Capital-energy substitution: evidence from a panel of Irish manufacturing firms[☆]

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Abstract

We use a translog cost function to model production in the Irish manufacturing sector over the period from 1991 to 2009. We estimate both own- and cross-price elasticities and Morishima elasticities of substitution between capital, labour, materials and energy. We find that capital and energy are substitutes in the production process. Across all firms we find that a 1% rise in the price of energy is associated with an increase of 0.04% in the demand for capital. The Morishima elasticities, which reflect the technological substitution potential, indicate that a 1% increase in the price of energy causes the capital/energy input ratio to increase by 1.5%. The demand for capital in energy-intensive firms is more responsive to increases in energy prices, while it is less responsive in foreign-owned firms. We also observe a sharp decline in firms' responsiveness in the first half of the sample period.

Keywords: factor demand, substitution between energy and capital, firm-level panel data

[☆]This work makes use of data from the Central Statistics Office (CSO). The possibility for controlled access to the confidential micro data set on the premises of the CSO is provided for in the Statistics Act 1993. The use of CSO data in this work does not imply the endorsement of the CSO in relation to the interpretation or analysis of the data. This work uses a research dataset which may not exactly reproduce statistical aggregates published by the CSO. We thank Kevin Phelan and Gerard Doolan of the CSO for support with the data and clearance. We gratefully acknowledge financial support from the ESRI Energy Policy Research Centre. Hyland also acknowledges funding from Science Foundation Ireland. We thank Liam Murphy for valuable research assistance on an earlier version of this paper. We are grateful for econometric advice from Steve Bond and from the late Denis Conniffe. We also wish to thank Valeria Di Cosmo, John Fitz Gerald, Alessia Lo Turco, Seán Lyons, Laura Malaguzzi-Valeri, Richard Tol and seminar participants at the ESRI and the IAEE Düsseldorf for helpful comments and suggestions. All remaining errors are our own responsibility.

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1. Introduction

The oil price shock in 1973 first gave centre stage to the debate on whether energy and in particular capital, but also other factors of production, are complements or substitutes in the production process. An increase in energy prices only leads to an increase in the demand for new - presumably less energy-intensive - physical capital if capital and energy are substitutes. Thus, whether energy and capital are substitutes or complements has important implications for firms', industries' and ultimately countries' responses to increases in energy prices or to policies that increase energy prices. This question has been analysed extensively at the country and industry level, only to a lesser extent at the firm level. There is evidence of both substitutability and complementarity between energy and capital in this body of work. This ambiguity combined with the ongoing restructuring of energy sources[1], indicate that future rises in energy prices, and their knock-on effects on the demand for other factor inputs, continue to be a real concern. Thompson (2006), emphasizing the need for further research on this topic, notes that "the empirical literature on energy cross-price elasticities is thin relative to the economic impact". He highlights that energy substitution will affect the outcomes of, for example, environmental policy, capital taxes and labour policy, amongst other issues.

We contribute to the literature on factor substitution by examining the elasticities of substitution between different factors of production at the firm level using a census of Irish manufacturing firms. Thus, we are able to perform the analysis at the level of the decision-making unit, namely the firm in contrast to earlier studies that relied on industry- or country-level data. Our data is an unbalanced panel over a period of nearly 20 years from 1991 to 2009. We estimate factor share equations derived from a translog cost function using iterated seemingly-unrelated regressions. We calculate both own- and cross-price elasticities of demand as well as Morishima elasticities of substitution across the average of all manufacturing firms. To allow for heterogeneity across firms, we further compare elasticities of substitution for firms of different sizes, energy intensity, ownership and trade orientation. We also investigate changes over the sample period.

A large number of papers have examined whether energy and capital, as well as other factors of production, are substitutes or complements. However, most studies have been at the country or industry-level. Berndt and Wood (1975) were first to use the translog model initially developed by Christensen et al. (1973) to estimate a factor demand model on US industry-level data. They find energy and labour to be substitutes but energy and capital to be complements. Griffin and Gregory (1976) find capital and energy to be substitutes in their study using aggregate cross-country data. Solow (1987) argues that ultimately the question of whether capital and energy

[1]For example the International Energy Agency (IEA, 2012) notes that around the world many aging power plants will need to be replaced in coming years, which will put pressure on energy prices. Increased promotion of renewable energy sources and potentially more stringent CO_2 pricing in the future are other possible factors that could drive energy prices up.

are substitutes or complements can only be satisfactorily settled at the micro level as aggregation will bias any measured elasticities at more aggregate levels. Despite these insights, there have been few studies based on micro data: Arnberg and Bjørner (2007) using a panel of Danish manufacturing firms for four years between 1993 and 1997, find complementarity between energy and capital. Woodland (1993) finds strong substitution between factors of production including different types of energy and capital in a panel of firms in New South Wales, Australia 1977-1985. Nguyen and Streitwieser (2008) find that capital and energy are substitutes in a cross-section of US manufacturing plants in 1991.

We add to this literature in four ways. First, we use a census of Irish manufacturing firms; an analysis based on micro data is less likely to suffer from aggregation bias.[2] Our dataset comprises all but the very smallest of Irish manufacturing firms. Second, we consider two alternative measures of substitution; cross-price elasticities and Morishima elasticities of substitution. Third, we examine whether these elasticities differ for firms of different types and sizes; this gives us insight in which types of firms are better able to respond to changing factor prices by adjusting their input mix. Finally, in contrast to the earlier literature our panel covers almost two decades (from 1991 to 2009). Thus, our analysis captures a longer and a more recent period than previous studies. This allows us to also examine whether substitution patterns change over time.

Our results show that all factor inputs are substitutes in the production process. We find that energy is the most elastic factor input and that labour is the least elastic. According to the cross-price elasticities energy and capital are weak substitutes, but the Morishima elasticities reveal a stronger technical substitution potential. We do find some variation in the substitutability between energy and capital depending on firm types: more energy-intensive firms tend to be more responsive to increases in the prices of energy, while foreign-owned firms tend to be less responsive. We also observe a sharp decline in the cross-price elasticity of substitution between energy and capital during the first half of the sample period in the 1990s. We attribute this to a drop in energy-intensity of the Irish industrial sector around the time driven by efficiency improvements, movements up the value chain and possibly an emerging policy focus on energy efficiency and pollution control. The technical substitution potential does not vary significantly across firm types, but the decline from the first half of the sample period to the second half is confirmed by the Morishima elasticities of substitution.

The remainder of this paper is structured as follows. Section 2 summarises the related literature. The econometric model is outlined in Section 3; this section also includes a brief discussion of alternative measures of elasticity. Section 4 describes the dataset and provides summary statistics. Section 5 presents our results. Section 6 briefly concludes.

[2] We should add the caveat, however, that our data are at firm level, rather than product level to which Solow's argument (Solow, 1987) specifically referred.

2. Related Literature

Berndt and Wood (1975) analyse industry-level data from US manufacturing for 1947-1971. They employ a translog model using four inputs - capital, labour, energy and intermediate materials and find energy and capital to be complements. These results are supported by other industry- or national-level studies for a single country such as Fuss (1977) and Magnus (1979). Griffin and Gregory (1976) use aggregate data from several countries throughout the 1950s and 1960s. They too utilise a translog model although they only use three inputs - capital, labour and energy. In contrast to Berndt and Wood (1975), they find energy and capital to be substitutes. Pindyck (1979) in his multi-country study also finds capital and energy to be substitutes. A more recent paper using industry-level data is that of Tovar and Iglesias (2013) who estimate a five-factor model in which capital is split into working and physical capital. The authors find that energy is complementary to both types of capital in the long run, and that the relationship between these inputs is not significant in the short run. In sum, the elasticities estimated from macro data mostly indicate a complementary relationship between energy and capital; a particularly strong complementary relationship was found by Tovar and Iglesias (2013) who estimated a cross-price elasticity of -0.738 between energy and building capital for the food sector. By contrast the estimates by Berndt and Wood (1975) range from -0.14 to -0.16.

Various explanations have been put forward to reconcile the fact that some papers show energy and capital to be substitutes while other studies show them to be complements. One suggestion is that the substitution results typically found in cross-section studies capture the long-run industry response while time-series studies pick up the short-run complementary relationship between the two inputs (Griffin and Gregory, 1976; Apostolakis, 1990). However, there are exceptions to this rule, e.g. Chung (1987) uses the same data employed by Berndt and Wood and finds that all inputs, including energy and capital, are substitutes. According to Chung (1987)'s esimtates, a 1% increase in the price of energy causes the demand for capital to rise by between 0.045 and 0.023%, depending on the estimation procedure used. Other explanations for the contradictory findings relate to differences in model specification, differences in the definition of inputs and differences in the aggregation of energy inputs. In fact, Koetse et al. (2008) conduct a meta-analysis of capital-energy substitution elasticities on the basis of a large number of studies at industry and country-level. Their analysis suggests that the differences between results can be explained largely by differences in model specification, type of data, regions and time periods analysed. Based on this they conclude that capital and energy are substitutes in the production process, with cross-price elasticities ranging from 0.178 to 0.520 depending on whether the estimates refer to long-run or short-run elasticities, and on the time period and region in question.

Solow (1987) shows analytically that estimates of factor substitutability at the aggregate level capture more than just technological substitution. He concludes that the question can ultimately only be settled at the micro (product) level as differences in energy intensities are large and aggregate results will be driven by composition effects. Similarly, Miller (1986) argues that substitution effects in production can only be estimated precisely if the output vector is truly held constant, i.e., the product mix is held fixed. As the scope for the product mix to change is greater in cross-section studies (even at 2- or 3-digit industry level) the findings from these studies are biased toward finding high elasticities of substitution. Nguyen and Streitweiser (2008) illustrate the impact of aggregation bias; by aggregating their firm-level data to the two-digit industry level they find the elasticity estimates increase substantially in value. In contrast, time-series studies essentially pick up cyclical movements where energy prices and investment moved in the same direction and hence are more likely to show complementarity.

There have been a small number of studies using micro data. Woodland (1993) focuses on energy and factor substitution among manufacturing firms in New South Wales, Australia, using a panel for the period 1977-1985. He finds that substitution between fuel and the other factors of production, including capital, is significantly larger than interfuel substitution.[3] Nguyen and Streitwieser (2008) estimate elasticities of substitution in a cross section of U.S. manufacturing firms in 1991. They use four factor inputs - capital, labour, materials and energy. They find energy and capital to be substitutes. From their estimates based on micro data, they estimate a cross-price elasticity of 0.01 and a Morishima elasticity of substitution of 3.97. In an earlier paper (Nguyen and Streitwieser, 1999) they use the same dataset to show that the the degree of factor substitution does not differ markedly between firms grouped into different firm-size classes. Arnberg and Bjørner (2007) estimate input substitution among Danish manufacturing firms in the mid-1990s using panel data. This model has four inputs - capital, labour, electricity and other energy. Using both translog and linear-logit approaches, they find that electricity and other energy are both complements with capital. Based on their fixed-effects linear-logit specification (which is their preferred model), the estimated elasticities indicate that a 1% increase in the price of electricity causes the demand for capital to decrease by 0.023% and a that a 1% increase in the price of other energy causes the demand for capital to decrease by 0.017%

3. The empirical model

Elasticities of substitution can be obtained from the estimation of a production function, or its dual cost function (Berndt and Wood, 1975; Thompson, 2006). We choose to estimate a cost function as it is based on the prices of factor inputs, as opposed to the inputs themselves, and thus is less likely to suffer from simultaneity. In order to estimate a cost function it is necessary to specify a functional form. We follow Berndt and Wood (1975) and

[3] Woodland (1993) estimates the own and cross-price elasticities separately for nine different patterns of fuel usage and 12 different industries and presents a large range of estimates of the elasticity of capital demand to changes in energy prices. However, his results indicate, almost universally, that capital is substitutable with all fuels.

Woodland (1993), amongst others, and estimate a translog cost function as it is a flexible functional form which does not place any a-priori restrictions on the relationships between factor inputs, which is important as this is what we wish to estimate. In order to improve estimation efficiency (as discussed by Diewert (1974)) we augment the cost function with factor share equations which, following Shepard's lemma, are obtained by differentiating the cost function.

The basic cost function is:

$$\begin{aligned} \ln(C_f) &= b_0 + \textstyle\sum_{i=1}^{n} a_i \ln(P_{if}) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} \ln(P_{if}) \ln(P_{jf}) \\ &+ \textstyle\sum_{i=1}^{n} c_i ln(P_{if}) ln(y_f) + \gamma ln(y_f) + \sum_{i=1}^{n} u_{if} ln(P_{if}),\ i \neq j \end{aligned} \tag{1}$$

where ln is the natural log; f indexes firms and i factors of production, namely capital, labour, materials and energy. C is cost; y is output; and P_i refers to the price of each of the four factor inputs; u_i is the residual. Using logarithmic differentiation gives the factor share equations:

$$S_{if} = a_i + \sum_{j=1}^{n} b_{ij} ln(P_{jf}) + c_i ln(y_f) + u_{if},\ i = k, l, m, e \tag{2}$$

Firms differ from each other in important ways and there is a long time dimension to our panel. We take account of heterogeneity across firms in different sectors by including NACE 2-digit industry dummies. In total there are 22 NACE 2-digit industries. These are included in such a way that the a_i are allowed to vary across sectors. Note that, 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 (a_i 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 additional control variables. In the cost function we include a dummy variable indicating whether a firm has multiple production units, a dummy variable indicating whether the firm is foreign owned, and a categorical variable to indicate its trade status (no trade, exports only, imports only, exports and imports). These are all comprised in the vector Z_f in equation (3). To capture differences over time we include time dummies (λ_t); this is a simple and commonly-used method of modelling Hicks-neutral technical change. The inclusion of industry dummies and control variables allows us to directly take account of the fact that the cost function is not homogeneous across all firms in our data, and that firms in different industries will be characterised by different production technologies. In order to further identify how patterns of substitution between factors of production vary across different firms, we also estimate the cost function and evaluate the elasticities separately for different types and sizes of firms.

Thus, the basic translog cost function is modified as follows:

$$\begin{aligned} \ln(C_f) &= b_0 + \sum_{i=1}^{n} a_i \ln(P_{if}) + \tfrac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij}\ln(P_{if})\ln(P_{jf}) + \sum_{i=1}^{n} c_i ln(P_{if}) ln(y_f) \\ &+\gamma ln(y_f) + \sum_{i=1}^{n} ln(P_i)\sum_{g=1}^{G} d_{ig} IND_{gf} + \sum_{i=1}^{n} u_{if} ln(P_{if}) + Z_f + \lambda_t,\ i \neq j \end{aligned} \tag{3}$$

And the resulting factor-share equations are now:

$$S_{if} = a_i + \sum_{j=1}^{n} b_{ij} ln(P_{jf}) + c_i ln(y_f) + \sum_{g=1}^{G} d_{ig} IND_{gf} + u_{if},\ i = k, l, m, e \tag{4}$$

where IND is a dummy variable equal to one if firm f is in industry g, and zero otherwise. We impose the following constraints on the model to ensure that the cost function is symmetric and homogeneous of degree one in input prices[4]:

$$\begin{aligned} &\sum_{i=1}^{n} a_i = 1; \sum_{i=1}^{n} b_{ij} = 0,\ j = 1, \ldots, n; \sum_{i=1}^{n} c_i = 0; \sum_{i=1}^{n} d_i = 0 \quad \text{(homogeneity)} \\ &b_{ij} = b_{ji}, i, j = k, l, m, e; i \neq j \quad \text{(symmetry)} \end{aligned} \tag{5}$$

Equations 3 and 4 are estimated jointly using Zellner's iterated seemingly unrelated regression (iSUR) technique, to account for potential correlation between the errors from the equations. Standard errors are adjusted for clustering at the firm level. As the four factor shares must sum to one, we arbitrarily drop one of the factors from the estimation (materials) and compute it as a residual. Using iterated SUR ensures that the estimated parameters are invariant with respect to the omitted factor. Jointly estimating the cost function and factor share equations is the first step in a two-step procedure. In the second step the elasticities are computed directly from the estimated parameters of the cost function and the predicted cost shares, using the delta method to compute the standard errors.

We estimate own- and cross-price elasticities of demand (PED) as well as Morishima elasticities of substitution (MES). The own-price elasticities give the percentage change in the demand for a factor of production given a one percent change in its own price. The cross-price elasticities give the percentage change in demand for one factor of production in response to a one percent change in the price of another factor of production. The PED is computed as follows from the estimated parameters of the cost function:

$$\eta_{x_i p_j} = \sigma_{ij} * S_i = \frac{b_{ij} + S_i * S_j}{S_i} \tag{6}$$

The own- and cross-price elasticities may be useful to policymakers who wish to know what the potential impact of, for example, a carbon tax would be on the demand for energy as well as the demand for other factors

[4] This is a less strict condition than imposing that the production function is homogenous of degree one. However, as discussed in Section 5, we also re-estimate the model imposing homogeneity of the production function as a robustness check.

of production. Indeed, many papers to date which have focused on factor substitution have estimated own- and cross-price elasticities, and Allen elasticities of substitution, σ - which is simply the cross-price elasticity divided by the factor share. However, it has been argued that the PED is not the best measure of factor substitutability, as it does not measure the curvature of the production isoquant. Blackorby and Russell (1989) argue that the Morishima elasticity of substitution (MES) is a theoretically superior measure of substitution and is closer to the original definition of substitution as outlined in Hicks (1932). The MES is calculated as follows:

$$MES_{ij} = \eta_{x_i p_j} - \eta_{x_j p_j} = \frac{\partial ln(X_i/X_j)}{\partial ln(P_j)}, \tag{7}$$

where X_i and X_j are the demand for inputs i and j, and $\eta_{x_i p_j}$ and $\eta_{x_j p_j}$ are the cross- and own-price elasticities. Thus, the MES adjusts the cross-price elasticities for changes in the demand for a factor input when its own price changes. It captures the change in the ratio of two inputs (X_i/X_j) when the price of one of the inputs (P_j) changes. According to this measure, factors i and j are substitutes if the i/j input ratio increases in response to an increase in P_j. Thus, if in the face of rising energy prices, the demand for both capital and energy falls, but the demand for capital falls by less, capital and energy would be classified as Morishima substitutes, reflecting the fact that the production process is now more capital intensive, as outlined by Bettin et al. (forthc.). Blackorby and Russell (1989) note that the MES may also be considered a superior measure of substitutability in a multi-input case.

In this paper we present estimates of substitution based on both measures, as both may be useful depending on the question being asked. While the cross-price elasticity between energy and capital measures the actual change in the demand for capital in response to an increase in the price of energy, the Morishima elasticity measures the percentage change in the capital/energy input ratio, and illustrates the technical substitution potential between the inputs. Blackorby and Russell (1989) note that the MES preserves the salient features of Hicks' original definition, and that it is an exact measure of the ease of substitution between two inputs. On the other hand, Frondel (2004) argues that for any practical purposes, the cross-price elasticity of demand is preferable to the Morishima elasticity of substitution.

4. Data and Descriptive Statistics

4.1. Data

As mentioned previously, the data on which we base our analysis of factor substitution is a richer data source compared to previous micro analyses. While Nguyen and Streitwieser (1999, 2008) use a rich data set (the US Manufacturing Energy Consumption Survey for 1991), there is no time dimension to their analysis. Those micro studies which have included a time dimension (Woodland, 1993; Arnberg and Bjørner, 2007) are based on relatively short panels - Woodland (1993)'s data covers eight years from 1977 to 1985, and Arnberg and Bjørner (2007)'s four years during the mid-1990s. Our data set covers 19 years including the first 10 years of the 21st century when energy efficiency became an increasingly topical issue and energy prices increased drastically. This allows us to also observe changes in factor substitution over time.

Our data set is the Census of Industrial Production (CIP) for the Republic of Ireland - a firm-level panel data set. The CIP is conducted annually by the Central Statistics Office (CSO); response to the survey is compulsory. In its current format it has been in place since 1991; we use data from 1991 to 2009. The purpose of the census is to provide structural information on various accounting measures such as industry classification, location, sales, employment, intermediate inputs, capital acquisitions and trade. The CIP covers all firms with 3 or more persons engaged in the mining, manufacturing and utilities sectors. The analysis here focuses on the core manufacturing NACE Rev. 1.1 sectors 15-36. The CIP is conducted at enterprise (firm) level and requires firms with multiple production units to break some of their aggregate figures down to the level of the local unit (plant). Since the information at the firm level is more comprehensive, we use data at the firm level. Only 3% of Irish manufacturing firms are multi-unit firms; we control for multi-unit status in our regressions.

The data are checked for digit issues and outliers and cleaned where appropriate. The industry classification changed between 2007 and 2008 from NACE rev. 1.1 to NACE rev. 2. More detailed information on data cleaning and how we deal with the change in industry classification is provided in the appendix. Further, the CSO estimate or impute data for non-respondents and incomplete returns. We exclude firms where 50% or more of their observations in the census are imputed or estimated. We also exclude observations if capital stock to output ratios are in excess of a factor 7 (just less than the top decile).

We examine substitution between four inputs, namely capital, labour, energy and materials. Estimation of the translog cost function requires expenditures and prices. The labour input is the number of employees, and the expenditure on labour is the total wage bill. The price of labour is the firm's expenditure on wages and salaries as well as other labour costs (i.e. social insurance, employers' pension contributions and training costs), per employee. The CIP records investments in capital assets. We obtain capital stocks using the perpetual inventory method for industrial buildings and machinery and equipment as described in the appendix. The price of capital we use in our model is the market cost of capital as estimated by Žnuderl and Kearney (2013). The authors calculate an index for the price of two different types of capital - machinery and equipment, and industrial buildings - for Irish manufacturing firms on an annual basis for the period from 1985 to 2011. Their annual cost of capital estimate is derived from a model of investment behaviour based on the neoclassical theory of optimal capital accumulation, according to which the cost of capital is the implied rental rate of the capital services that a firm supplies to itself, and is expressed as a percentage of the price of investment. As we have information on the capital stocks of buildings and of machinery and equipment for each firm in each year, we create a firm-specific measure of the price index by weighting the indices from Žnuderl and Kearney (2013) with each firm's shares of the two types of capital stock.

Expenditure on materials is recorded directly in the CIP. We create a price index for materials by weighing the prices of intermediate inputs (mostly at the 2-digit level) obtained from EU-KLEMS (EUKLEMS (2009), for a detailed description see O'Mahony and Timmer (2009)) by each industry's input mix according to the input-output tables; this gives us a price index for materials that varies by industry and over time. For more details on the construction of this, and other variables, please refer to the appendix.

Expenditure on energy is recorded in the CIP as purchases of fuel and power. We construct an industry-level energy price based on the price of oil, electricity and gas to industrial users in Ireland, as given by the International Energy Agency's "Energy Prices and Taxes" publication (IEA, 2011), weighted by industry-level fuel consumption data for Ireland, available from the Sustainable Energy Authority of Ireland (SEAI, 2012).

Thus, the prices for labour and capital are at the firm level whereas the prices for materials and energy are at the industry level. Finally, output is measured as sales.

4.2. Descriptive Statistics

Table 1 presents descriptive statistics. The average firm in our dataset employs 52 people, utilizes €6.6 million worth of capital, spends approximately €7.3 million on materials and €276,000 on fuel per year. The average wage is €23,700 and the average price of a tonne of oil equivalent (TOE) of fuel is €553. The average firm produces €18.8 million worth of output, and the average ratio of output to capital is approximately 0.9. On average across the sample, approximately 3% of firms are multi-unit firms, and 14% of firms are foreign owned. The table also reports standard deviation, the quartiles of the distribution of these variables and their variation over time. Not surprisingly we observe differences across firms and changes over time. There is a notable decrease in the capital/output ratio in the early to mid 1990s. The fall in this ratio is consistent with aggregate patterns observed for Ireland noted in Backus et al. (2008), however the level we observe is lower than that noted by the authors for the macro economy.

Figure 1 below shows the average share, across all firms, of each of the four factor inputs in each year. It shows that, on average, the share of capital in manufacturing firms' inputs decreased somewhat over the period. This is accompanied by increases in the shares of labour and materials.

Figure 2 shows the changes in average factor prices over the sample period, with the price of each factor set to 100 in 1991 for illustration. All factor prices increased relative to 1991. The most striking increases are for the prices of energy and labour. The price of energy inputs increased almost 2.5 fold over the sample period. Most of this increase took place in the second half of the sample. As discussed by SEAI (2013) increases in the price of energy in Ireland have been driven by rising oil and gas prices; these have a particularly strong effect in Ireland due to a high level of dependence on fossil fuels.

Table 1: Descriptive Statistics

	Mean	Std. dev.	Quartile 1st	2nd	3rd	Mean value 1991	2000	2009
Capital (€1000)	6600.9	50973.8	316.4	861.5	2937.0	5940.6	6392.1	8145.7
Labour (employees)	51.5	146.5	7.0	15.0	39.0	49.6	56.2	42.5
Material (€1000)	7280.9	90221.2	178.9	531.2	2161.4	4620.9	8694.8	8019.1
Energy (€1000)	276.3	2019.6	9.7	29.7	110.9	285.0	239.1	270.8
Price capital (% of investment)	15.8	3.8	13.1	15.4	18.6	15.3	10.5	22.1
Price labour (€1000)	23.7	17.4	13.9	20.9	30.3	14.8	22.8	34.2
Price material (index)	0.8	0.5	0.4	0.8	1.0	0.6	0.7	1.0
Price energy (€/TOE)	553.0	234.3	387.5	465.1	674.1	387.8	436.9	938.0
Output (€1000)	18773.6	194772.5	511.6	1329.8	4843.7	9380.0	20092.3	24702.4
Capital/Output	0.91	0.95	0.32	0.60	1.12	1.32	0.81	0.84
Multi-unit dummy	0.03	0.16				0.03	0.03	0.02
Foreigh-owned dummy	0.14	0.35				0.17	0.14	0.11

The sample comprises of 80,514 observations.

Žnuderl and Kearney (2013) note that the market cost of capital for machinery and equipment was relatively flat and in fact fell towards the end of the period; however the market cost of investing in industrial buildings increased more than two-fold over the period of our anlysis. The increase in the market cost of investing in industrial buildings was particulary high from 2006-2009. In our data approximately 52% of the capital stock consists of industrial buildings. The effect of the increase in the cost of this type of capital on the overall price of capital can be observed in Figure 2.

5. Results

As the estimated parameters of the cost function have little intuitive sense given the complexity of the translog functional form, they are relegated to Table A1 in the appendix. All the coefficients reported in Table A1 are significant. Of the large number of control variables that are not reported in Table A1 only 14 are not statistically significant; for details please refer to the note to the table. In this section we discuss the estimated elasticities which are calculated from the estimated parameters as described in Section 3.

Before discussing the elasticity estimates, it is important to test the performance of the cost function. To check the validity of the model estimates, we first compare the cost shares predicted by our model with the sample average cost shares observed in the data. Table 2 shows that across the sample the estimated cost shares are close to the cost shares observed in the data.

Secondly, if our estimated cost function is well-behaved, conditions of monotonicity and quasi-concavity should not be violated. Monotonicity implies that the estimated cost shares are non-negative; 99.9% of observations in our data satisfy monotonicity, and those observations that do not satisfy the monotonicity condition are dropped from our estimation before we compute the elasticities. Quasi-concavity is satisfied if the Hessian matrix from the

Figure 1: Factor shares 1991-2009

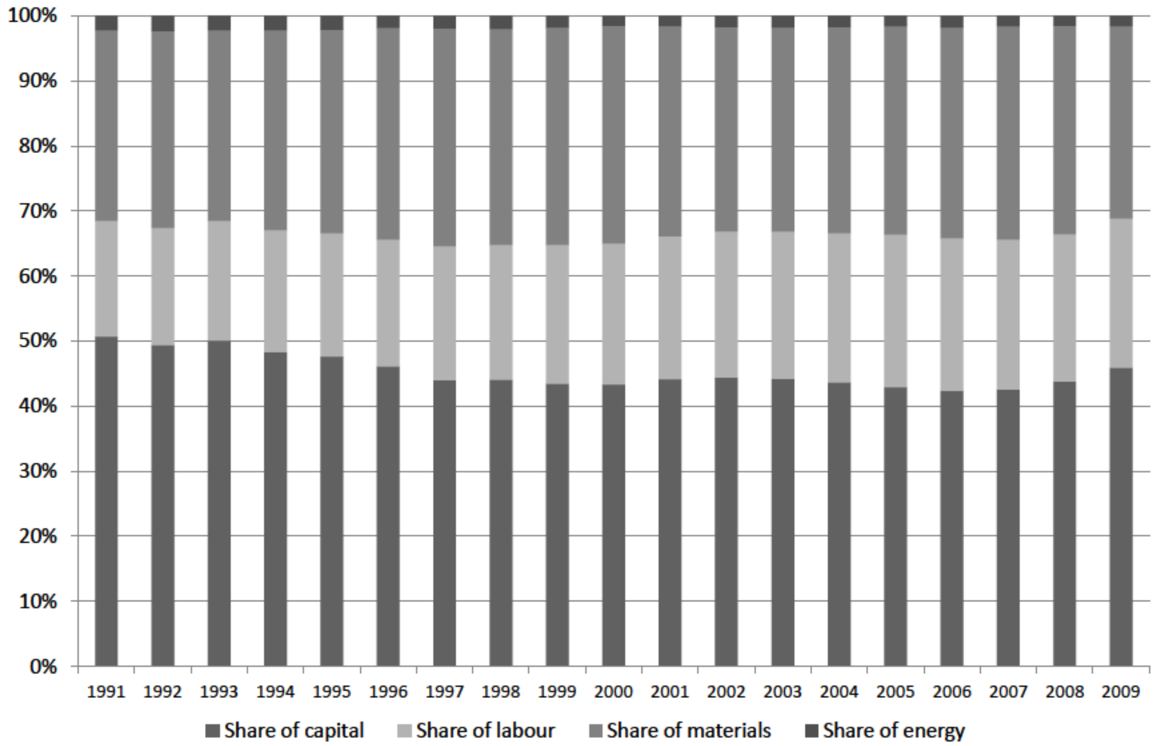


Table 2: Comparison of predicted and sample average cost shares

	Predicted		Sample averages	
	Mean	SD	Mean	SD
Capital	0.457	0.100	0.452	0.198
Labour	0.211	0.052	0.212	0.120
Materials	0.314	0.091	0.318	0.179
Energy	0.018	0.007	0.018	0.018

estimation is negative semi-definite; thus, the estimated own-price elasticities, evaluated at the mean of the sample, should be non-positive, which is generally satisfied in our case. In total only 0.3% of the observations in our sample violated the quasi-concavity conditions.[5]

Table 3 below presents the own- and cross-price elasticities estimated across all firms. We find that energy is the most elastic input, with an estimated price elasticity of demand of -1.46%; and that labour, with an elasticity of

[5]We also validated these at the median and quasi-concavity was maintained. An anonymous referee brought to our attention that Berndt (1991) states that a strict quasi-concavity condition requires that elasticities of substitution should be negative semi-definite at each observation, and not just at the mean. We verified that elasticity estimates based on only those observations that satisfy *strict* quasi-concavity are not significantly different from those reported.

Figure 2: Input price index 1991-2009 (1991 = 100)

-0.48%, is least responsive to changing prices.[6] Comparing these results to previous estimates based on micro data, our results are broadly in line with the literature. Nguyen and Streitwieser (1999) also find that energy is the most elastic factor input, albeit with a much higher PED of -3.766%, while Arnberg and Bjørner (2007) find that, with a PED of -0.355%, machinery is the most elastic [7], followed by (non-electric) energy ($\eta_{EE} = -0.233\%$). As suggested by our results, Arnberg and Bjørner (2007) also find that labour is the least elastic input ($\eta_{KK} = -0.052$), whereas Nguyen and Streitwieser (1999) find that capital is the least elastic factor ($\eta_{KK} = -1.106$), followed by labour ($\eta_{LL} = -1.615$).

Our results show that for Irish manufacturing firms, all factor inputs are substitutes in the production process, as indicated by the positive cross-price elasticities. The substitutability varies notably from factor to factor, and in general the elasticities are asymmetric. While the demand for energy exhibits a strong response to changing capital prices ($\eta_{EK} = 0.92$), the demand for capital is relatively unresponsive to changing energy prices ($\eta_{KE} =$

[6] This is similar to estimates based on macro data for Ireland; Bergin et al. (2013) estimate an own elasticity of demand for labour of -0.4.

[7] The results discussed for Arnberg and Bjørner (2007) are based on their fixed-effects linear-logit specification

Table 3: Own and cross-price elasticities of demand

	Capital		Labour		Materials		Energy
η_{KK}	-0.623 (0.006)***	η_{LK}	0.296 (0.009)***	η_{MK}	0.653 (0.007)***	η_{EK}	0.921 (0.022)***
η_{KL}	0.137 (0.004)***	η_{LL}	-0.475 (0.009)***	η_{ML}	0.113 (0.005)***	η_{EL}	0.133 (0.015)***
η_{KM}	0.449 (0.005)***	η_{LM}	0.168 (0.007)***	η_{MM}	-0.790 (0.008)***	η_{EM}	0.405 (0.015)***
η_{KE}	0.037 (0.001)***	η_{LE}	0.012 (0.001)***	η_{ME}	0.024 (0.001)***	η_{EE}	-1.459 (0.024)***

Notes: Elasticities are based on coefficient estimates from Equation 3, the results of which are presented in Table A1, and the estimated factor shares. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

0.04). While the estimated elasticity is small, its positive value indicates that rising energy prices will not cause a reduction in capital investment. The relative unresponsiveness of the demand for capital in response to changing energy prices is unsurprising given that the share of energy in total input costs is small (see Figure 1). Our results show that labour and materials are also weakly substitutable with energy.

The estimated Morishima elasticities of substitution (henceforth, MES), presented in Table 4, confirm the substitutability between all factor inputs; however, they reveal a stronger technical substitution potential than the cross-price elasticities suggest. According to the MES estimates, a 1% increase in the price of energy causes the capital-energy input ratio to increase by 1.5%. The MES adjusts the cross-PED for changes in the demand for a factor when its own price changes. Given that energy is the most elastic input it is not surprising that the MES estimates for changing energy prices are significantly larger than the cross-PED estimates.

Elasticities by firm type

In the following we assess whether the estimated elasticities vary for different groups of firms and over time. We examine differences between firms in terms of size, energy intensity, ownership and trading status. For this purpose we estimate the model described in Section 3 separately for each of the subsamples and calculate the elasticities of

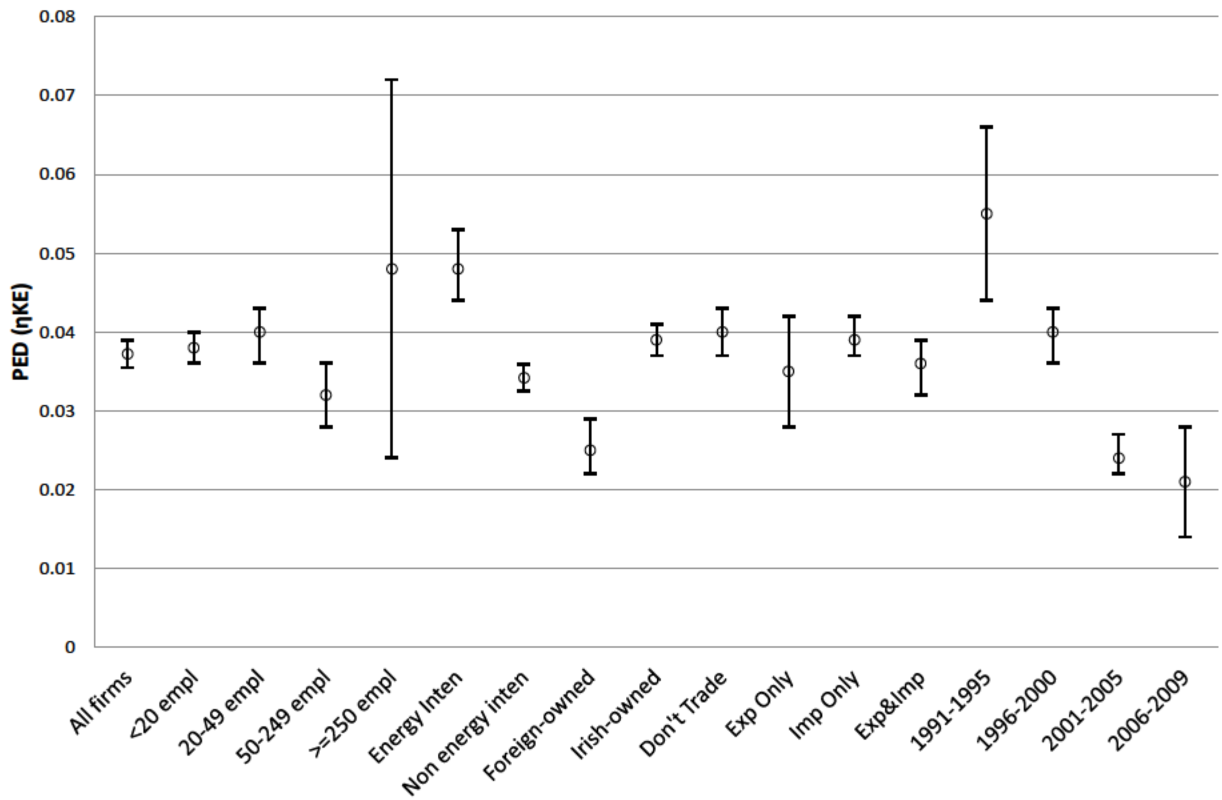
Table 4: Morishima elasticity of substitution estimates

	Capital		Labour		Materials		Energy
σ^m_{KL}	0.612 (0.012)***	σ^m_{LK}	0.918 (0.014)***	σ^m_{MK}	1.276 (0.013)***	σ^m_{EK}	1.543 (0.023)***
σ^m_{KM}	1.238 (0.012)***	σ^m_{LM}	0.958 (0.012)***	σ^m_{ML}	0.588 (0.012)***	σ^m_{EL}	0.608 (0.018)***
σ^m_{KE}	1.496 (0.024)***	σ^m_{LE}	1.470 (0.024)***	σ^m_{ME}	1.482 (0.024)***	σ^m_{EM}	1.195*** (0.0182)***

Notes: Elasticities are computed as per Equation 7. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

substitution based on these subsamples. In the following we focus on the elasticity of substitution between capital and energy. The elasticities for all factors of production in the different subsamples are presented in Tables A2 to A4 in the appendix, and show that the patterns of substitution vary across the factor inputs. In Figure 3 we present the elasticity estimates for capital with respect to the price of energy graphically together with their 95% confidence intervals. The left-most estimate in the figure is that which is reported in Table 3 for all firms.

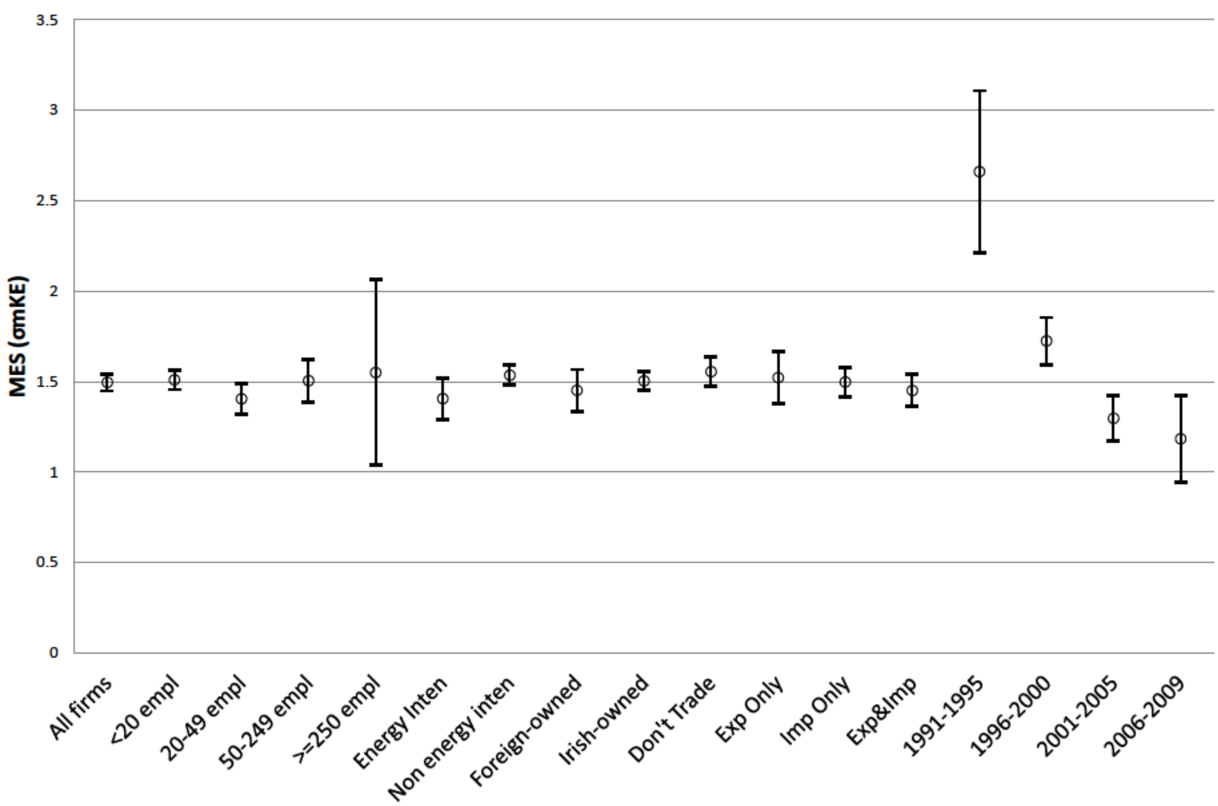
Figure 3: PED for all firms and by subsample; point estimates and 95% confidence intervals



Note: Cross-price elasticities and 95% confidence intervals of the demand for energy with respect to capital (η_{KE}) based on coefficient estimates from Equation 3 on subset of firms as indicated.

We start by splitting the sample into four firm-size groups. Firms are assigned to size classes based on their median employment over their period in the sample. The question of whether small or large firms are more responsive in terms of adjusting their input use to changes in prices is ultimately an empirical one. Larger firms may be more responsive if they are less likely to be financially constrained and more innovative than small firms. In turn, if smaller firms are more flexible in their organisation or more price sensitive they may be more responsive. Figure 3 shows that the elasticity of capital with respect to the price of energy shows no consistent pattern across firm size. The largest firms appear to be most responsive, but this elasticity is estimated with a very large standard error due to the small sample size. In fact, the estimated elasticities for all firm size classes are not significantly different to those of the dataset comprising all firms. This finding concurs with the results of Nguyen and Streitwieser (1999), who find that the degrees of substitution do not vary notably by firm size in a cross section of US manufacturing firms for 1991.

Figure 4: MES for all firms and by subsample; point estimates and 95% confidence intervals



Note: Morishima elasticities of substitution and 95% confidence intervals of the demand for energy with respect to capital (σ^m_{KE}) based on coefficient estimates from Equation 3 on subset of firms as indicated.

Next we compare firms by energy intensity. Firms are classified as energy intensive if they are in a NACE 2-digit sector in which the median share of energy inputs in total inputs across the time period is in the top quartile of the distribution. Being in the top quartile of the distribution equates to having an average sector-level energy share greater than 2%. The sectors classified as energy intensive are NACE rev. 1.1 sectors 15 (Manufacture of food, beverages and tobacco), 25 (Manufacture of rubber and plastic products) and 26 (Manufacture of other non-metallic mineral products). Figure 3 shows that the firms in sectors with a relatively high level of energy intensity adjust their capital demand much more in the face of rising energy prices.

We also split our sample into domestic and foreign-owned firms as well as by firms' trading status. Foreign-owned firms have been shown to be larger, more productive and more technology intensive than domestic firms (for Ireland see e.g. Barry et al. (1999)). As a consequence they may be using more advanced production technologies and upgrade their production facilities and machinery more frequently. If this is the case they should also embody more energy-efficient technologies. A similar argument holds for firms that are engaged in international trade. Firms that both export and import tend to be larger and more capital intensive than firms that serve only the domestic market, import only or export only (for Ireland see e.g. Haller (2012)). The estimated elasticities for the sample of foreign-owned and the sample of Irish-owned firms show that the elasticity of substitution of capital with respect to energy in the sample of domestic firms is not significantly different from that of all firms whereas the elasticity of substitution between energy and capital is significantly lower for foreign-owned firms. When we split the sample by firms' trading status, we find that the responsiveness to increases in energy prices is strongest for firms that do not trade and for firms that import only. However the elasticities of substitution between capital and energy by firms' trading status are not significantly different from that of the full sample.

The final four bars in Figure 3 show results of the elasticities over time. They indicate a sharp decline in substitutability between capital and energy in the first half of the sample period. On the one hand this is surprising; the real price of energy has increased significantly over the time period of our data, which may lead us to expect a higher degree of substitution. On the other hand, Figure 1 shows that the energy share of inputs has been falling over time in our sample, which would lead us to expect a declining responsiveness to energy prices. This period was associated with a large drop in energy-intensity of the Irish industrial sector, driven by both efficiency improvements and movements up the value-chain towards less energy-intensive production (Howley et al., 2004). Another factor possibly playing a role in this might be that it was also around this time that policy started to focus on pollution control and energy efficiency.[8] It is likely that once initial investments in energy-saving capital equipment were made in the early 1990s, further improvements in energy-efficiency were increasingly difficult to achieve, and thus the rate at which capital could be substituted for energy fell.

Figure 4 presents the Morishima elasticities of substitution for the same sample splits. For the majority of subsamples the estimated elasticities are not significantly different from those of the full sample. This is true for the splits by firm size, country of ownership and trade status. Interestingly, while the cross-PED estimates showed that energy-intensive firms adjusted their demand for capital in response to rising energy prices more than non-energy intensive firms; the MES estimates indicate that the technical substitution potential is lower for energy-intensive firms, but the difference is not statistically significant. The lower estimate for the energy-intensive firms is due to

[8] The European Community Council directive 96/61/EC concerning integrated pollution prevention and control came into force in September 1996.

the fact that the own-price elasticity of demand for energy inputs (η_{EE}) is lower for these firms. This could be a result of the fact that some energy-intensive firms may have negotiated contracts for the purchase of energy inputs and thus respond less to changes in the market price of energy inputs, faced by other firms. The results for four two time periods confirm those from the PED estimates: the responsiveness of the demand for capital to changing energy prices is significantly lower in the later time period.

Robustness

To further verify the validity of our results we exploit additional information in the data set. While the above estimates are based on an energy price which only varies at the industry level, our data set contains a detailed breakdown of firms' energy use by fuel type from enterprises with 20 or more employees collected every three years. We employ this energy use data for the firms and years when it is available (1992, 1995, 1998, 2001, 2005, 2008) to re-create the energy price variable based on firm-level as opposed to industry-level energy use, and re-estimate the own- and cross-price elasticities for these firms. Comparing these results to those reported above shows that our estimates are not notably compromised by using industry- rather than firm-level energy use data to compute energy prices.[9]

As a second robustness check we re-estimate the own- and cross-price elasticities based on a fully-constrained cost function in which we impose homogeneity of the production function and constant returns to scale. Taking the derivative of the cost function with respect of output gives:

$$dlnC/dlnY \quad = \sum_{i=1}^{n} c_i ln(P_{if}) + \gamma \tag{8}$$

Constant returns to scale is satisfied if $\gamma = 1$, and to ensure homogeneity of the production function we further impose:

$$c_i = 0 \quad \forall \quad i \tag{9}$$

The results of our main model (see Table A1) are based on a cost function in which we impose only that the underlying production function is homogeneous of degree one in input prices. The parameter estimates of this model show that constant returns to scale is rejected by the partially constrained model ($\ln(Y) = 1.018$, with a standard error of 0.0069), however, Table A5 in the appendix shows that the estimated elasticities from a fully-constrained cost function are qualitatively similar. Differences in excess of one decimal point are observed for the elasticities relating to materials and labour only. We chose to focus on the results from the partially-constrained model as it imposes less restrictions on the data.

[9]Results, not presented for brevity, are available from the authors on request.

6. Discussion and concluding remarks

In this paper we contribute to the literature on the substitutability between factors of production by providing new estimates of the elasticities of substitution between energy and other inputs. To do so we use a richer data source than has been applied to the issue to date. We use a census of manufacturing firms in Ireland for the period 1991-2009. We estimate a translog cost function in which we model firm heterogeneity directly by including additional firm characteristics in our equations. Furthermore, rather than basing our results on a single measure of elasticity, we compute both the price elasticities of demand and Morishima elasticities of substitution. Both measures have merit depending on the policy inference in question. Koetse et al. (2008) note that policy makers considering, ex-ante, the likely effect of a carbon tax on the demand for capital will be interested in the cross-price elasticities, whereas engineers may be more interested in the technological substitution potential between energy and capital, as given by the MES.

Our results indicate that across all Irish manufacturing firms a 1% increase in the price of energy raises the demand for capital by 0.04%. The Morishima elasticities, which reflect the technological substitution potential, indicate that a 1% increase in the price of energy causes the capital/energy input ratio to increase by 1.5%. Comparing our results to the elasticities calculated by Koetse et al. (2008) in their meta-analysis of industry- and country-level studies of capital-energy substitution, our estimated Morishima elasticities are larger than those estimated for both North America and Europe, although are estimates are closest to those calculated for North America. Our estimated cross-price elasticities, on the other hand, are much smaller than their calculated elasticities for all time periods and regions; this corroborates the conclusions of Miller (1986) who notes that studies based on more aggregate data are biased towards finding higher degrees of substitution. Comparing our results to other micro studies, our estimated cross-price elasticities are larger than those estimated by Nguyen and Streitwieser (2008), as are our estimated Morishima elasticities (their cross-price and Morishima elasticity estimates were 0.01 and 1.26 respectively).

In terms of the price elasticities of demand for firms of different types and sizes, we find that the responsiveness of the demand for capital to changing energy prices does not vary significantly by firm size. We find stronger differences when we split the sample according to other firm characteristics. The demand for capital in foreign-owned firms is less responsive to increases in energy prices. We also observe a sharp decline in the price elasticity of the demand for capital with respect to energy prices during the first half of the sample period. This is in line with a large drop in energy-intensity of the Irish industrial sector driven by efficiency improvements, production moving up the value chain and possibly an emerging policy focus on energy efficiency and pollution control.

There is less variation in the Morishima elasticities of substitution across different types of firms. However, we do find that the sharp decline during the first half of the sample period is confirmed by this measure of technological substitution. This may well reflect that in the second half of the sample period firms already responded to the increase in energy prices by improving the energy efficiency of their production facilities and machinery; a conclusion that the observed decline of the factor share of energy would support.

To summarise, despite some differences in the size of the elasticities when we split the data, in all cases the substitutability between capital and energy holds. The policy implications are important - the imposition of a carbon tax, or other polices likely to increase the price of energy, are not expected to be associated with a decline in capital investment.

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Appendix

Detailed tables

Table A1: Translog cost function estimates: main variables

Dependent variable: total cost		
$ln(P_k)$	0.785	(0.014)***
$ln(P_k)ln(P_k)$	-0.036	(0.003)***
$ln(P_l)$	0.237	(0.007)***
$ln(P_l)ln(P_l)$	0.066	(0.002)***
$ln(P_m)$	-0.079	(0.012)***
$ln(P_m)ln(P_m)$	-0.032	(0.002)***
$ln(P_e)$	0.057	(0.002)***
$ln(P_e)ln(P_e)$	-0.009	(0.000)***
$ln(P_k)ln(P_l)$	-0.034	(0.002)***
$ln(P_k)ln(P_m)$	0.062	(0.002)***
$ln(P_k)ln(P_e)$	0.009	(0.000)***
$ln(P_l)ln(P_m)$	-0.031	(0.002)***
$ln(P_l)ln(P_e)$	-0.001	(0.000)***
$ln(P_m)ln(P_e)$	0.002	(0.000)***
$ln(y)$	0.994	(0.006)***
$ln(y)ln(P_k)$	-0.020	(0.001)***
$ln(y)ln(P_l)$	-0.022	(0.001)***
$ln(y)ln(P_m)$	0.042	(0.001)***
$ln(y)ln(P_e)$	0.000	(0.000)***
Observations	80514	
Firms	9,446	

Note: Standard errors, adjusted for clustering at the firm level, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. As detailed in equations (3) and (4) the model further includes industry dummies, their interaction terms with prices, year as well as firm-specific multi-unit, trade status and ownership dummies. These are available from the authors on request. Out of the 127 variables in the full cost function equation, only 14 are not statistically significant. Those variables which were not significant are: the interaction of the capital price with the dummies for NACE sectors 16 (manufacture of tobacco products), 24 (manufacture of chemicals and chemical products), 32 (manufacture of radio, television and communication equipment and apparatus) and 35 (manufacture of other transport equipment); the interaction of the labour price with dummies for sectors 24 and 34 (manufacture of motor vehicles, trailers and semi-trailers); the interaction of the materials price with sectors 19 (manufacture of leather and leather products), 23 (manufacture of coke, refined petroleum products and nuclear fuel), 24, 25 (manufacture of rubber and plastic products), 33 (manufacture of medical, precision and optical instruments, watches and clocks) and 35; the interaction of the energy price variable with sector dummy 23; and trade status exporting only.

Table A2: PED and MES estimates by firm size and for energy- versus non-energy intensive firms

	<20 empl		20-49 empl		50-245 empl		>=250 empl		Energy intensive		Non-energy intensive	
PED												
η_{KK}	-0.588	(0.007)***	-0.665	(0.013)***	-0.728	(0.018)***	-0.742	(0.041)***	-0.514	(0.012)***	-0.642	(0.007)***
η_{KL}	0.122	(0.004)***	0.120	(0.010)***	0.163	(0.011)***	0.224	(0.022)***	0.137	(0.007)***	0.134	(0.005)***
η_{KM}	0.428	(0.005)***	0.505	(0.011)***	0.533	(0.016)***	0.470	(0.037)***	0.329	(0.009)***	0.474	(0.006)***
η_{KE}	0.038	(0.001)***	0.040	(0.002)***	0.032	(0.002)***	0.048	(0.012)***	0.048	(0.002)***	0.034	(0.001)***
η_{LL}	-0.389	(0.011)***	-0.406	(0.025)***	-0.514	(0.026)***	-0.627	(0.042)***	-0.525	(0.019)***	-0.461	(0.011)***
η_{LK}	0.271	(0.010)***	0.244	(0.021)***	0.336	(0.022)***	0.511	(0.050)***	0.394	(0.019)***	0.264	(0.01)***
η_{LM}	0.111	(0.007)***	0.157	(0.013)***	0.160	(0.022)***	0.084	(0.050)*	0.113	(0.018)***	0.188	(0.008)***
η_{LE}	0.007	(0.001)***	0.005	(0.003)*	0.018	(0.005)***	0.032	(0.016)**	0.018	(0.004)***	0.009	(0.001)***
η_{MM}	-0.806	(0.008)***	-0.806	(0.016)***	-0.719	(0.018)***	-0.602	(0.056)***	-0.538	(0.013)***	-0.863	(0.009)***
η_{MK}	0.703	(0.009)***	0.676	(0.015)***	0.602	(0.018)***	0.546	(0.044)***	0.455	(0.012)***	0.702	(0.008)***
η_{ML}	0.082	(0.005)***	0.104	(0.009)***	0.087	(0.012)***	0.043	(0.025)*	0.054	(0.008)***	0.141	(0.006)***
η_{ME}	0.022	(0.001)***	0.026	(0.002)***	0.030	(0.003)***	0.013	(0.010)	0.028	(0.004)***	0.020	(0.001)***
η_{EE}	-1.472	(0.027)***	-1.365	(0.042)***	-1.474	(0.060)***	-1.502	(0.251)***	-1.358	(0.058)***	-1.501	(0.028)***
η_{EK}	1.021	(0.025)***	0.878	(0.036)***	0.700	(0.043)***	0.990	(0.249)***	0.873	(0.041)***	0.984	(0.025)***
η_{EL}	0.090	(0.018)***	0.054	(0.035)	0.194	(0.048)***	0.285	(0.142)**	0.113	(0.026)***	0.132	(0.018)***
η_{EM}	0.361	(0.018)***	0.433	(0.028)***	0.580	(0.051)***	0.227	(0.168)	0.372	(0.057)***	0.386	(0.018)***
MES												
σ^m_{KL}	0.511	(0.014)***	0.527	(0.034)***	0.677	(0.034)***	0.850	(0.056)***	0.662	(0.023)***	0.595	(0.015)***
σ^m_{KM}	1.234	(0.013)***	1.312	(0.025)***	1.252	(0.032)***	1.072	(0.09)***	0.866	(0.021)***	1.336	(0.013)***
σ^m_{KE}	1.510	(0.028)***	1.405	(0.043)***	1.505	(0.061)***	1.550	(0.261)***	1.406	(0.058)***	1.536	(0.028)***
σ^m_{LK}	0.859	(0.015)***	0.909	(0.031)***	1.064	(0.035)***	1.253	(0.076)***	0.908	(0.028)***	0.906	(0.016)***
σ^m_{LM}	0.917	(0.013)***	0.964	(0.024)***	0.879	(0.034)***	0.686	(0.094)***	0.651	(0.026)***	1.050	(0.014)***
σ^m_{LE}	1.480	(0.028)***	1.370	(0.044)***	1.492	(0.063)***	1.534	(0.265)***	1.376	(0.059)***	1.511	(0.028)***
σ^m_{MK}	1.290	(0.015)***	1.342	(0.025)***	1.330	(0.034)***	1.288	(0.08)***	0.968	(0.023)***	1.344	(0.015)***
σ^m_{ML}	0.471	(0.014)***	0.510	(0.03)***	0.602	(0.035)***	0.670	(0.057)***	0.580	(0.023)***	0.602	(0.014)***
σ^m_{ME}	1.494	(0.027)***	1.391	(0.043)***	1.503	(0.062)***	1.515	(0.247)***	1.386	(0.061)***	1.521	(0.028)***
σ^m_{EK}	1.608	(0.027)***	1.544	(0.039)***	1.429	(0.046)***	1.732	(0.263)***	1.386	(0.046)***	1.626	(0.026)***
σ^m_{EL}	0.479	(0.022)***	0.461	(0.048)***	0.708	(0.057)***	0.912	(0.145)***	0.639	(0.033)***	0.592	(0.022)***
σ^m_{EM}	1.167	(0.021)***	1.239	(0.036)***	1.299	(0.055)***	0.829	(0.202)***	0.909	(0.062)***	1.248	(0.021)***
Obs	45,956		18,222		13,152		3,165		21,586		58,928	
Firms	6,352		1,683		1,152		255		2,526		7,090	

Notes: Elasticities are based on coefficient estimates from Equation 3, estimated separately for each subsample, and the estimated factor shares. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3: PED and MES estimates by country of ownership and by trade status

	Foreign owned		Irish owned		Don't trade		Only export		Only import		Export&Import	
PED												
η_{KK}	-0.708	(0.02)***	-0.631	(0.006)***	-0.592	(0.011)***	-0.653	(0.024)***	-0.610	(0.010)***	-0.662	(0.010)***
η_{KL}	0.205	(0.012)***	0.143	(0.004)***	0.128	(0.007)***	0.140	(0.016)***	0.116	(0.006)***	0.176	(0.006)***
η_{KM}	0.478	(0.018)***	0.448	(0.005)***	0.424	(0.008)***	0.478	(0.02)***	0.454	(0.007)***	0.451	(0.008)***
η_{KE}	0.025	(0.002)***	0.039	(0.001)***	0.040	(0.002)***	0.035	(0.004)***	0.039	(0.001)***	0.036	(0.002)***
η_{LL}	-0.684	(0.028)***	-0.468	(0.010)***	-0.370	(0.014)***	-0.445	(0.038)***	-0.433	(0.013)***	-0.589	(0.015)***
η_{LK}	0.454	(0.026)***	0.309	(0.009)***	0.262	(0.014)***	0.309	(0.035)***	0.258	(0.013)***	0.385	(0.013)***
η_{LM}	0.214	(0.025)***	0.149	(0.007)***	0.101	(0.011)***	0.110	(0.03)***	0.169	(0.011)***	0.192	(0.012)***
η_{LE}	0.016	(0.004)***	0.010	(0.001)***	0.008	(0.002)***	0.025	(0.006)***	0.006	(0.002)***	0.013	(0.002)***
η_{MM}	-0.749	(0.025)***	-0.795	(0.008)***	-0.820	(0.014)***	-0.762	(0.029)***	-0.835	(0.012)***	-0.731	(0.012)***
η_{MK}	0.599	(0.022)***	0.669	(0.007)***	0.714	(0.014)***	0.668	(0.028)***	0.693	(0.011)***	0.592	(0.011)***
η_{ML}	0.121	(0.014)***	0.103	(0.005)***	0.083	(0.009)***	0.070	(0.019)***	0.116	(0.007)***	0.115	(0.007)***
η_{ME}	0.030	(0.003)***	0.023	(0.001)***	0.022	(0.002)***	0.023	(0.003)***	0.026	(0.002)***	0.023	(0.002)***
η_{EE}	-1.427	(0.059)***	-1.465	(0.026)***	-1.515	(0.039)***	-1.487	(0.071)***	-1.458	(0.041)***	-1.416	(0.044)***
η_{EK}	0.641	(0.046)***	0.962	(0.025)***	1.061	(0.042)***	0.824	(0.086)***	0.970	(0.033)***	0.854	(0.039)***
η_{EL}	0.183	(0.048)***	0.116	(0.016)***	0.100	(0.026)***	0.274	(0.07)***	0.069	(0.022)***	0.141	(0.024)***
η_{EM}	0.603	(0.059)***	0.387	(0.015)***	0.353	(0.028)***	0.389	(0.048)***	0.419	(0.029)***	0.421	(0.028)***
MES												
σ^m_{KL}	0.889	(0.036)***	0.612	(0.013)***	0.498	(0.019)***	0.585	(0.050)***	0.549	(0.017)***	0.765	(0.02)***
σ^m_{KM}	1.228	(0.041)***	1.244	(0.012)***	1.244	(0.021)***	1.239	(0.046)***	1.289	(0.018)***	1.181	(0.019)***
σ^m_{KE}	1.452	(0.059)***	1.504	(0.027)***	1.555	(0.04)***	1.522	(0.073)***	1.498	(0.042)***	1.451	(0.046)***
σ^m_{LK}	1.163	(0.039)***	0.940	(0.014)***	0.854	(0.022)***	0.961	(0.052)***	0.867	(0.021)***	1.047	(0.021)***
σ^m_{LM}	0.963	(0.043)***	0.944	(0.012)***	0.921	(0.021)***	0.872	(0.048)***	1.004	(0.019)***	0.922	(0.020)***
σ^m_{LE}	1.443	(0.061)***	1.475	(0.026)***	1.522	(0.040)***	1.513	(0.074)***	1.465	(0.042)***	1.429	(0.045)***
σ^m_{MK}	1.307	(0.039)***	1.299	(0.013)***	1.306	(0.023)***	1.321	(0.048)***	1.302	(0.020)***	1.255	(0.02)***
σ^m_{ML}	0.805	(0.037)***	0.571	(0.012)***	0.453	(0.020)***	0.515	(0.049)***	0.549	(0.017)***	0.705	(0.020)***
σ^m_{ME}	1.456	(0.06)***	1.489	(0.026)***	1.537	(0.040)***	1.510	(0.071)***	1.484	(0.042)***	1.439	(0.045)***
σ^m_{EK}	1.349	(0.048)***	1.593	(0.026)***	1.653	(0.045)***	1.477	(0.088)***	1.579	(0.037)***	1.516	(0.041)***
σ^m_{EL}	0.867	(0.057)***	0.585	(0.019)***	0.471	(0.03)***	0.719	(0.084)***	0.503	(0.026)***	0.730	(0.029)***
σ^m_{EM}	1.352	(0.067)***	1.182	(0.018)***	1.173	(0.032)***	1.151	(0.061)***	1.254	(0.031)***	1.152	(0.033)***
Obs	11,213		69,301		18,909		21,843		4,938		34,824	
Firms	1,194		8,482		3,801		4,360		1,110		4,095	

Notes: Elasticities are based on coefficient estimates from Equation 3, estimated separately for each subsample, and the estimated factor shares. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4: PED and MES estimates over time

	1991-1995		1996-2000		2001-2005		2006-2009	
PED								
η_{KK}	-0.772	(0.018)***	-0.738	(0.008)***	-0.598	(0.010)***	-0.500	(0.020)***
η_{KL}	0.202	(0.008)***	0.149	(0.006)***	0.178	(0.006)***	0.245	(0.009)***
η_{KM}	0.515	(0.015)***	0.549	(0.007)***	0.396	(0.008)***	0.235	(0.018)***
η_{KE}	0.055	(0.006)***	0.040	(0.002)***	0.024	(0.001)***	0.021	(0.004)***
η_{LL}	-0.499	(0.019)***	-0.531	(0.012)***	-0.419	(0.013)***	-0.487	(0.014)***
η_{LK}	0.542	(0.022)***	0.319	(0.012)***	0.343	(0.011)***	0.469	(0.016)***
η_{LM}	-0.050	(0.023)**	0.199	(0.010)***	0.064	(0.012)***	0.003	(0.016)
η_{LE}	0.008	(0.003)***	0.014	(0.002)***	0.012	(0.002)***	0.015	(0.003)***
η_{MM}	-0.910	(0.015)***	-0.898	(0.010)***	-0.618	(0.012)***	-0.345	(0.026)***
η_{MK}	0.844	(0.024)***	0.742	(0.009)***	0.546	(0.012)***	0.323	(0.025)***
η_{ML}	-0.031	(0.014)**	0.125	(0.006)***	0.046	(0.008)***	0.002	(0.011)
η_{ME}	0.097	(0.009)***	0.031	(0.001)***	0.026	(0.002)***	0.020	(0.005)***
η_{EE}	-2.606	(0.223)***	-1.685	(0.065)***	-1.273	(0.062)***	-1.163	(0.120)***
η_{EK}	1.221	(0.127)***	0.969	(0.043)***	0.631	(0.036)***	0.559	(0.096)***
η_{EL}	0.063	(0.025)**	0.157	(0.018)***	0.154	(0.021)***	0.214	(0.038)***
η_{EM}	1.323	(0.123)***	0.559	(0.026)***	0.487	(0.038)***	0.390	(0.101)***
MES								
σ^m_{KL}	0.701	(0.024)***	0.680	(0.017)***	0.597	(0.017)***	0.733	(0.020)***
σ^m_{KM}	1.425	(0.028)***	1.448	(0.016)***	1.013	(0.019)***	0.579	(0.043)***
σ^m_{KE}	2.661	(0.228)***	1.725	(0.066)***	1.297	(0.063)***	1.184	(0.122)***
σ^m_{LK}	1.313	(0.037)***	1.057	(0.018)***	0.941	(0.019)***	0.970	(0.031)***
σ^m_{LM}	0.860	(0.029)***	1.097	(0.018)***	0.682	(0.020)***	0.348	(0.035)***
σ^m_{LE}	2.614	(0.223)***	1.699	(0.065)***	1.284	(0.062)***	1.179	(0.120)***
σ^m_{MK}	1.615	(0.040)***	1.480	(0.016)***	1.143	(0.020)***	0.823	(0.043)***
σ^m_{ML}	0.468	(0.028)***	0.657	(0.016)***	0.465	(0.019)***	0.490	(0.021)***
σ^m_{ME}	2.704	(0.231)***	1.716	(0.066)***	1.299	(0.064)***	1.183	(0.123)***
σ^m_{EK}	1.992	(0.128)***	1.706	(0.044)***	1.229	(0.037)***	1.059	(0.101)***
σ^m_{EL}	0.561	(0.032)***	0.689	(0.021)***	0.573	(0.026)***	0.702	(0.042)***
σ^m_{EM}	2.233	(0.114)***	1.457	(0.028)***	1.105	(0.040)***	0.735	(0.108)***
Obs	19,929		21,544		21,646		17,395	
Firms	4,865		5,626		5,470		5,537	

Notes: Elasticities are based on coefficient estimates from Equation 3, estimated separately for each subsample, and the estimated factor shares. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5: PED and MES estimates from a fully-constrained cost function

	Capital		Labour		Materials		Energy
PED:							
η_{KK}	-0.621	η_{LK}	0.368	η_{MK}	0.604	η_{EK}	0.922
	(0.006)***		(0.008)***		(0.007)***		(0.022)***
η_{KL}	0.168	η_{LL}	-0.705	η_{ML}	0.214	η_{EL}	0.168
	(0.004)***		(0.008)***		(0.005)***		(0.018)***
η_{KM}	0.415	η_{LM}	0.322	η_{MM}	-0.840	η_{EM}	0.375
	(0.005)***		(0.007)***		(0.008)***		(0.016)***
η_{KE}	0.037	η_{LE}	0.015	η_{ME}	0.022***	η_{EE}	-1.464
	(0.001)***		(0.002)***		(0.001)***		(0.026)***
MES:							
σ^m_{KL}	0.874	σ^m_{LK}	0.989	σ^m_{MK}	1.225	σ^m_{EK}	1.543
	(0.011)***		(0.013)***		(0.013)***		(0.023)***
σ^m_{KM}	1.256	σ^m_{LM}	1.163	σ^m_{ML}	0.919	σ^m_{EL}	0.873
	(0.012)***		(0.0123)***		(0.011)***		(0.020)***
σ^m_{KE}	1.501	σ^m_{LE}	1.486	σ^m_{ME}	1.486	σ^m_{EM}	1.215
	(0.027)***		(0.027)***		(0.027)***		(0.019)***

Notes: Elasticities are based on coefficient estimates from a fully-constrained cost function in which we impose homogeneity of the production function and constant returns to scale. Standard errors, calculated using the delta method, are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Variable definitions:

$foreign_f$ Dummy equal to 1 if the firm's ultimate beneficial owner is located outside Ireland.

IND_{gf} Dummy variable equal to 1 if firm f is in NACE 2-digit industry g, and zero otherwise.

$Trade_f$ Trade orientation. We control for a firm's trade orientation based on whether it does not trade (i.e. neither exports nor imports), exports only, imports only, or both exports and imports.

K_f Capital stocks. Expenditure on capital is recorded in the CIP. 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 δ_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 (CSO, 2009a). 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.[10]

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, 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 use. 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.

P_e Price of energy. We create an aggregate energy price variable by weighting the price of oil, gas and electricity, as given by the IEA (IEA, 2011) for Ireland, by industry-level energy use data (in TOE), by energy type, from SEAI's Energy Balances (SEAI, 2012).

[10]We thank Kieran Culhane of the CSO for providing capital stocks at NACE 2-letter level.

L_f Labour inputs. 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.

M_f Material inputs. 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. Weights based on the 1998 I-O table should be appropriate for our purposes as this is approximately mid-way through the data period we use. The formula used to calculate the deflator for material inputs (ESRI, 2012) is as follows:

$$\begin{aligned}&PriceDeflator_{Materials} = PriceDeflator_{Agri} * IOWeight_{Agri} + PriceDeflator_{HiTech} *\\ &IOWeight_{HiTech} + PriceDeflator_{Trad} * IOWeight_{Trad} + PriceDeflator_{Food} * IOWeight_{Food} +\\ &VADeflator_{Distribution} * IOWeight_{Distribution} + VADeflator_{T\&C} * IOWeight_{T\&C} +\\ &VADeflator_{P\&FServices} * IOWeight_{P\&F} + Deflator_{Imports} * IOWeight_{Imports}\end{aligned} \tag{.1}$$

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 tables. We have three input-output tables for our sample period, we use the input-output table for 1998 (CSO, 2004) for the period up to and including 1998. We use the input-output table for 2000 (CSO, 2006) for the period 1999-2002 and the input-output table for 2005 (CSO, 2009b) from 2003 onwards. 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 €1000 deflated using wholesale/producer price indices at the 2-3 digit NACE (Rev. 1.1/Rev. 2) level.

Note: Unless otherwise noted, 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 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. Parts of our analysis require 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 there are up to 21 potential matches from the new to the old classification; however, for most of these firms there are only two or three possible matches. To these firms 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.