from the carbon tax simulation suggest that a domestic carbon tax of €15/tonne $CO_2$ would achieve only modest reductions in $CO_2$ emissions from oil and gas use in the industrial sector. Emissions from power generation are regulated under the European Emissions Trading Scheme (EU ETS), and thus in Ireland the price of electricity does not increase when a domestic carbon tax is imposed as sectors covered by the ETS are exempt. If the carbon tax were also applied to electricity,[3] the emissions reduction would be considerably larger due to, firstly, the importance of electricity as an energy source in the Irish manufacturing sector; secondly, the high carbon intensity of grid-supplied electricity in Ireland; and, thirdly, the high total elasticity for electricity demand. Furthermore, as electricity is substitutable with oil and gas for the majority of firms in our sample, part of the decrease in emissions from oil and gas is offset by an increase in emissions from electricity. As a rise in the ETS price would affect all firms (all firms use electricity), the same reduction in emissions could be achieved by a considerably smaller increase in the ETS price.

Our paper is structured as follows: Section 2 discusses the relevant literature on fuel substitution. Section 3 outlines the methodology used. Section 4 gives an overview of the data. Section 5 presents the results. Finally, in Section 6 we draw some concluding remarks.

[2]Reports from Ireland's National Economic and Social Council (see Cahill (2012) and Curtin (2012)), highlight the importance of fuel switching in order to achieve long-term decarbonisation. In particular Curtin (2012) notes that for decarbonisation, an increasingly electrified economy will achieve the best outcomes.

[3]For example, the UK government exert control over the price of carbon in the electricity sector in Great Britain by placing a floor on the EU ETS price for this sector.

# 2 Related literature

Seminal papers in the literature on fuel substitution include those of Fuss (1977) and Pindyck (1979), both of whom pioneered the use of two-stage production models to estimate own and cross-price elasticities of demand for fuels. While Fuss (1977) and Pindyck (1979) use very different datasets (Fuss looks at the Canadian manufacturing sector, while Pindyck's analysis covers the industrial sector of ten OECD countries), both studies conclude that the price elasticity of demand for electricity is low.

Since these seminal works, many authors have estimated fuel substitution elasticities using a variety of datasets and methodologies, and a heterogeneous pattern of results has emerged. Numerous authors have estimated elasticities based on industry or country level data for the US. For example, Jones (1995) employs a dynamic linear logit model and finds that electricity is the least elastic input, and that the relationship between most fuel inputs is weak substitutability. In contrast, Taheri and Stevenson (2002), find that light oil and coal are the least elastic inputs. More recently estimates from Serletis et al. (2010a) suggest that oil is the least responsive to changes in its own price. They find that all fuels are substitutable, with the exception of gas and coal.

Examples of other studies based on data from a single country include Floros and Vlachou (2005) and Steinbuks (2012). Using sectoral-level data for the Greek manufacturing sector, Floros and Vlachou (2005) find that, across almost all sectors, electricity demand is the least responsive to changes in its own price, and that other fuels are weakly substitutable with electricity. Steinbuks (2012) uses data for the UK manufacturing sector, and estimates the elasticities separately for aggregate energy use and thermal heating processes (where, he posits, fuel substitution is technologically feasible). In line with his priors, Steinbuks (2012) finds that substitution possibilities are much higher for thermal heating processes, which highlights how the use of aggregate energy-use data can result in biased estimates.

A number of studies have also estimated fuel substitution possibilities based on cross-country data, the earliest example being Pindyck (1979). He finds a high variation in the estimated elasticities across the 10 OECD countries studied. Much more recent examples of cross-country studies are Serletis et al. (2010b) and Steinbuks and Narayanan (2015), both of whom find important difference across countries based on the structure of the economies. Serletis et al. (2010b) find that fuel substitution possibilities are higher for more developed countries, while Steinbuks and Narayanan (2015) find that fuel substitution possibilities are greater in fossil fuel producing countries.

To date, the majority of studies, including those cited above, have looked at the question of interfuel substitution using aggregate country- or industry-level data. Only a handful of studies have looked at the issue using firm-level data, despite the fact that numerous authors (see, for example, Nguyen and Streitwieser (1999), Bjørner and Jensen (2002a,b) and Arnberg and Bjørner

(2007)) have highlighted the superiority of micro data when estimating elasticities of substitution. Solow (1987), in particular, discusses the issue in more detail as it relates to the estimation of interfactor elasticities. He notes that studies using aggregate data will likely result in aggregation bias as changes in the combination of inputs used will be confounded with changes in the product mix.

The first study to look at the elasticity of substitution between fuels using micro data is Woodland (1993). Using Australian data for the period 1977-1985, he estimates an interfactor model in which coal, oil, gas and electricity enter as individual factors of production. He provides separate estimates for different patterns of fuel usage and finds that, where all fuels are used, coal is the least responsive to changes in its own price, followed by electricity. In contrast, gas and oil have relatively high own price elasticities of demand (PEDs). However, he finds that the cross-price elasticities reveal much weaker price responsiveness. While the elasticities vary by pattern of fuel usage, his results show that electricity and oil and electricity and gas are always complementary inputs, although the point estimates are small.

Firm-level estimates of fuel substitution are also provided by Bjørner and Jensen (2002b). Looking at the substitution possibilities between electricity, district heating and a composite of other fuels, for Danish manufacturing from 1983-1997, the authors find that interfuel substitution possibilities are low. Furthermore, they find that the own-price elasticities are lower than previous estimates based on more aggregate data which, they suggest, is indicative of aggregation bias in previous estimates.

However, not all studies based on micro data find low substitution possibilities. Looking at a cross section of French manufacturing firms, Bousquet and Ladoux (2006) show that adopting an alternative modelling strategy can result in much higher estimated elasticities. While most papers assume that the pattern of fuel usage is fixed, and therefore exogenously determined, Bousquet and Ladoux (2006) assume that fuel-use patterns are flexible and, therefore, that zero consumption of a particular fuel is the result of endogenous rationing by the firm. Comparing their results from a fixed versus flexible-technology model, they find that while electricity is always the least elastic fuel, its own-PED is much higher when endogenous rationing is assumed (with elasticities ranging from -0.72 to -1.18, depending on the fuel-use patterns), relative to the fixed-technology case (where elasticities range from -0.43 to -0.72).

Bardazzi et al. (2015) estimate factor and fuel price elasticities for Italian manufacturing firms. Based on elasticities estimated over the period from 2000-2005, the authors find that fuel demand exhibits a high degree of price sensitivity. On average across all firms, fuel oil is the most price elastic fuel, with an estimated own-PED of -1.44; while natural gas and gasoil have own-PEDs close to minus one. However, their estimates do show that, based on the partial cross-price elasticities, electricity demand is price inelastic with an elasticity, on average across all firms, of -0.46. While most fuels are substitutable, they find that on average fuel oil and gasoil are complements.

While this overview of the literature reveals heterogenous estimated elasticities based on a wide variety of methods and data sources, some general patterns emerge: estimates of interfuel substitution generally find that fuels are substitutable in the production process. Another pattern that is evident in the literature is the weak responsiveness of the demand for electricity to changes in its own price, and in the price of other fuels.

# 3 Methodology

## 3.1 Factor and fuel elasticities of substitution

Pindyck (1979) illustrates how total interfuel elasticities can be estimated using a two-step model. In the first step firms choose the mixture of fuels they will use in aggregate energy consumption in order to minimize total energy costs. In the second step firms choose the optimal quantities of capital, labour, material and energy inputs to minimise total costs associated with producing a given level of output. Thus, we define a production function where total output ($Y$) is a function of capital ($K$), labour ($L$), material ($M$) and energy ($E$) inputs. Within this model we assume that there exists an energy sub-model, comprised of electricity, gas and oil demand, that is weakly separable. The assumption of weak separability is commonly employed in studies of interfuel substitution (see for example Pindyck (1979), Floros and Vlachou (2005), Serletis et al. (2010a) and Steinbuks (2012), to name a few). It implies that substitution possibilities between individual fuels is independent of substitution between the aggregate factors. While this will not always be a realistic assumption, in earlier work we show that for Irish manufacturing firms changes in energy prices have only weak effects on the demand for other factor inputs (Haller and Hyland, 2014). This is largely due to the low energy intensity of the Irish manufacturing sector.

The production function can be expressed using its dual cost function ($C$), also assumed to be weakly separable in inputs, as follows:

$$C = f(P_K, P_L, P_M, P_e(P_{Oil}, P_{Gas}, P_{Elec}), Q) \tag{1}$$

In order to estimate the factor and fuel models it is necessary to specify a functional form. We follow Berndt and Wood (1975) and use the translog function as it is flexible and does not place any a-priori restrictions on the relationship between inputs.[4] One criticism of the translog model is that it can lead to theoretical irregularities such as positive own-price elasticities and negative

[4]The use of the translog functional form in this literature is well-established. Earlier papers that employ this functional form include Halvorsen (1977) and Hall (1986), while more recent examples include Steinbuks and Neuhoff (2014) and Bardazzi et al. (2015).

cost shares.[5] Further (Jones, 1995) has shown that the translog is inferior to the linear logit model in a dynamic setting. However, in our case the application of the translog model leads to very few violations of the regularity conditions; across the sample only 0.26% of the observations violate monotonicity and only 0.6% violate quasi-concavity. As it is generally "well behaved" in our context, and due its flexibility, we choose to utilise the translog functional form. Applying the translog form and adding a number of control variables, equation (1) is transformed as follows:

$$\begin{aligned}\ln(C_f) &= \alpha_0 + \alpha_Q logQ_f + \textstyle\sum_{i=1}^{n} \alpha_i \ln(P_{if}) + \frac{1}{2}\gamma_{QQ}(logQ_f)^2 + \sum_{i=1}^{n} \gamma_{Qi} ln(Q_f)(P_{if}) \\ &+ \tfrac{1}{2} \textstyle\sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln(P_{if}) \ln(P_{jf}) + \sum_{i=1}^{n} d_{ig} ln(P_{if}) \sum_{g=1}^{G} IND_g + Z_f + \lambda_t,\ i \neq j,\end{aligned} \tag{2}$$

where $C$ is total cost, $Q$ is output and $P$ refers to prices; $i$ and $j$ index factors, and $f$ denotes that the unit of observation is the firm.[6] To control for the fact that firms in different industries will have different abilities to respond to changing prices, we include industry-price interaction terms; $IND_{gf}$ is a dummy variable equal to one if firm $f$ is in industry $g$, and zero otherwise. We also model firm-level heterogeneity directly by controlling for the following firm characteristics: *multiunit* which is a dummy variable equal to one if the firm has multiple production units; *foreign* a dummy variable equal to one if the firm is foreign owned; *trade status* - a set of dummy variables indicating whether a firm both exports and imports, exports only, imports only or does not trade (the omitted category); and the firm's size class based on the number of employees (<20, 20-49, 50-245 and 250+ employees). These are all comprised in the vector $Z_f$ in equation (2).[7] Finally, to capture differences over time we include time dummies ($\lambda_t$) as this is a simple and commonly-used method of modelling technological change.

To improve estimation efficiency, the cost function is augmented with factor-share equations ($S_i$) following Shephard's Lemma:

$$S_{if} = \alpha_i + \gamma_{Qi} logQ_f + \textstyle\sum_{j=1}^{n} \gamma_{ij} ln(P_{jf}) + \sum_{g=1}^{G} d_{ig} IND_g,\ i,j = k,l,m,e \tag{3}$$

As $P_E$ is the price per unit of energy, it is also the cost per unit for the optimising agent, thus the

[5] For a more detailed discussion refer to Bjørner and Jensen (2002a).

[6] As we are using panel data, all variables have a time dimension; we omit the $t$ subscript here for clarity of exposition.

[7] Another possible way of accounting for firm-level heterogeneity is by the inclusion of firm-level fixed effects. However, when jointly estimating the cost function and the share equations, accounting for heterogeneity between firms by including firm-level fixed effects is not computationally feasible as the intercept in the share equations is the coefficient on price in the cost function. Instead we exploit the richness of data by choosing to model firm heterogeneity directly through the inclusion of industry dummies and the additional control variables listed above.

energy cost function can be expressed as:

$$\begin{aligned}\ln(P_{Ef}) &= \alpha_0 + \textstyle\sum_{i=1}^{n} \alpha_i \ln(P_{if}) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln(P_{if}) \ln(P_{jf}) \\ &+ \textstyle\sum_{i=1}^{n} d_{ig} ln(P_{if}) \sum_{g=1}^{G} IND_g + Z_f + \lambda_t,\ i \neq j\end{aligned} \tag{4}$$

And the fuel shares ($S_{Ei}$) are:

$$S_{Eif} = \alpha_i + \textstyle\sum_{j=1}^{n} \gamma_{ij} ln(P_{jf}) + \sum_{g=1}^{G} d_{ig} IND_g,\ i,j = elec, oil, gas \tag{5}$$

Estimation of the energy cost function yields an estimate of the energy price ($\hat{P}_e$), which is used as an instrumental variable in the subsequent estimation of the total cost function. Thus, model estimation is achieved in two steps: Firstly, we jointly estimate the energy cost function and fuel share equations (equations (4) and (5)) and form an estimate for $P_e$ (i.e. $\hat{P}_e$). Secondly, we jointly estimate the total factor cost and factor share equations (equations (2) and (3)), using $\hat{P}_e$ as an instrument for $P_e$. As noted by Cho et al. (2004), this two-stage process yields consistent estimates of the total price elasticities.

The energy cost function is assumed to be a homothetic function with constant returns to scale. For the factor cost function, we impose only the minimal necessary constraints on the model; these are linear homogeneity in prices: $\sum_{i=1}^{n} \alpha_i = 1; \sum_{i=1}^{n} \gamma_{ij} = 0; \sum_{i=1}^{n} \gamma_{Qi} = 0$, and symmetry: $\gamma_{ij} = \gamma_{ji}; i \neq j$. As both the fuel and factor shares should each sum to one, in the estimation of both sets of equations, we drop one of the inputs and compute its share as a residual. The models are estimated using Zellner's iterated seemingly unrelated regression (iSUR) procedure to account for correlation between errors across equations and to ensure that the resultant parameter estimates are invariant to the omitted factor or fuel. Standard errors are adjusted for clustering at the firm level.

Following Pindyck (1979), the own-price elasticities ($\eta_{x_i p_i}$) and cross-price elasticities ($\eta_{x_i p_j}$) for the fuels and factors of production are calculated from the estimated parameters of the total cost, energy cost, and factor and fuel share equations[8]:

$$\eta_{x_i p_i} = \frac{\gamma_{ii} + S_i^2 - S_i}{S_i}; \eta_{x_i p_j} = \frac{\gamma_{ij} + S_i * S_j}{S_i} \tag{6}$$

However, the fuel elasticities estimated from equation (6) are only the *partial* elasticities, as they assume the total quantity of energy consumed remains constant (Pindyck, 1979). The formulae for the *total* fuel elasticities adjust the partial elasticities for the response in the demand for aggregate energy to changing fuel prices, and for the share of each fuel in total energy costs. Thus they take account of the feedback effect between the interfactor and interfuel models. The formulae for the

[8]For the interfuel elasticities $S_i$ and $S_j$ are replaced by $S_{Ei}$ and $S_{Ej}$ in this formula

total own- and cross-price elasticity of demand for fuels are:

$$\eta_{ii}^{*} = \eta_{x_i p_i} + \eta_{EE} * S_{Ei} \text{ and } \eta_{ij}^{*} = \eta_{x_i p_j} + \eta_{EE} * S_{Ej}, \tag{7}$$

where $\eta_{EE}$ is the own-price elasticity of aggregate energy, calculated using equation (6); $\eta_{x_i p_i}$ and $\eta_{x_i p_j}$ are the partial own- and cross-price elasticities for the fuels; and $S_{Ei}$ and $S_{Ej}$ are the shares of fuels $i$ and $j$ in total fuel cost, as estimated by equation (5). As discussed by Floros and Vlachou (2005), calculating the total fuel elasticities is necessary in order to simulate the impacts of a carbon tax.

One of the modelling issues which we encounter is that for a large number of firms in our data, we observe zero consumption of certain fuels in some or all years. In the literature on interfuel substitution, the common approach to modelling this issue is to assume that zero consumption of a fuel is due to technological or physical constraints and thus is a result of exogenous rationing. This approach, which has been applied by Woodland (1993), Bjørner and Jensen (2002b), Serletis et al. (2010a) and Steinbuks (2012), amongst others, assumes that patterns of fuel consumption are given and thus the elasticities are estimated for each pattern of fuel usage. We choose to follow this fixed-technologies approach because, in our data, we do not observe frequent switching by firms between patterns of fuel usage.

## 3.2 Application to carbon pricing

Following the methodology outlined by Floros and Vlachou (2005), we use the total inter-fuel elasticities to simulate the effects of a carbon tax on energy-related $CO_2$ emissions in the Irish manufacturing sector. This involves calculating the increase in fuel prices following the imposition of a carbon tax.[9] The carbon tax on fuels is a function of their emission intensity ($tCO_2$/kWh) and the level of the carbon tax (€/$tCO_2$), and it is calculated as:

$$\text{Carbon tax}(\text{€/kWh}) = \text{Carbon coefficient}(tCO_2/\text{kWh}) * \text{Tax level}(\text{€}/tCO_2) \tag{8}$$

According to Howley and Holland (2013), the carbon coefficients for oil and gas used in Ireland are 264g and 205g $CO_2$/kWh respectively. We then use the total fuel elasticities estimated via equation (7), to calculate the average change in demand for these fuels across firms in our data. These changes in demand for individual fuels are aggregated to calculate the average change in

[9] A domestic carbon tax was introduced in Ireland in 2010, which is after the period covered by our data. We follow the methodology used to calculate rise in fuel prices from the actual carbon tax to calculate the price rise from our simulated carbon tax. A detailed description of the Irish domestic carbon tax is provided by Convery et al. (2013).

$CO_2$ emissions in the non-EU ETS industrial sector, based on 2009 patterns of energy use and emissions.

The carbon tax levied by the Irish government only applies to those firms not already regulated under the EU ETS. Therefore, we re-estimate the elasticities excluding those firms regulated by the EU ETS. As the CIP data does not indicate whether a particular firm participates in the EU ETS, we must infer EU ETS participation based on information available in our data. We follow the methodology used by Haller and Murphy (2012), who infer participation in EU ETS based on the firm's sector of operation and level of emissions. A firm is assumed to be subject to the EU ETS if its annual $CO_2$ emissions exceed a threshold of 4,700 tonnes and if it operates in one of the following NACE sectors: Pulp&Paper; Publishing&Printing; Coke/Refined Petroleum Products/Nuclear Fuel; Other Non-Metallic Mineral Products; Basic Metals; Fabricated Metal Products.

# 4 Data

Our data set is the Census of Industrial Production (CIP) for the Republic of Ireland. The CIP is conducted annually by the Central Statistics Office (CSO), and response to the survey is compulsory. The purpose of the census is to produce structural information on various accounting measures such as industry classification, location, sales, employment, intermediate inputs, capital acquisitions and trade. Larger firms are asked to complete a more detailed questionnaire which includes information on energy expenditure by fuel. Until 2003, enterprises with 13 or more employees were sent these most comprehensive forms. In 2004, the threshold increased to 20 or more persons engaged, however some firms below this new threshold who had previously been completing these more detailed forms, continued to do so. As a compromise between minimising error due to imputed or estimated data and keeping as many observations as possible, we have chosen to exclude all firms which answered the less detailed questionnaire for half or more of their observations; firms with a median of fewer than 18 employees over their time in the census, and firms that have half or more of their observations estimated or imputed by CSO. Furthermore, we exclude from our analysis firms directly engaged in the energy sector, i.e. those involved in mining and extraction, and utilities.

We concentrate our analysis on the period from 2004 to 2009, when data on fuel expenditure were collected on an annual basis, leaving us with approximately 8,600 firm-year observations. We focus on substitution between oil, gas and electricity. The majority of firms reporting the use of coal are those involved in cement production where coal is not used as a fuel, but rather as a production input.

Estimation of the energy cost function requires data on fuel prices and expenditure shares. In our data we observe the firms' expenditure by fuel type, but neither the fuel price nor the quantity purchased, thus fuel prices are obtained from a number of external data sources. The price of oil is from the ESRI Databank (ESRI, 2012), while gas and electricity prices are from Eurostat.[10] Details of these data sources and how they are incorporated into our data are provided in the Variables Definition section of the Appendix.

Estimation of the total factor cost function requires expenditures and prices for factor inputs. Expenditure on labour is the sum of wages and salaries as well as other labour costs (i.e. social insurance, employers' pension contributions and training costs). The price of labour is the firm's labour expenditure divided by the number of employees. The CIP records investments in capital assets. We obtain capital stocks using the perpetual inventory method for industrial buildings and machinery and equipment. The price of capital we use in our model is the market cost of capital in Ireland as estimated by Žnuderl and Kearney (2013). Expenditure on materials is recorded directly in the CIP. To obtain the price of materials we weigh the prices of intermediate inputs (mostly at the 2-digit level) obtained from EUKLEMS (2009)[11] by each industry's input mix according to the input-output tables. A more detailed description of these variables can be found in the Appendix.

There are four patterns of fuel usage which we observe in our data: Firms either (i) consume all three fuels, (ii) consume electricity and gas but no oil, (iii) consume electricity and oil but no gas, or (iv) consume only electricity. These patterns are summarised in Table 1 below.

Table 1: Patterns of fuel use

| Demand regime | Frequency |
|---|---|
| Electricity, natural gas and oil | 23% |
| Electricity and natural gas | 26% |
| Electricity and oil | 28% |
| Electricity only | 23% |

Figure 1 shows the average fuel cost share by pattern of fuel usage (excluding the electricity-only pattern). It illustrates that total energy costs are, in all cases, dominated by electricity.

Table 2 presents some descriptive statistics for the data. It shows that firms are highly heterogeneous in terms of their expenditures on energy inputs, as well as in terms of their level of output and size (as measured by the number of employees). Firms in this sub-sample of the CIP (i.e. those that completed the aforementioned detailed fuel expenditure questionnaire) are large relative to the full CIP sample. In the full sample the average number of employees is 51 compared

[10]http://ec.europa.eu/eurostat/web/energy/data/main-tables

[11]For a detailed description see O'Mahony and Timmer (2009).

Figure 1: Fuel cost shares

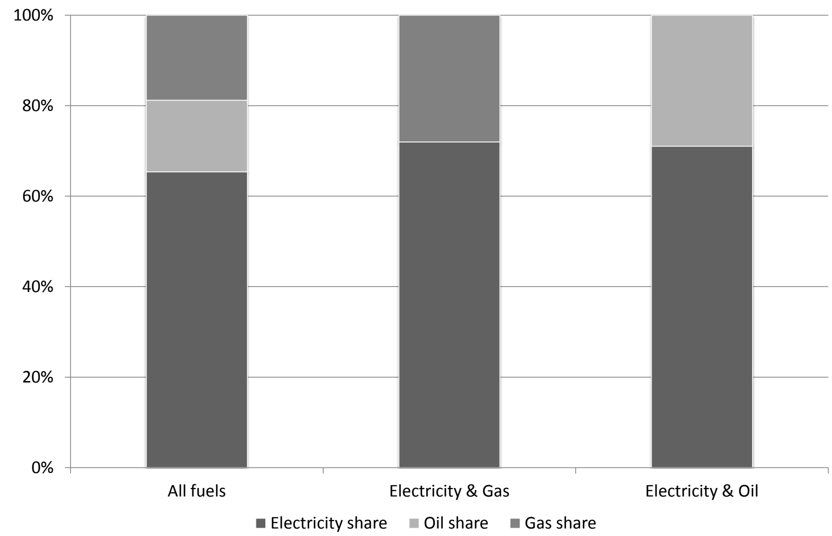


Table 2: Descriptive statistics

| | Mean | Std dev | Median | Mean by pattern of fuel use: All fuels | Elec&Gas | Elec&Oil | Elec only |
|---|---|---|---|---|---|---|---|
| Employees (#) | 121 | 251 | 49 | 117 | 170 | 110 | 84 |
| Output (€1000) | 74,423 | 492,579 | 7,848 | 58,443 | 146,179 | 38,302 | 52,457 |
| Expenditure - electr. (€1000) | 384 | 1,593 | 73 | 386 | 586 | 368 | 175 |
| Expenditure - gas (€1000) | 162 | 2,145 | 0 | 163 | 338 | | |
| Expenditure - oil (€1000) | 100 | 1,644 | 1 | 99 | | 177 | |
| Price - electricity (€/TOE) | 1,506 | 285 | 1,522 | 1,510 | 1,507 | 1,489 | 1,522 |
| Price - gas (€/TOE) | 459 | 128 | 427 | 464 | 460 | | |
| Price - oil (€/TOE) | 494 | 108 | 509 | 484 | | 498 | |
| Multi unit (0/1) | 0.06 | | | 0.08 | 0.07 | 0.06 | 0.05 |
| Foreign owned (0/1) | 0.28 | | | 0.22 | 0.38 | 0.28 | 0.22 |

Note: The median value for gas expenditure is exactly zero.

to 121 in our current sample, and the average level of output is €18.5 million compared to €74 million here. Furthermore, a higher proportion of this sample are foreign-owned; 28% compared to 14% in the full-sample CIP.

# 5 Results

## 5.1 Interfuel substitution

In the first step of our analysis we estimate the energy cost function and fuel share equations and calculate the partial fuel elasticities from the estimated parameters, using equation (6). The standard errors on the elasticities are calculated using the delta method. Table 3 below shows the partial fuel price elasticities by pattern of fuel consumption. Note that this is the change in the demand for each fuel when its own price changes, or when the price of other fuels change, ignoring the response of aggregate energy demand to price changes. The symmetry in the estimated elasticities for those patterns in which only two fuels are used is a result of linear homogeneity. For a given level of energy use if, in a two-fuel system, the demand for one fuel falls, the demand for the other fuel must rise.

Table 3: Partial fuel elasticities by pattern of fuel use

| | All fuels | | Electricity & Gas | | Electricity & Oil | |
|---|---|---|---|---|---|---|
| $\eta_{ElecElec}$ | -0.309 | (0.056)*** | -0.326 | (0.035)*** | -0.330 | (0.046)*** |
| $\eta_{ElecOil}$ | 0.057 | (0.038) | | | 0.330 | (0.046)*** |
| $\eta_{ElecGas}$ | 0.252 | (0.036)*** | 0.326 | (0.035)*** | | |
| $\eta_{OilOil}$ | -0.620 | (0.144)*** | | | -0.804 | (0.113)*** |
| $\eta_{OilElec}$ | 0.236 | (0.154) | | | 0.804 | (0.113)*** |
| $\eta_{OilGas}$ | 0.385 | (0.103)*** | | | | |
| $\eta_{GasGas}$ | -1.201 | (0.106)*** | -0.838 | (0.089)*** | | |
| $\eta_{GasElec}$ | 0.876 | (0.125)*** | 0.838 | (0.089)*** | | |
| $\eta_{GasOil}$ | 0.326 | (0.087)*** | | | | |
| Observations | 1,928 | | 2,218 | | 2,368 | |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We find that all fuels are substitutable in the production process, however the degree of substitutability varies from fuel to fuel, and by pattern of fuel usage. In all cases electricity is least responsive to changes in its own price.

Examining first the results for the pattern of fuel usage in which all fuels are used, the own-price elasticities show that the demand for electricity is inelastic ($\eta_{ElecElec} = -0.309$), oil demand is also quite inelastic ($\eta_{OilOil} = -0.620$), while gas demand exhibits a high degree of price-sensitivity

($\eta_{GasGas} = -1.201$). In terms of cross-PEDs, electricity responds little to changes in the price of gas ($\eta_{ElecGas} = 0.252$), while its response to changing oil price is smaller ($\eta_{ElecOil} = 0.057$) and not statistically significant. The elasticities show that the demand for oil is also unresponsive to changes in the electricity price; again the estimated elasticity ($\eta_{OilElec} = 0.236$) is small and not statistically significant. The results show that oil and gas are weakly substitutable: when the price of oil increases the demand for gas rises slightly ($\eta_{GasOil} = 0.326$), and vice versa ($\eta_{OilGas} = 0.385$). However, the demand for gas exhibits a high degree of substitutability with electricity ($\eta_{GasElec} = 0.876$).

Turning next to the fuel usage pattern where only electricity and gas are used, for these firms the demand for electricity is highly unresponsive to changes in its own price ($\eta_{ElecElec} = -0.326$). While the demand for gas is relatively more price sensitive ($\eta_{GasGas} = -0.838$).

Finally, similar patterns emerge when only electricity and oil are used: the demand electricity is highly unresponsive to changes in its own price ($\eta_{ElecElec} = -0.33$), but oil demand is more price sensitive ($\eta_{OilOil} = -0.804$).

It is not surprising that the demand for electricity is generally unresponsive to changing oil and gas prices: electricity is a much more expensive fuel (as shown in Table 2) and thus, in order to minimise energy costs, firms should already be using alternative fuels where the possibility to do so exists, as noted by Pindyck (1979). Our results concur with the majority of studies cited in Section 2 that also find that electricity is the least price-responsive fuel according to the partial elasticity estimates.

To test the generalisability of our results, we re-estimate the model for the firms in our sample that operate in the most energy-intensive sectors (defined as sectors where the median energy cost share over the period is in the top quartile). We find that for firms operating in these sectors, there are notable differences in the estimated elasticities for some, but not all, fuels. Table 4 below shows that, for firms using all three fuels, oil demand is more responsive in energy-intensive firms, both to changes in its own price, and to changes in the price of gas. Also of note is that the substitutability between electricity and oil is significant for these firms. For firms using only electricity and gas, and for those using only electricity and oil, the differences are small.

Table 5 shows the own price elasticity of demand for aggregate energy.[12] It shows that, across all patterns of fuel usage, the demand for aggregate energy is relatively responsive to changes in its own price; albeit for a shorter period, the elasticities are similar to those estimated by Haller and Hyland (2014) for the full set of CIP firms and over a longer time period.

Following Pindyck (1979), we combine the partial fuel elasticities with the price elasticity of demand for aggregate energy ($\eta_{EE}$) to calculate the *total* fuel elasticities, using equation (7). The

[12] The elasticities for capital, labour and materials are presented in Table 11 in the Appendix.

Table 4: Partial fuel elasticities - firms operating in energy-intensive sectors

| | All fuels | | Electricity & Gas | | Electricity & Oil | |
|---|---|---|---|---|---|---|
| $\eta_{ElecElec}$ | -0.388 | (0.100)*** | -0.298 | (0.077)*** | -0.434 | (0.143)*** |
| $\eta_{ElecOil}$ | 0.134 | (0.067)** | | | 0.434 | (0.143)*** |
| $\eta_{ElecGas}$ | 0.254 | (0.068)*** | 0.298 | (0.077)*** | | |
| $\eta_{OilOil}$ | -1.097 | (0.214)*** | | | -0.993 | (0.326)*** |
| $\eta_{OilElec}$ | 0.440 | (0.221)** | | | 0.993 | (0.326)*** |
| $\eta_{OilGas}$ | 0.657 | (0.151)*** | | | | |
| $\eta_{GasGas}$ | -1.414 | (0.181)*** | -0.718 | (0.185)*** | | |
| $\eta_{GasElec}$ | 0.791 | (0.213)*** | 0.718 | (0.185)*** | | |
| $\eta_{GasOil}$ | 0.623 | (0.143)*** | | | | |
| Observations | 747 | | 689 | | 518 | |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Own-price elasticity for aggregate energy by pattern of fuel use

| | All fuels | | Electricity & Gas | | Electricity & Oil | | Electricity only | |
|---|---|---|---|---|---|---|---|---|
| $\eta_{EE}$ | -0.945 | (0.045)*** | -0.896 | (0.032)*** | -0.910 | (0.062)*** | -1.322 | (0.178)*** |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

total elasticities adjust the partial elasticities for the change in demand for aggregate energy, due to changes in individual fuel prices. The results are displayed in Table 6 below.

Compared to the partial elasticities of demand, the total elasticities reveal quite different results. First of all, the total elasticities show a much greater responsiveness of the demand for electricity to changes in its own price. This is because the demand for aggregate energy is highly responsive to price changes, and because the share of electricity in total energy costs is high, as illustrated by Figure 1. Furthermore, as we are no longer assuming a fixed level of energy demand, the elasticities are no longer symmetric for those firms only using two fuels.

Looking firstly at the results for firms that use all fuels, Table 6 shows that the own PED of electricity triples once we take account of the response of aggregate energy demand. On the other hand, as an increase in the price of gas results in a reduction in the demand for aggregate energy, the total fuel elasticities show a weaker substitutability between gas and electricity when the gas price rises, i.e. the substitution effect is partially offset by a reduction in aggregate energy demand. Looking at the relationship between electricity and oil demand - the feedback effect between the interfactor and interfuel models is strong enough to turn these fuels from weak substitutes under the partial elasticity measure to weak complements according to the total elasticity estimates. Thus, when the price of oil rises, the contraction in aggregate energy demand is strong enough

Table 6: Total fuel elasticities by pattern of fuel use

| | All fuels | Electricity & Gas | Electricity & Oil | Electricity only* |
|---|---|---|---|---|
| $\eta^*_{ElecElec}$ | -0.926 | -0.971 | -0.990 | -1.322 |
| $\eta^*_{ElecOil}$ | -0.093 | | 0.059 | |
| $\eta^*_{ElecGas}$ | 0.075 | 0.075 | | |
| $\eta^*_{OilOil}$ | -0.770 | | -1.075 | |
| $\eta^*_{OilElec}$ | -0.381 | | 0.144 | |
| $\eta^*_{OilGas}$ | 0.208 | | | |
| $\eta^*_{GasGas}$ | -1.378 | -1.089 | | |
| $\eta^*_{GasElec}$ | 0.259 | 0.193 | | |
| $\eta^*_{GasOil}$ | 0.176 | | | |

Note: For the firms that consume only electricity the total own-price elasticity for electricity is the same as the own-price elasticity for aggregate energy demand.

to mitigate any weak substitution effect from oil to electricity. The same holds for oil demand when the electricity price rises. Regarding oil and gas demand, the total fuel elasticities reveal a stronger demand response to changes in their own price, and they also show that oil and gas are weaker substitutes than the partial elasticities would suggest. However, for oil and gas demand, the change is not as large as it is in the case of electricity due to the lower energy-cost share of these fuels, as shown in Figure 1.

For the firms that use only electricity and gas, the own-PEDs are higher using the total elasticity measure, and the cross price elasticities are lower. This is because the contraction in aggregate energy demand is strong enough to offset most of the substitution effect. Finally, Table 6 shows that the same pattern of results holds for firms using only electricity and oil.

Our results are in line with those of Pindyck (1979), who also finds much higher own-price elasticities under the total elasticity measure, especially in the case of electricity demand. Furthermore, his results indicate that, in some cases, certain fuels that are substitutes according to the partial elasticity measure are actually complementary inputs once the feedback effect between the interfactor and interfuel models is taken into account. Floros and Vlachou (2005) find a similar result in their study of energy demand in the Greek manufacturing sector at industry level.

## 5.2 Carbon tax application

Following the methodology used by Floros and Vlachou (2005) we use the total interfuel elasticities to calculate the likely effectiveness of a carbon tax in reducing $CO_2$ emissions, based on the patterns of fuel use and fuel prices in the last year of our data, i.e. 2009. When the Irish domestic carbon tax was introduced in 2010, it was set at €15/tonne $CO_2$; we apply this tax rate to the 2009 prices for gas and oil, and use the carbon coefficients listed in Section 3. This leads to an 11% increase in the price of gas and an 8% increase in the price of oil.[13]

As we want to simulate the impact of the carbon tax only on those firms that are subject to domestic carbon taxation (i.e. all firms other than those which we have identified as participating in the EU ETS), we re-estimate the elasticities excluding the EU ETS firms. The resulting total elasticities are presented in Table 7 below - these do not differ substantially from those estimated across all firms, which is not surprising given that relatively few Irish manufacturing firms participate in the EU ETS.

Table 7: Total elasticities by pattern of fuel use for non-EU ETS firms

| | All fuels | Electricity & Gas | Electricity & Oil | Electricity only |
|---|---|---|---|---|
| $\eta^*_{ElecElec}$ | -0.937 | -0.965 | -1.021 | -1.313 |
| $\eta^*_{ElecOil}$ | -0.086 | | 0.052 | |
| $\eta^*_{ElecGas}$ | 0.067 | 0.063 | | |
| $\eta^*_{OilOil}$ | -0.802 | | -1.100 | |
| $\eta^*_{OilElec}$ | -0.366 | | 0.131 | |
| $\eta^*_{OilGas}$ | 0.213 | | | |
| $\eta^*_{GasGas}$ | -1.373 | -1.065 | | |
| $\eta^*_{GasElec}$ | 0.238 | 0.163 | | |
| $\eta^*_{GasOil}$ | 0.178 | | | |

Combining the oil and gas price increases with the estimated total elasticities, Table 8 shows the decrease in the demand according to each fuel-use pattern and as a weighted average across all patterns of fuel usage, based on the proportion of firms that fall into each pattern.

Table 8: Change in fuel demand by pattern of fuel consumption and on average

| | All fuels | Electricity & Gas | Electricity & Oil | Average |
|---|---|---|---|---|
| Electricity | 0.09% | 0.7% | 0.4% | 0.3% |
| Gas | -14.2% | -12.1% | - | -13.1% |
| Oil | -3.8% | - | -8.6% | -6.4% |

In order to approximate the total decrease in non-EU ETS industrial energy-related $CO_2$ emissions across Irish manufacturing firms (and not only those that responded to the detailed fuel-expenditure questionnaire), we apply the weighted average decrease in demand to aggregate energy-related industrial emissions in Ireland (based on SEAI's Energy Balance data for 2009[14]). This results in a hypothetical reduction in energy-related $CO_2$ emissions from the industrial sector

[13] Note that while natural gas is less carbon-intensive than oil, its relative price increase is larger as its price is lower.

[14] www.seai.ie/Energy-Data-Portal/Energy-Balance/Previous_Energy_Balances/

as a whole of approximately 280kt$CO_2$. Assuming that energy use by the non-EU ETS sector is proportional to energy-related $CO_2$ emissions, this would result in a reduction in non-EU ETS energy-related emissions of approximately 24kt$CO_2$. According to Howley et al. (2012), energy-related $CO_2$ emission in the non-EU ETS industrial sector were 719kt$CO_2$ in 2009. This implies that the domestic carbon tax leads to a reduction in non-EU ETS emissions of 3.3%. The reduction in emissions is modest as the largest reduction in fuel demand comes from natural gas, which is the cleanest of the three fuels used.

It is interesting to consider the increase in the ETS price necessary to achieve the same reduction in emissions. In order to do so we simulate an increase in the price of electricity[15] as a result of a rise in the ETS permit price and find that a price increase of just €1.15/t$CO_2$ would achieve an approximately equivalent reduction in emissions (i.e. a reduction in emissions of approximately 24kt$CO_2$). This reflects the fact that a rise in the price of electricity, via the ETS permits, affects all firms in the manufacturing sector as all firms consume electricity. Furthermore, all heavy emitters, many of whom are exempt from the carbon tax due to their participation in the ETS, would be affected by the price increase.

# 6 Conclusions

In this paper we estimate the partial and total elasticities of fuel inputs for firms in the Irish manufacturing sector. By calculating the total elasticities we are taking into account the feedback effect between the interfactor and interfuel models, and adjusting the partial elasticities for changes in aggregate energy demand due to individual fuel price changes - an effect ignored by much of the previous literature.

Regarding the partial fuel price elasticities, our results show that, in line with previous research, the demand for electricity is highly insensitive to changes in its own price and to changes in the price of other fuels. As highlighted by Pindyck (1979), this is a logical result as the high price of electricity relative to other fuels suggests that firms should already be using oil or gas where the possibility to do so exists. Oil is also generally insensitive to changes in its own price, whereas the responsiveness of gas to changes in its own price depends a lot upon whether firms using gas are also using oil. For firms that use all three fuels, gas is own-price elastic.

While the partial elasticities give us a general view of the price responsiveness of fuel demand, it is the total elasticity estimates that will tell us about the potential effectiveness of carbon pricing

[15] An increase in the ETS permit price would also increase the price of oil and gas, but only for those firms participating in the ETS. In this simple calculation we ignore this effect as we do not have elasticities for this sample of firms due to the small number of observations. Thus our estimate provides an upper bound on the necessary increase in the ETS permit price.

at encouraging energy-saving behaviour and fuel switching. The total price elasticities show that the partial elasticities greatly understate the fuel-saving possibilities. The high price elasticity of aggregate energy, as estimated via the interfactor model, means that the contractions in demand due to price changes are larger than the partial elasticities suggest, and that the substitution effects are in fact smaller. This finding concurs with previous estimates at from the literature on partial and total price elasticities.

The results of our carbon tax simulation suggest that a carbon tax of €15/t$CO_2$ levied on the manufacturing sector would achieve only a very modest reduction in $CO_2$ emissions. Applying the reductions in fuel demand and energy-related $CO_2$ emissions calculated for the firms in our data to all energy-related emissions in the non-EU ETS industrial sector would lead to a reduction in $CO_2$ emissions of approximately 3.3%. The effectiveness of the carbon tax is limited because it causes the greatest contraction in the demand for natural gas, which is the cleanest of the three energy sources used. An interesting avenue for future research would be to conduct an ex-post evaluation of the Irish domestic carbon tax, when data covering the period during which the carbon tax was in place become available. We leave this analysis to future work.

Our results are based on the assumption that the carbon tax only applies to non-EU ETS firms, and is not levied on electricity use (whose carbon price reflects the price of EU ETS permits). As the carbon tax is not applied to electricity, electricity becomes a relatively less expensive energy source and, therefore, part of the reduction in emissions due to contractions in oil and gas demand is offset by an increase in demand for and emissions from electricity. This result depends on the mix of fuels being used by firms, as the total elasticities do indicate weak complementarity between electricity and oil in some situations. It is worth noting that the rise in electricity demand, and the associated rise in emissions, would be mitigated if the price of EU ETS permits were to increase as well. In fact, increasing the price of electricity could result in large reductions in industrial $CO_2$ emissions due to a number of factors: firstly, because electricity is an important fuel source for firms in the Irish manufacturing sector. Secondly, the high carbon intensity of grid-supplied electricity in Ireland means that it is significant source of energy-related $CO_2$ emissions. And, finally, our estimated *total* elasticities show that electricity demand is highly sensitive to changes in its own price, and thus its demand would contract were its price to rise.

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# Appendix

## 6.1 Additional Tables

Table 9: Estimated parameters from the energy cost function

| Dependent variable: Total energy cost | | | |
|---|---|---|---|
| | All fuels | Electricity & gas | Electricity & oil |
| $ln(P_{elec})$ | 0.629 | 0.775 | 0.727 |
| | (0.0483)*** | (0.0363)*** | (0.0409)*** |
| $ln(P_{elec}) * ln(P_{elec})$ | 0.0246 | -0.0331 | -0.0277 |
| | (0.0363)*** | (0.0249)*** | (0.0328)*** |
| $ln(P_{oil})$ 0.256 | | 0.273 | |
| | (0.0323)*** | | (0.0409)*** |
| $ln(P_{oil}) * ln(P_{oil})$ | 0.0351 | | -0.0277 |
| | (0.0230)*** | | (0.0328)*** |
| $ln(P_{gas})$ | 0.115 | 0.225 | |
| | (0.0333)*** | (0.0363)*** | |
| $ln(P_{gas}) * ln(P_{gas})$ | -0.073 | -0.0331 | |
| | (0.0198)*** | (0.0249)*** | |
| $ln(P_{elec}) * ln(P_{oil})$ | -0.0664 | | 0.0277 |
| | (0.0245)*** | | (0.0328)*** |
| $ln(P_{elec}) * ln(P_{gas})$ | 0.0417 | 0.0331 | |
| | (0.0235)* | (0.0249)*** | |
| $ln(P_{oil}) * ln(P_{gas})$ | 0.0313 | | |
| | (0.0164)* | | |
| Observations | 1,928 | 2,218 | 2,368 |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Estimated parameters from the total cost function

| Dependent variable: Total cost | | | | |
|---|---|---|---|---|
| | All fuels | Electricity and gas | Electricity and oil | Electricity only |
| $ln(P_K)$ | 0.626 | 0.458 | 0.667 | 0.758 |
| | (0.076)*** | (0.075)*** | (0.069)*** | (0.067)*** |
| $ln(P_K) * ln(P_K)$ | -0.021 | 0.002 | 0.003 | -0.019 |
| | (0.019) | (0.019) | (0.015) | (0.017) |
| $ln(P_L)$ | 0.238 | 0.292 | 0.299 | 0.364 |
| | (0.037)*** | (0.039)*** | (0.036)*** | (0.056)*** |
| $ln(P_L) * ln(P_L)$ | 0.062 | 0.081 | 0.081 | 0.106 |
| | (0.008)*** | (0.010)*** | (0.009)*** | (0.013)*** |
| $ln(P_M)$ | 0.148 | 0.241 | 0.047 | -0.166 |
| | (0.075)** | (0.074)*** | (0.063) | (0.078)** |
| $ln(P_M) * ln(P_M)$ | 0.097 | 0.087 | 0.095 | 0.011 |
| | (0.021)*** | (0.020)*** | (0.015)*** | (0.016) |
| $ln(P_E)$ | -0.012 | 0.009 | -0.014 | 0.044 |
| | (0.011) | (0.004)** | (0.017) | (0.017)** |
| $ln(P_E) * ln(P_E)$ | 0.001 | 0.001 | 0.001 | -0.005 |
| | (0.001) | (0.0005)*** | (0.001) | (0.002)* |
| $ln(P_K)ln(P_L)$ | 0.010 | -0.002 | -0.009 | -0.041 |
| | (0.009) | (0.012) | (0.010) | (0.011)*** |
| $ln(P_K)ln(P_M)$ | 0.001 | -0.005 | 0.007 | 0.050 |
| | (0.018) | (0.018) | (0.012) | (0.014)*** |
| $ln(P_K)ln(P_E)$ | 0.0103 | 0.005 | -0.0002 | 0.010 |
| | (0.003)*** | (0.001)*** | (0.002) | (0.002)*** |
| $ln(P_L)ln(P_M)$ | -0.080 | -0.075 | -0.086 | -0.060 |
| | (0.009)*** | (0.010)*** | (0.009)*** | (0.010)*** |
| $ln(P_L)ln(P_E)$ | 0.008 | 0.001 | 0.014 | -0.004 |
| | (0.002)*** | (0.001) | (0.005)*** | (0.001)*** |
| $ln(P_M)ln(P_E)$ | -0.019 | -0.007 | -0.015 | -0.001 |
| | (0.004)*** | (0.001)*** | (0.005)*** | (0.002) |
| $ln(Y)$ | 0.926 | 0.850 | 0.968 | 0.811 |
| | (0.036)*** | (0.033)*** | (0.039)*** | (0.074)*** |
| $ln(Y)ln(P_K)$ | -0.025 | -0.009 | -0.027 | -0.028 |
| | (0.006)*** | (0.006) | (0.007)*** | (0.005)*** |
| $ln(Y)ln(P_L)$ | -0.038 | -0.038 | -0.046 | -0.040 |
| | (0.003)*** | (0.003)*** | (0.004)*** | (0.006)*** |
| $ln(Y)ln(P_M)$ | 0.065 | 0.048 | 0.076 | 0.068 |
| | (0.006)*** | (0.006)*** | (0.007)*** | (0.008)*** |
| $ln(Y)ln(P_E)$ | -0.003 | -0.001 | -0.002 | -0.001 |
| | (0.001)*** | (0.0004)*** | (0.001)* | (0.0003)* |
| Observations | 1,928 | 2,218 | 2,368 | 1,947 |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Elasticities from the inter-factor substitution model

| | All fuels | | Electricity and gas | | Electricity and oil | | Electricity only | |
|---|---|---|---|---|---|---|---|---|
| $\eta_{KK}$ | -0.636 | (0.046)*** | -0.583 | (0.047)*** | -0.591 | (0.037)*** | -0.675 | (0.044)*** |
| $\eta_{KL}$ | 0.226 | (0.022)*** | 0.216 | (0.029)*** | 0.191 | (0.024)*** | 0.137 | (0.029)*** |
| $\eta_{KM}$ | 0.365 | (0.044)*** | 0.34 | (0.042)*** | 0.381 | (0.030)*** | 0.497 | (0.038)*** |
| $\eta_{KE}$ | 0.045 | (0.006)*** | 0.028 | (0.004)*** | 0.019 | (0.006)*** | 0.041 | (0.005)*** |
| $\eta_{LL}$ | -0.49 | (0.038)*** | -0.435 | (0.047)*** | -0.407 | (0.040)*** | -0.325 | (0.051)*** |
| $\eta_{LK}$ | 0.462 | (0.046)*** | 0.405 | (0.055)*** | 0.360 | (0.045)*** | 0.208 | (0.044)*** |
| $\eta_{LM}$ | -0.03 | (0.047) | 0.012 | (0.046) | -0.039 | (0.042) | 0.122 | (0.041)*** |
| $\eta_{LE}$ | 0.058 | (0.012)*** | 0.018 | (0.005)*** | 0.086 | (0.024)*** | -0.004 | (0.005) |
| $\eta_{MM}$ | -0.369 | (0.059)*** | -0.4 | (0.057)*** | -0.374 | (0.041)*** | -0.607 | (0.045)*** |
| $\eta_{MK}$ | 0.417 | (0.050)*** | 0.398 | (0.050)*** | 0.421 | (0.034)*** | 0.513 | (0.039)*** |
| $\eta_{ML}$ | -0.017 | (0.026) | 0.007 | (0.029) | -0.023 | (0.025) | 0.083 | (0.028)*** |
| $\eta_{ME}$ | -0.031 | (0.010)*** | -0.005 | (0.004) | -0.023 | (0.014)* | 0.011 | (0.005)** |
| $\eta_{EE}$ | -0.945 | (0.045)*** | -0.896 | (0.032)*** | -0.910 | (0.062)*** | -1.322 | (0.178)*** |
| $\eta_{EK}$ | 0.924 | (0.131)*** | 0.758 | (0.098)*** | 0.388 | (0.116)*** | 1.098 | (0.138)*** |
| $\eta_{EL}$ | 0.584 | (0.119)*** | 0.257 | (0.073)*** | 0.957 | (0.273)*** | -0.073 | (0.081) |
| $\eta_{EM}$ | -0.563 | (0.181)*** | -0.119 | (0.093) | -0.436 | (0.260)* | 0.297 | (0.128)** |

Note: Standard errors adjusted for clustering at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## Variable definitions:

$foreign_f$ Dummy variable equal to one if the firm's ultimate beneficial owner is located outside Ireland.

$Trade_f$ Trade orientation. Four dummy variables equal to one if a firm both exports and imports, exports only, imports only or does not trade, respectively.

$Size_f$ Firm size. We control for firm size by including size-class categorical variables based on the number of employees. The size classes are: <20, 20-49, 50-245 and >=250 employees.

$K_f$ Capital stocks. Capital stocks are calculated based on capital investments using the perpetual inventory method, where firm $i$'s stock of capital asset $x$ at time $t$ is obtained from investments $I$ and depreciation $\delta_x$ as: $CS_{xit} = (1 - \frac{\delta_x}{2})[I_{xt} + (1-\delta_x)I_{xt-1} + (1-\delta_x)^2 I_{xt-2} + \ldots]$. Assets are buildings, machinery and equipment and transport equipment. Asset lives, implied depreciation rates and deflators are those underlying CSO's calculations of industry level capital stocks (**?**). Total capital stock for each firm is the sum over individual assets. Capital stocks are calculated from 1985 onwards to make sure that they are driven as much as possible by firm's capital acquisitions rather than by starting stocks. The sampling frame in the Census of Industrial Production was different until 1990, however, for the mostly larger firms that are still in operation after 1991 the data are comparable. Starting stocks in 1985 and for firms that entered after 1985 are obtained by breaking down the previous year's end-of-year industry-level capital stock obtained from CSO to the firm level using the firm's share in industry-level fuel use.[16]

$P_k$ Price of capital. This is the aggregate price of capital for each firm which comes from the market cost of capital, as measured by Žnuderl and Kearney (2013) who estimated the cost of debt-financed capital for Irish manufacturing firms, based on the concept of the user cost of capital. They estimate the cost of capital separately for machinery and equipment and industrial buildings. As we have data on the stock of different types of capital for firms in our dataset,[17] we weight these two capital costs based on the share of the respective types of capital stocks each year to create an aggregate price of capital that varies at the firm level. The cost of capital calculated by Žnuderl and Kearney (2013) is measured as a fraction of the price of investment.

$E_f$ Energy input. This is firm-level expenditure on fuel. It is calculated as the total firm-level expenditure on fuel per year deflated by the Wholesale Price Index for fuels.

$L_f$ Labour input. Expenditure on labour is the total wage bill deflated using the Consumer Price Index.

$P_l$ Price of labour. This is the total wage bill deflated using the Consumer Price Index, divided by the number of employees.

[16]We thank Kieran Culhane of the CSO for providing capital stocks at NACE 2-letter level.
[17]For details of how the capital stocks are calculated, refer to the Appendix of Haller and Hyland (2014).

$M_f$ Material input. Expenditure on materials is recorded directly into the CIP. The variable we use to deflate expenditure on materials comes from the ESRI Databank (ESRI, 2012). It is calculated as a weighted index of various price deflators, weighted by the input share from the 1998 Input-Output table produced by the CSO. The formula used to calculate the deflator for material inputs (ESRI, 2012) is as follows:

$$PriceDeflator_{Materials} = PriceDeflator_{Agri} * IOWeight_{Agri} + PriceDeflator_{HiTech} * IOWeight_{HiTech} + PriceDeflator_{Trad} * IOWeight_{Trad} + PriceDeflator_{Food} * IOWeight_{Food} + VADeflator_{Distribution} * IOWeight_{Distribution} + VADeflator_{T\&C} * IOWeight_{T\&C} + VADeflator_{P\&FServices} * IOWeight_{P\&F} + Deflator_{Imports} * IOWeight_{Imports}, \quad (9)$$

where $T\&C$ refers to transport and communication services, and $P\&F$ refers to professional and financial services. Dividing materials expenditure data from the CIP by this deflator gives us the total real expenditure on material inputs.

$P_m$ Price of materials. The price of materials we use is an index that varies at the industry level. We weight the prices of intermediate inputs (mostly at the 2-digit level) obtained from EU-KLEMS by each industry's input mix according to the input-output table for 2005 (CSO, 2009). As the EU-KLEMS data are available only up to 2007, for 2008 and 2009 we use two additional data sources; the price index for manufacturing produce comes from the Industrial Price Index, and for the price index for services used by the manufacturing sector we use value-added deflators for agriculture, construction and the marketed and non-marketed services sectors, available from the ESRI Databank (ESRI, 2012).

$Y_f$ Log Turnover (sales) in deflated using wholesale/producer price indices at the 2-3 digit NACE (Rev. 1.1/Rev. 2) level.

$Elec_f$ Expenditure on electricity as recorded in the CIP.

$P_{Elec}$ The price of electricity comes from Eurostat's price series for industrial users.[18] The Eurostat price data vary according to the quantity of fuel used. However, as we do not observe the quantity used, we assign firms to consumption-based price bands based on average sectoral energy-intensity and firm-level output. Using data on sectoral output and sectoral fuel use, we calculate the energy intensity of output by sector for electricity use (i.e. total electricity use by sector divided by total sectoral output). This allows us to infer, for each firm, its electricity consumption based on the firm's output, as recorded in the CIP, and the sector in which it operates. Based on this inferred consumption, we assign firms to Eurostat price bands for electricity. Thus we are assuming that the energy intensity of output varies across, but not within, sector of operation.

$Gas_f$ Expenditure on gas as recorded in the CIP.

[18] http://ec.europa.eu/eurostat/web/energy/data/main-tables

$P_{Gas}$ The price of gas comes from Eurostat's price series for industrial users. We use the same procedure discussed above for electricity to assign firms to Eurostat price bands for natural gas.

$Oil_f$ Expenditure on oil as recorded in the CIP.

$P_{Oil}$ The oil price data come from the ESRI Databank (ESRI, 2012). We combine the price of three different oil types - light fuel oil, heavy fuel oil and kerosene, and construct an aggregate industry-level oil price variable that is weighted by annual, industry-level consumption of each of these three oil types.

Note: All price indices are obtained from CSO and the base year is 2007.

## Data checking and cleaning

Variables in the CIP data are checked for a number of different measurement issues: industry (NACE), county and ownership changes are ignored if they revert in the following year. A similar procedure applies where first or last observations differ from those after or before. Since the employment variable refers to employment in the first week of September this may be zero whereas wages may be positive. Where this is the case only in a single year, employment is estimated based on information from previous or following observations. Sales are checked for digit issues based on large changes in sales per employee and deviations from the mean. Fuels, materials and wages are checked for large changes from one year to the next and whether they exceed turnover both individually as well as taken together. Export and import shares are checked for big changes from year to year as well as for once-off zero observations.

### Change in industry classification

The official European industry classification changed from NACE rev. 1.1 to NACE rev. 2 between 2007 and 2008. Our analysis requires a classification that is consistent over time, thus we bring all firms to the NACE rev. 1.1 classification. For the year 2008 the firms in the CIP were coded according to both classifications. We use this information for firms that are present in both 2008 and 2009 if their NACE rev. 2 classification did not change between the two years. Using this method we are able to obtain NACE rev. 1.1. codes for 95.6% of firms in 2009. For the remaining firms we use the concordance table provided by Eurostat. For a further 2.2% of firms there is a one-to-one match between the old and the new classification. For the few remaining firms where there is more than one possible match between the old and the new classification we assign the NACE rev. 1.1. code that firms with this NACE rev. 2 code are most frequently matched to based on the observations that have both codes assigned in 2008.

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