Interfuel Substitution and Technical Change in the US Electricity Generating Industry Under the Tradable Sulphur Allowance Scheme: 1990–2004

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Abstract

This paper uses monthly firm-level data to characterize fuel choice and technical change in the US electricity generating industry under the tradable sulphur allowance program. We use data covering the years 1990–2004 in a flexible translog cost function model to determine demand and substitution elasticities for the three main fossil fuel inputs (coal, oil, and natural gas) and the rate and direction of technical change. Capital is assumed fixed, implying a short run analysis. Three variable cost models are presented: one including three fuel inputs which incorporates the sulphur allowance price into the fuels' relative input prices, one with four inputs (three fossil fuels plus sulphur permits) which assumes firms treat allowances as a separate input of their own right, and a third that excludes allowance prices from the cost model. Model 1 is shown to fit the data slightly better, and firm heterogeneity is shown to be present. The interfuel substitution elasticities and technical change estimates presented are therefore based on the fixed effects seemingly unrelated regression (SUR) estimation of Model 1's restricted variable cost function and associated fuel cost share equations.

Introduction

Because of the fuel-specificity of much of the combustion capital for electricity generation, the putty-clay argument[1] is often made about input choice in the industry, and short run fuel use in response to cap-and-trade allowance schemes becomes a question. The conclusions of Tuthill (2008a) and Blyth et al. (2007), namely that uncertainty in environmental policy leads to a delay and reduction in capacity investment, and particularly in *clean* capacity investment, combined with Ellerman's (1998) observation of the 'seemingly indefinite' life-extension of US power plants, highlight the importance of the short run impacts of emissions policy. The goal of this research is therefore to enhance understanding of short run interfuel substitution in the US electricity generating industry under the sulphur dioxide (SO_2) scheme described in Section 2.

As noted, technology in electricity generation is often assumed to exhibit putty-clay characteristics, and interfuel substitution is often treated as negligible and/or a strictly *ex ante* issue related to capital-choice. In order to reduce market risk factors, however, electricity generating firms generally own a number of different plants with a variety of generating units. These are seldom, if ever, operated at full capacity because of state-level generating reserve margin requirements, and the incentive that high prices during times of high demand provide for excess capacity. Söderholm (1997, 1998, 2000) thus notes the flaws in this putty-clay line of reasoning and states that *ex post* interfuel substitution is possible through three avenues when the question is addressed from the firm-level rather than the plant- or aggregate-level: within-unit substitution at multi-fuel plants, between-unit substitution via changes in merit order dispatch, and low cost changes to the capital stock that give single-fuel units multi-fuel capabilities. Thus a cost-minimizing electricity generating firm *does* have the ability to change its fuel input usage in response to changes in relative fuel price in the short run, and our aim is to characterize the short run fuel-use decisions in an industry facing SO_2 emission prices.

[1] The argument states that fuel choice is completely flexible until the point of capital investment, but that the fuel mix with a given capital stock is effectively inflexible.

We will show in our discussion of the dataset in Section 4 that the differing characteristics of the fossil fuels combusted in steam electric generation translate into differential price effects under tradable emissions schemes, and we incorporate this effect into an analysis of short run interfuel substitution in US electricity generation. Our objective is to determine the extent and direction of fuel substitution possibilities in order to analyse the fuel-choice effects of market-based environmental policy on fossil fuel input demands. To accomplish this, we use estimated cost function parameters to calculate interfuel substitution elasticities and technical change. We focus on the effects of the tradable sulphur permits established in the USA in 1995 by the Clean Air Act Amendments (CAAA) of 1990, though the methodology has wider applications. We assume that electricity generating firms operate with the objective of cost minimization[2,3], and as such, they react to changes in relative input prices.

The first portion of our research is concerned with correctly specifying the cost function model. The fossil fuel inputs we focus on are coal, petroleum and natural gas.[4] In Model 1, we construct fuel prices so that they incorporate the effects of environmental policy (i.e. emissions prices) and they have two distinct components. One is the fuel's standard market price (¢/mmBtu) whose effects have been studied extensively. The other is the price associated with the fuel's emissions, which depends upon the cost of emissions ($ per ton of SO_2 in the case of sulphur allowances), the quality of the fuel (sulphur content per unit of heat input), the emissions conversion factor of the firm's combustion unit, and firm-specific characteristics (percentage of capacity falling under regulation, percentage of capacity covered by scrubbers, etc.). These components are discussed further in Section 4. Model 2 separates the SO_2 price from the Btu price and considers allowances as a fourth and separate input. Model 3 excludes the SO_2 price entirely, considering only the delivered thermal price of the fuels. We find the data fits the first model best, indicating that the SO_2 price did, indeed, alter firms' cost minimizing behaviour, and we therefore proceed with this model to analyse our data from both a pooled and fixed effect perspective for the full period (1990–

[2] Note that Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) are responsible for balancing the grids. These organizations (effectively the same, except that an RTO generally covers a larger area and may cross state borders) take supply bids from firms and accept them in an ascending manner (i.e. cheapest power gets put through first). Thus, generating firms (utilities and non-utilities) are competing against others under the same grid jurisdiction and, assuming no gaming or collusion, would therefore want to minimize costs. I am grateful to Malcolm Keay for a discussion on this point.
[3] We do not claim firms are necessarily successful in attaining these cost-minimizing objectives. This is discussed further in Tuthill (2008b).
[4] We have aggregated to the fuel-type level, though we note that much of the fuel-switching that occurred as a result of the SO_2 scheme was from high-sulphur sub-bituminous coal to lower-sulphur bituminous coal. See, e.g., Ellerman et al. (2000).

2004), and for three five-year intervals: 1990–1994, 1995–1999 and 2000–2004, representing the period prior to the SO_2 scheme, Phase I and Phase II, respectively.

Once the issues of model fit and selection have been dealt with, the panel nature of our dataset suggests several modelling considerations related to stationarity and firm heterogeneity. After addressing these, we proceed with a fixed effects formulation of Model 1 and estimate a system of equations (namely the translog variable cost function and fuel cost share equations) using the iterated seemingly unrelated regression (ITSUR) methodology. We present results related to derived demand and interfuel substitution elasticities for our three fossil fuel inputs, as well as the magnitude and direction of technical change.

As noted, the dataset covers the years 1990–2004 and includes monthly cost and fuel consumption data on 37 electric utilities. We lack reliable capital price data, so we assume weak separability of the cost function, and analyse instead a restricted short run variable cost function that includes capital as a quasi-fixed quantity variable such that firms are assumed to minimize variable costs conditional on capital quantities.[5] This corresponds to cost-minimization over the fossil fuel input subset, subject to the quantity of capital[6], meaning that our analysis is short run in nature. Some capital adjustment is sure to have occurred across the period, though Hansen (1998) found most steam electric generating units have a life of 30–40 years and Ellerman (1996 and 1998) noted the 'seemingly indefinite' extension of plant lives. This, combined with our own findings related to investment delay under policy uncertainty (see Tuthill (2008a)), indicates the short run nature of this study does not appear inappropriate.

The remainder of this paper is organized as follows: Section 2 provides background on the US electricity generating industry and the tradable sulphur scheme established by the Clean Air Act Amendments of 1990. We then provide a review of the applied production analysis methodology and the related literature in Section 3, after which we describe our dataset (Section 4), and then present our models in Section 5. We discuss model selection in Section

[5] Capital stock levels may not, in fact, be at their long run optimal levels, particularly given that the industry was heavily regulated through the early 1990's. It may also be true that the optimal capital stock prior to environmental regulation differs from the optimal capital stock after environmental regulation, as noted in Tuthill (2008b). We acknowledge these points, but continue with the weak-separability assumption, as we lack reliable capital price data.
[6] The restricted cost function approach is related through duality to the restricted profit function introduced by Samuelson (1953–1954), Lau (1976), and McFadden (1978). See also Halvorsen and Smith (1986).

6 and panel issues in Sections 7 and 8 which address the issues of pooling vs fixed effects and panel unit roots, respectively. Several technology-related modelling hypotheses are tested in Section 9. We present our elasticity estimates in Section 10, followed by technical change estimates in Section 11, and finally the predicted fuel demand responses to hypothetical policy scenarios in Section 12. Section 13 concludes.

2 Industry and Policy Background

2.1 Current Industry Overview

According to the Energy Information Administration (EIA), net electricity generation in the United States in 2006 totalled 4,065 million megawatt-hours (MWh), 70.6 per cent of which was generated through the combustion of fossil fuels.[7] Of the fossil fuels, coal plays the largest role in generation, followed by natural gas and then petroleum, with each representing 70 per cent, 28 per cent, and 2 per cent of 2006's total net generation, respectively[8] (EIA, 2007a).

While the progress and effectiveness of the deregulation of the US electric power industry is not the focus of this research, the cost-minimising assumption made below is partly justified by the fact that deregulation has led to increased competition within the industry. Historically, the American electric power industry was dominated by vertically-integrated investor-owned electric utilities that were granted a regulatory area within which they would provide all generation, transmission, distribution, and retail energy services. The Public Utilities Regulatory Policies Act (PURPA) – originally passed by Congress in 1978 to encourage generation from renewable sources – however, opened the market to qualifying non-utility Independent Power Producers (IPPs), forcing electric utilities to purchase power from these IPPs at avoided cost.

Competition was augmented with the Energy Policy Act of 1992, when Congress voted to increase competition in the bulk power markets, and in 1996, the Federal Energy Regulatory Commission (FERC) implemented Orders 888 and 889 to execute the intentions of the Energy Policy Act. The goal was to increase competition in the wholesale electricity market, and to provide more efficient and lower cost electricity to the nation (EIA, 'Restructuring'). These relatively new competitive pressures within the industry are forcing power plant operators to reduce their construction and operating costs as they try to increase profits and

[7] Nuclear provided 19.4 per cent of total net generation and hydro provided 7per cent. The remainder was generated through other renewables (mostly biomass and municipal solid waste).
[8] Note that petroleum's contribution to net generation fell by over 50per cent in 2006 because of increasing oil prices that year.

protect their market shares (see Beamon and Leckey (1999), Considine (1999) and Hansen (1998)). Orders 888 and 889 prompted state-level restructuring within the wholesale markets, which led to the more diverse structure seen within the industry today. Approximately 35 per cent of 2006's net generation was generated by IPP and CHP power plants, while approximately 65 per cent was generated by electric utility plants (EIA, 2007a).

Electric power plants seldom, if ever, operate at their full capacity, making it unsurprising that the net summer capacity in 2006 was significantly greater than the amount required for the year's total net generation at 986,215 megawatts (MW). Of that, 312,950 MW were attributed to coal-fired units, 58,097 MW to petroleum plants, 388,294 MW to natural gas and natural gas dual-fired units, 100,334 MW to nuclear plants, 77,821 MW to hydroelectric plants, and 24,113 MW to other renewables. (EIA, 2007a)

It is obvious, then, that fossil fuel combustion plays a major role in meeting the growing energy demand in the United States, despite its negative environmental externalities. Coal continues to be the most prevalent, though generation through its combustion produces more carbon dioxide (CO_2), sulphur dioxide (SO_2) and nitrogen oxides (NO_x) than any other fossil fuel, both because of coal's high sulphur and carbon content, and the quantity of coal combustion units across the country (EIA, 'Elec. Pwr. Indust.', Ch. 6). After the Organization of the Petroleum Exporting Countries (OPEC) oil embargo of 1973, coal-fired generation became even more important, and the passage of the Power Plant and Industrial Fuel Use Act and the Natural Gas Policy in 1978 encouraged additional coal use by the electric industry (EIA, 'Elec Pwr. Indust.', Ch. 3). Despite its dirty environmental qualities, coal-fired generation accounts for 49.8 per cent of total generation, and its delivered price has generally fallen over the 15 year period covered by our dataset (EIA, 2006). [9,10] Much of coal's favoured position within the electricity generating industry is due to the fact that coal plants are the cheapest and most profitable plants to operate, particularly in the absence of environmental regulation. In 2006, coal's average price per mmBtu[11] was just 169 cents, or 24 per cent of that for natural gas, whose average price was 694 cents per mmBtu, and 27 per cent of petroleum's price of 623 cents per mmBtu (EIA, 2007a).

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[9] See Section 4 for a description of the dataset.

[10] Coal generally comes from one of three regions in the US: the Appalachian Region, the Interior Region and the Western Region. The delivered cost of coal can vary state to state depending on 1) extraction costs, 2) the firm's proximity to the extraction site, and 3) State-level environmental restrictions on the coal-types power plants are permitted to burn. (EIA, 'Elec. Pwr. Indust.', Ch. 4 and EIA, 2007a)

[11] Note that mmBtu stands for one million British thermal units, a measure of heat input.

Petroleum is currently employed in less than 5 per cent of electricity generation, though it was used much more extensively during the early 1970's. The increased petroleum prices following the 1973 OPEC oil embargo and the Iranian revolution in 1979 and 1980 caused utilities to reduce their construction of large petroleum-fired generating units, and the firms that did use petroleum as a major input often converted their steam units to coal (EIA, 'Elec. Pwr. Indust.', Ch. 3). Most of the utilities that continue to use petroleum in electricity generation are located in New England, New York, Florida, and Hawaii, and the majority of the petroleum that these firms use is heavy petroleum, of number 4, 5, or 6. These are lower-grade fuels than number 2, light oil, which is more expensive, and thus employed less frequently. The delivered cost of petroleum varies from state to state, though the higher the fuel grade, the higher the delivered cost of the fuel (EIA, 'Elec. Pwr. Indust.', Ch. 4).

As for natural gas, demand by electric utilities has often taken second priority to the demand for home heating and for commercial and industrial use. Up until the mid 1980's, there was no conventional natural gas market in the United States, and the series of federal price regulation attempts led to inefficiency and shortages. There were times during the 1970's, most notably the winter of 1976–1977, when utilities were actually denied natural gas when the pipelines serving heating demands reached capacity during winter months. The interstate price structure for natural gas was attractive, but the supply was unreliable, and so utilities used the less expensive gas when it was available, and switched to more expensive fuels when it was not.

With the passage of the Natural Gas Policy Act in 1978, natural gas became more available to electric utilities, and the repeal of the Industrial Fuel Use Act in 1987 created the opportunity to again construct gas-fired generation units (EIA, 'Elec. Pwr. Indust.', Ch. 3). This, combined with the establishment of a natural gas market in the USA through the Federal Energy Regulatory Commission's (FERC) Order 452 in 1985, a series of intervening orders, and Order 636 in 1992, has made natural gas a viable option in generating technologies (VanVactor (2004)). The West South Central Census Division and California have readily accessible supplies of natural gas, and it is piped in large volume to the Middle Atlantic and South Atlantic Census Divisions. Electric utilities use the most natural gas during the summer months, when electricity demand is high and natural gas demand for heating purposes is low. Despite availability, gas consumption for electricity generation can vary annually, as some firms switch from gas to petroleum in dual-fired generating units, while fuel prices change and environmental regulations are imposed. As a cleaner-burning fuel, natural gas is often used in preference to other fossil fuels, to comply with environmental regulations (EIA, 'Elec. Pwr. Indust.', Ch.4).

Thus, coal and natural gas are the industry's biggest fossil-fuel inputs; coal for its low relative price per Btu of heat input, and natural gas for its characteristics as a cleaner-burning fossil fuel.[12] Nuclear power is a relatively efficient source of a large quantity of energy, and produces no (or negligible) atmospheric emissions, and while it represents the second largest portion of current net generation, there has not been a new nuclear facility constructed in the USA since 1979. Hydroelectricity provides a small but significant portion of the nation's net generation, but construction of new hydro plants is difficult, given the location and river flow requirements. As for other renewable fuels (solar, wind, biomass, etc.), the costs involved with electricity generation via their use are basically too high relative to those of fossil fuel generation for a firm to choose renewable generation in the absence of environmental regulation (Hansen, 1998).

Given the prevalence of fossil fuel generation and its environmental impacts, the research in this thesis is concerned with the firm-level responses of electric utilities to market-based environmental policy. We discuss the SO_2 scheme in the following section and note that knowledge of its implementation is useful in understanding the models, and assumptions in the models presented below.

2.2 Emissions Regulation in the USA: The Case of the Clean Air Act

The Clean Air Act (CAA) was originally passed in 1963, and focused on the reduction of SO_2 and NO_x emissions, because of their responsibility for the acid deposition problem in the USA. The purpose of this section is simply to describe the history and implementation of the CAA, as the resulting cap-and-trade SO_2 scheme is directly relevant to the models below.

[12] Gas-fired plants are also favourable for their shorter construction time and faster start-up times, making them a common choice for peak load generation.

At the outset, and up until 1990, the emissions regulations of the CAA were all of the command-and-control type. In 1970, the Environmental Protection Agency (EPA) was granted the power to establish enforceable air quality standards, and in 1971, the Agency established New Source Performance Standards (NSPS). The NSPS permitted coal-fired utility boilers built after 17 August 1971 to emit no more than 1.2 lbs of SO_2 per million Btu of heat input.[13] NO_x requirements were less rigid, as they allowed from 0.2 to 0.9 lbs per million Btu, depending on the fuel input and the combustion technology employed. The CAA was amended in 1977 to require that States establish limits on existing pollution sources in regions not attaining the goals of the original Act. In 1979, the EPA established the Revised New Source Performance Standards (RNSPS), which retained the provisions of the NSPS, but required that all new or modified boilers reduce SO_2 emissions by 90 per cent, unless such a reduction would bring emissions below 0.6 lbs per million Btu, when a 70–90 per cent reduction is acceptable. The CAA was again amended in 1990 to create America's first national, long-term environmental programme based around the trading of emissions permits. It is this amendment that will be important for our analysis.

Title IV of the CAA Amendments of 1990 (CAAA 1990) prescribed a 10 million ton reduction in SO_2 emissions and a 2 million ton reduction in NO_x emissions by electric utilities from 1980 levels, with an ultimate annual cap of 8.95 million tons of SO_2 by the year 2010 (Burtraw et al. (2005)). The programme has been implemented in two phases to achieve these reductions. The first, Phase I, covering the years 1995 to 1999, identified and capped the emissions of 263 'Table A' units, the dirtiest generating units in the USA which accounted for 17 per cent of capacity in 1990 (Schmalensee et. al., 1998). Phase II, which began in 2000, brought almost every new and existing fossil fuel generating unit in America under tighter emissions standards. To accomplish these emissions reductions, Title IV established a market-based tradable permit system that deviated quite radically from the more prevalent command-and-control alternatives.

The permits (or allowances) are, and have been, allocated at no cost to the owners of the units regulated under Phase I and Phase II. Each represents the right to emit one ton of SO_2, and each has a specific year, called its vintage, during which it can first be used as an emissions right. Once a firm has been allocated its permits, it is free to sell them, use them, or bank

[13] This effectively required the installation of flue gas desulphurization (FGD) systems, or 'scrubbers', as this was the only means of attaining the performance standard. (Burtraw et al. (2005)).

them for future use or sale.[14] In order to encourage the development of a permit market, Title IV implemented allowance auctions to be managed by the EPA. The goal of Title IV, then, was to maximize economic efficiency, subject to the chosen environmental standards through the use of a free market for emissions permits, allowing firms to choose their own least-cost emissions reduction methods. For more details on the trading and auctioning of SO_2 permits, see Joskow et al. (1998) or EPA (July 2000).

Before the permit scheme had been implemented, there was a wide range of estimates as to what the market price of the allowances would actually be, with some figures as high as $1,500 (Insley, 2003). In 1990, the EPA provided $750 as their best estimate of what the permits would cost (Bohi and Burtraw (1997)). After the first inter-utility trades were recorded in 1992 at prices between $250 and $300, the Electric Power Research Institute predicted in 1993 that under favourable trading conditions, the equilibrium allowance price would be approximately $273 (Montero and Ellerman, 1998). In reality, the allowance price began around $150 per ton and fell to $70 in 1996, mostly due to the accessibility of low sulphur coal made possible by rail deregulation in 1990. (See, e.g., Montero (1998)). Prices rose again, and generally stayed between $100 and $220 per ton until 2003, when they began rising. By the end of 2004, allowances had reached $700 per ton because of increased demand for coal-fired generation, as both electricity demand and natural gas prices rose (Burtraw et al. (2005)).

What has made the tradable permit scheme so appealing, compared to more standard command-and-control policies, is the promotion of efficiency through the establishment of a free allowance market. Here, the firms with the lowest marginal abatement costs are capable of choosing to reduce their emissions in favour of either banking or selling their permits, while those firms with higher marginal abatement costs are able to purchase the permits they require for their emissions on the allowance market. The ability of firms to select individual abatement methods has proven to be very important in the electricity generation industry, as deregulation has caused increases in competition over the past two decades, and cost minimization has become increasingly important.

[14] Burtraw et al. (2005) note that trading has been significant, with peak trading volume reached in 2000 at nearly 15 million allowances. Approximately 8 million allowances changed hands in 2003. See Ellerman et al. (2000) and Ellerman and Montero (2005) for a discussion of allowance trading and banking under the SO_2 scheme.

The political success, academic justification, and economic efficiency achievements of the allowance trading scheme of Title IV of the Clean Air Act provided motivation for the design of the European Union's CO_2 emissions trading scheme (EU ETS). While the necessity for emissions regulation is well understood and the theoretical superiority of market-based instruments for this purpose has been well documented, these policies do not operate in a vacuum, and firm response has not been extensively studied. We focus on the effects of the tradable SO_2 permit scheme in the USA because of the existence of a reasonable panel of data not yet available for the EU ETS.

3 Methodology and Literature Review[15]

The methodology employed in this paper finds much of its grounding in the KLEM (capital, labour, energy and materials) studies of the 1970s.[16] These studies generally focused on the manufacturing industry, and concerned themselves with the substitution between energy and non-energy inputs, and were motivated by the fuel shocks of the 1970s. As noted by Söderholm (1998), the seminal interfuel substitution articles[17] took the dual approach and estimated the flexible translog cost function and assumed weak separability of the inputs, which is the method we use here. This allows the cost minimizing decision to be modelled in two separate steps: one in which the fuel choices are made to minimize variable costs, and a second in which aggregate input choices are made in order to minimize total costs. As fuel demand and substitution elasticities are our concern, we focus on the first half of this procedure.

While the weak separability assumption and the use of the flexible translog functional form have appeared previously in the literature, our study differs from previous work in several ways. First, we explicitly address the short run vs. long run issue,[18] stating that our analysis focuses on short run, or possibly intermediate,[19] interfuel substitution, despite having pooled time series data. Previous studies often assume zero short run interfuel substitution, and focus on within-plant long run substitutability using plant-level time-series data. Some also explicitly model costly capital adjustment in a dynamic specification. Because of the complications involved, the lack of capital cost data, and the difficulties associated with the translog specification in a dynamic setting (see Griffin (1995)), we focus on fuel use, and do not explicitly incorporate dynamics into our model – another reason that our analysis can be interpreted as providing short run results. Second, we explicitly incorporate the price of SO_2

[15] Söderholm (1998 and 2000) provide good reviews of previous studies relating to electricity generation.
[16] See, e.g., Berndt and Wood (1975) and Halvorsen (1977). See Hartman (1979) for a review of similar papers and methodologies.
[17] Hudson and Jorgenson (1974), Fuss (1977), and Pindyck (1979).
[18] Söderholm (2000) notes that many previous studies leave this distinction ambiguous and/or rely on ad-hoc interpretations in order to present long run estimates. E.g. Griffin and Gregory (1976), Uri (1977), and Ball and Loncar (1991).
[19] Söderholm (1999 and 2000) notes that Haimor discusses intermediate interfuel substitution in US electricity generation in his 1980 Ph.D. thesis, using panel data.

emissions as determined by the permit prices under the CAAA 1990.[20] Third, the panel nature of our data allows us to incorporate firm fixed effects, thereby accounting for firm-specific differences not captured by the model. Finally, our analysis focuses on firms that have the capacity to generate using all three of the fossil fuel aggregates, but without hydro or nuclear capacity. This allows a greater understanding of short run fossil fuel substitutability.

The estimation issues, then, can be separated as follows: functional form, time horizon, dataset and methodology (cross section, time series, panel, etc), geographical and/or industry considerations, and explanatory variable inclusion. These issues will be highlighted throughout the review of previous studies. First, however, we provide a general background discussion of applied production analysis.

3.1 Applied Production Analysis[21]

The goal of applied production analysis, whether through the estimation of production, cost, profit, or distance functions, is the characterization of the underlying production technology – the technical constraints on the producer's decisions for a given production process. In electricity generation, the range of emissions and input/output ratios are constrained by installed capital, but exact input and output values for each unit remain flexible.[22] The production function represents the relationship between possible efficient input combinations and feasible output quantities, and is a useful representation of technology, but it contains no economic information. Thus, the single output production function,

$$y = f(x_1, ..., x_n) \qquad \textbf{Equation 1}$$

where y is the quantity of the single output and the x_i s are quantities of each of the n inputs, is strictly a technical relationship. We perform our analysis with a cost function rather than a production or distance function because of the exogeneity of the regressors in the cost

[20] Söderholm (1998 and 2000) note the importance of the inclusion of environmental regulations in cost function analyses, but the only previous study we are aware of that includes such a measure is Söderholm (2000), which includes a 'regulatory intensity' variable in a Generalized Leontief cost function in its analysis of Western European interfuel substitution.

[21] Much of the information in this section comes from Chambers (1988) and Cornes (1992), who provide excellent and detailed overviews of production analysis and duality.

[22] Total output, however, is exogenous as necessitated by grid-balancing requirements for matching consumer demand with output at all times.

function setting, and because of our focus on the effects of the SO_2 price on interfuel substitution. Elasticities are easier to calculate from cost functions, as are the cost share equations and the derived demands for inputs.

Cost Minimization

Economic information is introduced to production analysis through the cost function. Under the assumption of cost minimization and a given output level, it can be shown that a cost function dual to the production function Equation 1 exists and takes the form:

$$c(p, y) = \min_{x \geq 0} \left\{ \sum_i p_i x_i \middle| \vec{\mathrm{x}} \in V(y) \right\} \qquad \textbf{Equation 2}$$

where p_i are input prices, x_i are input quantities **x** is the vector of inputs, and $V(y)$ is the input requirement set for output y. Thus, the cost function depends on the underlying technology, and contains the economic information absent from the production function, making clear that the cost-minimizing input combination depends on factor prices (p_i) and the given output quantity (y). The use of duality theory and the analysis of cost-minimizing behaviour therefore provide information about the underlying technology and the possibilities for input substitution.

Properties of the Cost Function[23]

Assuming that the input requirement set $V(y)$ is non-empty and closed, and that the production function, Equation 1, satisfies the properties of monotonicity and weak essentiality, is finite, nonnegative, real-valued, and single-valued for all non-negative and finite input combinations, the cost function exists and has the following properties:

C.1) Non-negativity: $c(p, y) > 0$ for $p > 0$ and $y > 0$

C.2) No fixed costs[24]: $c(p, 0) = 0$

C.3) Monotonicity in y: if $y' \geq y$, then $c(p, y') \geq c(p, y)$

[23] See Samuelson (1948) and Shephard (1953) for the seminal works on cost functions and their analysis, and Chambers (1988, Chapter 2) for a discussion and proofs of the cost function's properties mentioned here.

[24] This property is relevant in a long run setting when all inputs are variable. Our analysis is short run, though we assume the cost function is weakly separable, which allows us to focus only on fossil fuel variable costs. Thus, despite our short run focus, our variable cost function exhibits zero fixed costs.

C.4) Monotonicity in p: if $p' \geq p$, then $c(p', y) \geq c(p, y)$

C.5) Concavity and continuity in p

C.6) Positive linear homogeneity: $c(\lambda p, y) = \lambda c(p, y)$

In addition to these, the cost function has the famous additional property of Shephard's Lemma which is exploited extensively in the examination of interfuel and interfactor substitution. When the cost function is differentiable in price, Shephard's Lemma states that a unique cost-minimizing vector of factor demands, **x**, exists and is equal to the first derivative of $c(p, y)$ with respect to input prices. Thus, the seventh property of a well-behaved cost function is:

C.7) Shephard's Lemma: $x_i(p, y) = \partial c(p, y)/ \partial p_i$, where $x_i(p, y)$ is the unique cost-minimizing demand for input i.

The cost-minimizing share equations can be equivalently derived via Shephard's Lemma by taking the derivative of the log of the cost function with respect to the log of P_i. i.e.

$$S_i = \frac{\partial \ln C}{\partial \ln P_i}.$$

Derived Demand for Inputs and Factor Share Equations

It is clear from Shephard's Lemma that input demand responses to changes in relative input prices will be reflected by the Hessian matrix of the cost function. It is also clear that the properties of these factor demands (or share equations) and of the Hessian itself will depend on the properties of the cost function outlined above. Property C.5 implies that the Hessian will be negative semidefinite, which, in addition to the implications of C.6, leaves us with the following properties for well-behaved input share equations:[25]

X.1) Homogeneity of degree zero in factor prices: $S_i(\lambda p, y) = S_i(p, y)$

X.2) Negative own-price effects: $\partial S_i(p, y)/ \partial p_i \leq 0$

[25] See Chambers (1988) Chapter 2 for proofs and further discussion.

X.3) Symmetric cross-price effects: $\partial S_i(p, y)/ \partial p_j = \partial S_j(p, y)/ \partial p_i$. [26]

The concepts of input demand and substitution elasticities follow from these properties and are discussed in Section 9.

3.2 Functional Form

As seen in Equation 2 above, the cost function derives from the production technology, in the sense that the cost-minimization problem is constrained by the requirement that inputs x are capable of producing at least output y. (See Chambers (1988).) Different assumptions about the underlying technology are therefore reflected in the cost function, and the choice of functional form becomes important in an applied setting. For example, cost functions associated with a Leontief technology assume fixed input combinations and no substitution, while those associated with a Cobb–Douglas technology allow for input substitution, but require a substitution elasticity of unity. The Constant Elasticity of Substitution (CES) production and (associated cost) function allows input substitution but, as the name implies, the elasticities are assumed to be fixed. Given our interest in the fuel-use response of firms to the relative input price changes brought about by the SO_2 scheme, these technologies are clearly too restrictive.

Instead, we use a flexible functional form, the translog, a member of the class of second-order differential approximations, in which a general linear technology

$$h(z) = \sum_{i=1}^{k} \alpha_i b_i(z) \qquad \textbf{Equation 3}$$

where $b_i(z)$ is a twice-continuously differentiable function of z, can approximate an arbitrary twice-continuously differentiable function, given suitable parameter choices. This linear technology can also be written as a second-order Taylor approximation of an arbitrary function (see Chambers (1988), Chapter 5), and when the second-order Taylor approximation of the *log* of this arbitrary function is taken, the transcendental logarithmic (or translog) functional form results. The translog form, originally introduced by Christensen et al. (1973),

[26] Note that this symmetry follows from the combination of Young's Theorem (i.e. $\partial^2 C(p, y)/ \partial p_i \partial p_j = \partial^2 C(p, y)/ \partial p_j \partial p_i$) and Shephard's Lemma, and does *not* necessarily imply symmetry of cross-price *elasticities*.

is flexible, in the sense that it does not impose restrictions on the underlying technology (indeed, the underlying technology is not mathematically tractable) nor, therefore, on the outcomes from its application.[27] It is for these reasons that we proceed with the translog cost function, and for these reasons that the translog is one of the most ubiquitous in the applied production literature.

3.3 Previous Studies on Fuel Use in Electricity Generation[28]

Ko and Dahl (2001) and particularly Söderholm (1998) provide excellent reviews of the literature pertaining to interfuel substitution in the electricity generating industry. Our objective in this section is to provide background, and highlight the aspects of previous work that are relevant to the present study. What follows is therefore a brief summary of the literature insofar as time horizon (short run vs. long run), functional form, data type (cross section, time series, or panel as well as aggregation level), and geographical focus is concerned, and the reader is referred to Söderholm (1998) and/or the individual papers for further detail. We note that cross sectional datasets are generally associated with short run studies, while models based on time series data can be interpreted as either short run or long run, depending on series length, model specifications, and the preferences of the author. We note also the prevalence of the translog functional form in these type of studies and the relevance of the data aggregation level.

The absence of environmental regulatory variables should be clear in the studies mentioned below, with the following few exceptions. Söderholm (2000) employed a 'regulatory intensity' variable to account for sulphur regulations in his study on Western European electricity generation, as did Lee (2007), and Uri (1977) used a dummy variable to model the presence or absence of environmental regulation in his study on regional interfuel substitution in the USA. Tran and Smith (1983) and Fuller (1987) included actual emissions as a right hand side variable, but focused on command-and-control emission regulation, and assumed

[27] We note that the translog function is only globally concave in input prices (as required by Property C.5) when the translog collapses to the Cobb–Douglas form. When the cost function is not globally concave, the negative slope of the derived demand equations is not ensured, and can present theoretical problems (see Griffin (1995) and Diewert and Wales (1987)). This does not appear to be an issue in our estimation (see the results in Sections 6 and 9).

[28] Related studies include aggregate KLEM-type models (e.g. Berndt and Wood (1975) and Halvorsen (1977)) and interfuel substitution studies on other industries (particularly manufacturing). See, e.g., Bjørner and Jensen (2002) and Arnberg and Bjørner (2006).

that actual emissions will always equal allowed emissions. To our knowledge, the only previous study to have addressed the effects of the CAAA 1990's SO_2 scheme on firm's behaviour in a cost function setting is that by Considine and Larson (2007), which focused on permit use and banking, using a panel dataset covering only Phase I of the programme. They included permits as a separate input to the production process, and did not disaggregate fuel inputs. Ours is the first study, to our knowledge, to address interfuel substitution under the SO_2 scheme and to incorporate a dataset covering the period prior to regulation, through Phase I, and into Phase II. We note also that several studies, particularly the older ones, use plant-level or aggregate regional data. As noted by Christensen and Greene (1976) and Considine (2000), firms, not plants, are responsible for generation decisions, and therefore the data in this study is firm-level.

Atkinson and Halvorsen (1976a) provided the first econometric study of interfuel substitution and fossil fuel demand in electricity generation. With US plant-level cross sectional data for 1972 grouped into dual-fuel pairs (coal–gas, coal–oil, and oil–gas), they estimated fuel input price elasticities using a translog normalized restricted profit function, and found that the conditions for a consistent fuel aggregator are not generally satisfied, and that substitution between fuels does, in fact, occur. Capital and labour are assumed fixed, and they include a capital vintage index to account for technological change. Oil was found to be the most own-price responsive, followed by coal, and they found an inappropriate, though insignificant, sign on the own-price elasticity of gas. They also found coal and oil to be the most cross-price elastic (with oil demand being more responsive to coal price changes than vice versa) and coal and gas the least. In a second study, Atkinson and Halvorsen (1976b) used aggregate monthly time series data for the years 1972–1974 and analysed short run substitution between all three of the fossil fuels, again with a translog profit function. This study covers the period of the 1973 oil embargo and finds almost no own-price response for coal or oil, and a large and significant own-price response for gas. Cross-price elasticities between gas and coal are found to be larger in the times series study, while all other cross-price elasticities are found smaller.

Griffin (1977) used pooled aggregate time series observations in five year intervals on each of 20 OECD nations in a translog cost function that is assumed separable in capital and labour. He did so with two separate models: one in which parameter estimates depended only on differences between countries, and one where intra-country differences were included. He questioned the use of time series data, and whether long run adjustments are truly being measured, with its use in static cost functions. His fuel price elasticity estimates are larger than those found previously with cross sectional data, confirming his concerns over the distinction between short and long run estimates, and the ability of time series data to address the latter. Griffin (1977) introduced a polynomial distributed lag to his model in an effort to distinguish between long and short run effects, but, as Ko and Dahl (2001) note, the greater elasticities found in this paper are possibly attributable to country-specific differences across the OECD-wide dataset, and not specifically to the inclusion of the distributed lag. We focus on a static analysis to avoid the complications associated with dynamic translog specifications (Ko and Dahl (2001), for example, noted Dahl's (1995) discussion of multicollinearity and other issues that arise in a dynamic translog setting).

Uri (1977 and 1978) used the translog cost function specification to assess interfuel substitution in US electricity generation. In his 1977 paper, Uri used pooled annual time series data on nine US regions for the years 1952–1974. To account for the sulphur emissions regulations imposed in 1969, he used a dummy in the cost share equations. He claimed his results were long run estimates, as they were based on pooled data and were larger than those found by Atkinson and Halvorsen (1976a). In his 1978 paper, Uri included a variable to account for national heating degree days, but did not account for environmental or any other regulations. He used aggregate monthly data for the USA from 1973 to 1976, and his use of time series data and his smaller elasticities led him to conclude that his results show short run elasticities despite, as Söderholm (1998) noted, only five of his nine reported elasticities being lower than his alleged long run estimates.

Mountain's (1982) study differs from the others mentioned in this section in that it incorporated imported electricity as an input in its translog cost function. His data is for New Brunswick and Nova Scotia in Canada, and he modelled the firm's generating decision as a two-stage problem. In the first stage, the optimal quantity of imported and domestic electricity is found, and in the second, fuel use in domestic electricity generation is determined given the now-exogenous quantity of domestic electricity. The data is pooled time series data for the years 1964–1975, and the analysis is short run, as Mountain explicitly assumed that fixed capital inputs. He found large substitution between domestic and imported electricity, and also found significant short run substitution between coal and oil.[29]

Seifi and McDonald (1986) analysed the first operational year of new fossil-fuel fired power plants built in the USA during the years 1955–1979. They noted a trend toward increased fuel input flexibility in new plant construction,[30] and first studied the fuel-type capacity construction decision with a probit-logit model using fossil fuel input price data along with data on labour, capital, and output prices in a manner similar to that of Joskow and Mishkin (1977). In a follow-on analysis, they estimated a translog cost function in order to assess short run fuel demand and interfuel substitution[31] within these plants. They found significant interfuel substitution in the *ex post* analysis and also found that a plant's percentage of a firm's total capacity and fuel efficiency played a significant role in fuel use decisions.

Bopp and Costello (1990) assessed short run interfuel substitution in US electricity generation using two translog cost function models: one with monthly time series data on five US regions, and a second with monthly time series data for the whole USA. The time period they studied was 1977–1987, and oil was found to be the most own-price elastic and gas the least. The low gas price elasticity they found was explained by Ko and Dahl (2001) as having potentially resulted from the prohibition of new gas capacity construction for the years 1978–1987. Ko and Dahl (2001) also noted that the smaller elasticities found in the Bopp and Costello (1990) study were probably due to the use of monthly rather than annual data. Bopp and Costello (1990) analysed the two most prominent fuels in each region only, and noted that the price elasticity of the dominant fuel generally tended to be lower than that of the second most prominent fuel. The results of their regional model suggest that regional differences do exist, and we think the addition of regional fixed effects could make an interesting and useful extension to the models presented below.

Söderholm (1998) and Ko and Dahl (2001) both described Ko's (1996) Ph.D. research which compared the translog and the linear logit models in the analysis of two different datasets. Ko

[29] Neither Nova Scotia nor New Brunswick had natural gas generating capacity during the years covered by Mountain's (1982) study.

[30] This, again, supports our argument that short run interfuel substitution is, in fact, a realistic possibility in the US electricity generating industry.

[31] Their formulation, however, as noted by Söderholm (1998), explicitly incorporated the price of capital, indicating variability in capital inputs, and implying that the analysis is not expressly formulated for short run analysis.

(1996) assumed separability of the production technology in both models with both datasets, and included data only on the fossil fuel input prices. Both datasets (time series from 1991–1993 and cross section for 1993) were used in his translog specification, while only the cross sectional dataset was employed in his linear logit model. As Söderholm (1998) noted, the elasticities found by both models indicate own-price sensitivity and cross-price insensitivity, and are similar regardless of the cost function's econometric specification. The elasticities using time series data, however, were approximately one quarter of those found using the cross sectional data, though no claim is made about the short- or long run nature of the estimates.

In a 1999 paper, Söderholm outlined the shortcomings of cost function analysis for long run interfuel substitution analysis, stating that most previous work claiming long run status does so through *ex post* interpretation and not through explicit long run modelling (i.e. most alleged long run studies include the price of capital in the cost function, but make no provisions or assumptions relating to the capital adjustment process). He mentioned discrete choice models like those of Joskow and Mishkin (1977), Seifi and McDonald (1986) and a Ph.D. thesis by Boontherawara (1993) as models that analyse *ex ante* substitution between fuels. However, the fact that fossil fuel choice is not associated one-for-one with discrete technologies and that older plants have been having their lives extended, led Söderholm (1999) to conclude that discrete choice models tell only part of the fuel choice story, and that short run analysis is more suited to cost function analysis, particularly with the adoption of a variable cost function under the assumption of weak separability of the fuel aggregate from capital inputs.

Thus, Söderholm (1999) analysed short run interfuel substitution in Western European electricity generation with a variable cost function and pooled annual aggregate national data covering the years 1978–1995 for seven Western European countries. He used the translog functional form and concluded that interfuel substitution is, in the aggregate, prevalent in Western Europe, with gas and oil being the most cross-price responsive.

In a more recent paper, Söderholm (2000) used the same dataset, and explicitly accounted for environmental regulation in a Generalized Leontief cost function analysis of short run interfuel substitution in Western European electricity generation. The Generalized Leontief function was chosen over the more prevalent translog form, because it allows the hypothesis of zero *ex post* interfuel substitution to be tested. He assumed separability, but included capital as a quasi-fixed input, so that capital is accounted for, but changes in it are not explained. He included the above-mentioned 'regulatory intensity' variable, and also a time trend to account for technological change.

The Generalized Leontief system produced elasticities with size and sign as we might expect, and Söderholm (2000) concluded that short run interfuel substitution in Western European power generation is substantial, while also noting that the aggregate national-level of his data presumably masks some of the firm-specific short run fuel use decisions. He noted also that the time trend and the regulatory intensity variable appear to explain the same thing, and that excluding the regulatory variable from the analysis did not significantly bias the elasticities as long as the time trend variable remains. This final result seems particular to a command-and-control policy setting, and is possibly also affected by the aggregate national level of the data.

Another recent study of interfuel substitution with a US focus was done by Ko and Dahl (2001) using monthly panel data for 185 US electric utilities in 1993, and splitting the data into fuel-use capability sets (i.e. coal–oil, oil–gas, gas–coal, and coal, oil gas). They used a translog cost function to analyse whether deregulation in the natural gas and electricity markets throughout the 1980s induced increased interfuel substitution. They concluded that the regulatory changes of the 1980s made firms more responsive to oil and gas prices, and less responsive to coal. They expected coal to become less attractive with further deregulation of the industry, and noted that the Clean Air Act Amendments and global warming concerns 'can also be expected to disfavour coal'. Further, they recommended additional work to test the hypothesis of increased fuel-price responsiveness, and a shift toward gas usage as the industry adjusts to deregulation. We find evidence of the latter, but not of the former (see Section 9).

In a more recent paper, Tauchmann (2006) addressed the fuel choice decision using annual micro data for German electricity generating firms from 1968–1998 with a different method. He opted for a simple non-structural model, citing the non-storability of electricity and lack of short interval data.[32] The model he proposed assumed a one-to-one relationship between

[32] Tauchmann (2006) notes that the production relationship in electricity generation, where output fluctuates almost immediately, requires data that is 'quasi continuous' in order to identify the production relationship, and he criticizes previous studies for use of quarterly, annual and cross section data. We note the instantaneous

each fuel and a particular technology, and broke the fuel-choice decision into two stages, thereby allowing the explicit analysis of short- and long run decisions. Tauchmann (2006) assumed a linear non-structural 'optimal capacities' function for the first stage that included fuel prices and their lags, as well as other explanatory variables. The generation decision, given capacities for different fuels, was then modelled in a non-structural log linear function relating the quantity of electricity produced with input *i* to a set of explanatory variables. Both stages incorporated firm-specific fixed effects, as well as a time dummy to indicate deregulation after 1995. The paper concluded little about the effect of potential CO_2 emissions regulation, and no substitution elasticities were presented, as the model does not provide the relevant parameters.

Tauchmann's (2006) findings indicate that German electricity firms have not adjusted their fuel choices to fuel prices, insofar as either fuel-specific generating capacity or fuel-use given existing capacity are concerned. These findings are in contrast to Söderholm's (1999 and 2000) findings that show small but significant short run interfuel substitution in German power production over a truncated but similar period. Söderholm (1999 and 2000) did find, however, that Germany demonstrates lower short run interfuel substitution activity than the other Western European nations in his studies, meaning Tauchmann's (2006) findings may be specific to both his modelling technique and to the data/nation he studies, particularly as the German studies mentioned use data almost entirely from a period of regulation.

We conclude that Tauchmann's (2006) study is valuable in its warnings regarding the use of aggregate annual data, and claims related to findings from earlier studies, but follow Söderholm (1997, 1999, 2000) and others in presuming the presence of short run interfuel substitution, particularly in response to environmental policy. We find the use of structural models based on producer theory and cost-minimizing behaviour are easier to interpret, and superior for their ability to provide intuitive substitution elasticities, particularly when disaggregate data is available and the time-horizon of the study is made explicit.

Two studies from outside the electricity industry are worth noting for their use of panel data. These are papers by Bjørner and Jensen (2002) who compared pooled and fixed effects models, and Arnberg and Bjørner (2007) who compared a panel fixed effect model with a

output issue, but as our objective is the calculation of interfuel substitution elasticities and technical change effects, we proceed with cost function analysis.

cross sectional model. Both used applied production analysis and micro panel data to study interfactor substitution in the Danish manufacturing industry with the translog and the linear logit specifications. Both found that the substitution elasticities gleaned from the two cost function specifications are similar, though Arnberg and Bjørner (2007) noted that the linear logit may be superior when cost shares are small and heterogeneous.

These Danish studies are interesting for their comparison of pooled and fixed effects models, and for their discussion of the ability of the time-series or cross sectional nature of a dataset to determine whether results should receive short- or long run interpretations. Bjørner and Jensen (2002) concluded that their pooled model exhibits higher substitution than the one including fixed effects, suggesting an omitted variable bias in repeated cross sectional analyses. Arnberg and Bjørner (2007) noted that time-series studies, where capital and energy complementarity has been found, tend to be touted as reflective of long run effects, while cross sectional studies are often said to reflect short run effects. They went on to note that a parallel could be drawn between the macro time series models and their panel (fixed effect) models, so that their panel results could be interpreted as short run effects, but suggested further research before a conclusion is drawn.

The final study we discuss is that of Considine and Larson (2006) which, as noted, considered the behaviour of firms under the SO_2 scheme with a focus on the use and banking of allowances. Their work is interesting because they introduced the environment as an input into a production model of the US electricity generating industry under the SO_2 allowance scheme. In equilibrium, the allowance price reflects the marginal cost of abatement, and therefore the value of avoided emissions, meaning that the allowance price is effectively an emissions price, which Considine and Larson interpreted as the price associated with the consumption of environmental resources. They treated these environmental resources as an input of their own right in a manner similar to our Model 2 (discussed in Section 5) and used a Generalized Leontief cost function incorporating high- and low-sulphur fuels, labour, and environmental resources as factors of production, and permit stocks and capital as quasi-fixed factors. They incorporated fixed effects into their restricted cost function model and estimate with a panel of 36 firms for the years 1995–1999.

Considine and Larson’s focus was on the permit use and banking activities of generating firms, and they did not, therefore, report results pertaining to interfuel substitution specifically, though they did report long- and short run Morishima elasticities of substitution for the inputs included in their model. They found ‘considerable substitution possibilities’ between emissions, fuels, labour, and capital, with relative fuel prices playing the largest role in determining factor substitution. They also found ‘disequilibrium wedges’ for permit costs from their permit-stock fixed effects, which they used to explain permit banking (even in the presence of user costs) as a means of hedging against uncertainty.

Their paper is relevant to the current research for its topic and time horizon, but also for its fixed effects panel analysis and the way in which emissions prices are incorporated as the price of a separate ‘environmental input’. Our Model 2 incorporates SO_2 prices in this manner, but we find a model where SO_2 prices are incorporated into the relative fuel input prices fits our data better.

This research thus adds to the literature a panel-data analysis that incorporates emissions prices in two different models and excludes them in a third. After assessing the stationarity of our panel (an issue not addressed in previous studies), we consider firm heterogeneity and conclude that it is indeed present, and that estimation with firm dummies is preferable to estimation with pooled data. We describe the three models in the next section, and eventually present results based on Model 1 in Sections 10–12, after first justifying its specification and our estimation techniques.

4 Data

Given our chosen method of short run variable cost estimation, we require data on costs, output quantities, capital, and fuel input prices, as well as various other firm characteristics. Our dataset is an unbalanced panel consisting of 5128 monthly firm-level[33] observations for 37 US electric utilities over the period 1990–2004,[34] representing approximately 8 per cent of total annual US generation and 10 per cent of annual generation from US electric utilities. Over the period, electric utilities accounted for a declining proportion of total annual US generation:[35] 89 per cent in 1995 to 63 per cent in 2004. Each firm has the ability to generate with coal, oil, *and* natural gas, but lacks hydro and nuclear capacity,[36] and each has a minimum of 84 time series observations.[37] The panel is unbalanced, with 1532 observations missing for reasons associated with data collection processes (e.g. sporadic data collection or clerical errors) and not due to market entry or exit. All nominal price data have been converted to real December 2004 values using the seasonally adjusted Producer Price Index (PPI): Intermediate Energy Goods (PPIIEG) (Federal Reserve Economic Data (FRED II)).

4.1 Sources[38]

We took monthly firm-level data on electricity generation, prime mover, and fuel type from the Form EIA-906 (formerly Form EIA-759) (Form EIA-759/906).[39] Fuel-specific data (i.e. fuel type, quantity, sulphur and thermal contents, and delivered costs) came from the Federal Energy Regulatory Commission (FERC) Form 423, ‘Monthly Report of Cost and Quality of

[33] We chose to aggregate to the firm-level (rather than the somewhat more common plant-level of aggregation) because it is at the firm-level that operating decisions affecting costs are made.
[34] Because the Frontier 4.1 software cannot cope with missing values, all observations with a missing value for any variable are omitted.
[35] This serves as defence for our cost-minimizing assumption.
[36] This is to ensure (1) a degree of homogeneity of production technology and (2) the ability to switch between fuels in response to the scheme. Note that hydro and nuclear accounted for approximately 30 per cent of total annual generation over the period.
[37] We eliminate firms with less than 84 observations because we later break the data into five-year time subsets. Each time subset represents 60 (monthly) time periods, and in order to ensure that a ‘reasonable’ amount of data was present across at least two time periods, we require at least 84 observations per firm.
[38] All raw data were imported, sorted, organized and aggregated with a programme written in SAS 9.1 for Windows. All fuel- and plant-specific data were compiled from Energy Information Administration (EIA) forms. The EIA is a statistical agency of the US Department of Energy.
[39] Form EIA-759, ‘Monthly Power Plant Report’ was discontinued in 2000 and replaced by the EIA-906, ‘Power Plant Report’.

Fuels for Electric Plants' as published by the Energy Information Administration (EIA) (EIA, FERC Form 423). Form 423's plant-level data is reported monthly by electric utilities for each plant having at least 50MW steam or combined-cycle capacity.

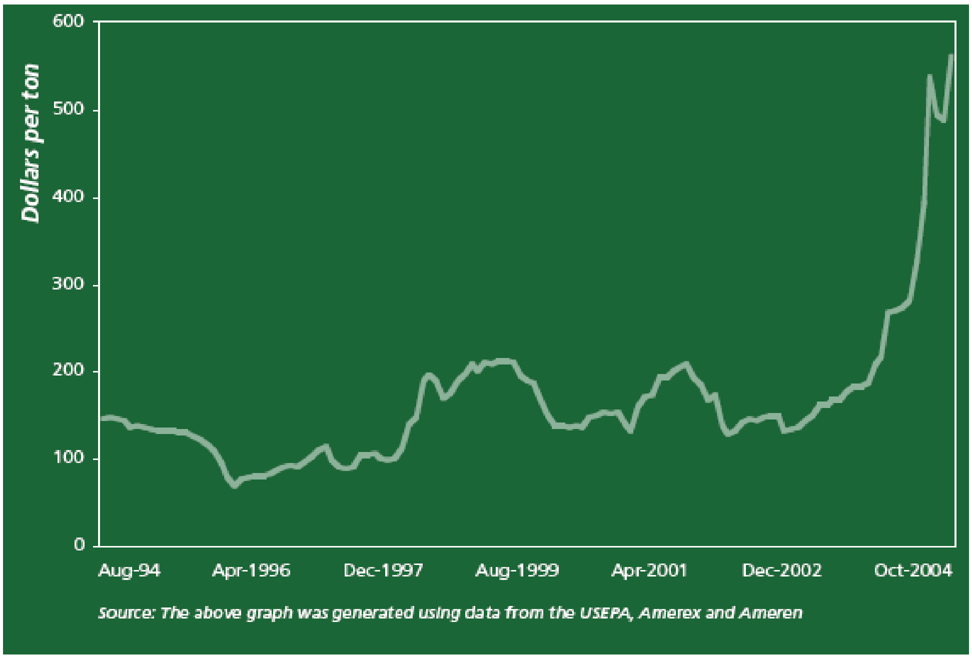
Capacity data came from the Form EIA-860 and EIA-860A, 'Annual Electric Generator Report' (Form EIA-860). Form EIA-860 is filed annually for all existing and proposed (to be completed within five years) plants of one or more MW, and contains data for both utilities and non-utilities. Prior to 2001, utility and non-utility data were filed separately with forms EIA-860A and EIA-860B, respectively.

We took monthly plant-level SO_2 emissions data from the Environmental Protection Agency's (EPA) 'Clean Air Markets- Data and Maps' website. (See 'EPA Clean Air Markets Data and Maps'.) When necessary, missing SO_2 emissions were calculated as described below using FERC 423 fuel data and emissions factors published in the EPA's AP-42 (EPA, 2000). We also used the EPA's 'Clean Air Markets- Data and Maps' to find unit-level data regarding scrubber installation and inclusion in Phase I of the Acid Rain Programme.

Cantor Fitzgerald (now CantorCO2e) is the main brokerage for sulphur permits, but their data are available only to paid registered users.[40] Thus, our historical allowance data come from the EPA ('Clean Air Markets') for the years 1994–2000 and from Evolution Markets, Inc.[41] for 2002–2004. For the intervening period, we estimated monthly permit prices from a chart by the Chicago Climate Exchange based on data from the EPA, Amerex and Ameren (Chicago Climate Futures Exchange (2004)), and presented as Figure 1 below. Note the rise in allowance prices in 2004 to the levels predicted prior to the scheme's commencement. This provides evidence of 'low hanging fruit' (mostly in the form of high-to-low sulphur coal switching made feasible by rail deregulation in the early 1990s) in the industry prior to the cap-and-trade scheme that was not exhausted until halfway through Phase II. This presumably had an effect on cost efficiency performance, and we investigate this further in Tuthill (2008b).

[40] See CantorCO2e.
[41] See Evolution Markets, Inc.

Figure 1: SO_2 Allowance Prices 1995-2004



4.2 Variables and Problems

Variables requiring explanation are discussed in this section. Fuel prices as required for our cost function analyses are assumed to have two components, one related to heat content and measured by the delivered price, and one related to sulphur content and the SO_2 allowance price, meaning that information on delivered costs, SO_2 emissions and sulphur prices were required. We use generating capacity as a proxy for capital, and measure output in 1000's MWh of electricity produced.

Fuel Price[42]

The main fossil fuel categories (coal, oil, and gas) are aggregates of more specific sub-types, each of which have differing thermal and environmental characteristics. In our data, the coal subtypes are BIT (bituminous coal), LIG (lignite), ANT (anthracite) and SUB (sub-

[42] NB: All prices (fuel, sulphur and permit prices) are real values measured in December 2004 US$.

bituminous coal). The oil subtypes FO2, FO4 and FO6 are generalized to subtype DFO (distillate fuel oil) following Forms EIA-906 and 860. Natural gas subtypes did not exist.

We calculated fuel prices in cents/mmBtu of heat input using the delivered cost data from the FERC Form 423. We calculated the monthly state average price for each fuel, and used it as a proxy for the observed fuel price when a firm reported a zero purchase quantity for a particular fuel but had capacity to generate with that fuel. For example, if a firm was able to generate with coal but reported no coal purchases in a given month, the average coal price for the firm's state in the corresponding month and year was substituted for the missing price value.

SO_2 Quantity

To find the SO_2 price for each fuel, we needed monthly emissions values. Where these values were unavailable from the EPA data, we calculated them using fuel-specific emissions, calculated using fuel-specific conversion factors (EPA, AP-42) along with sulphur and quantity data from the FERC Form 423. For example, missing SO_2 quantities for coal combustion were calculated as follows for each subtype:

$$\text{Quantity of } SO_2 \text{ from Coal Combustion} = (C \times \text{Sulphur} \times \text{Quantity}) \div 2000$$

where 'Sulphur' and 'Quantity' refer to the sulphur content and quantity of the fuel subtype, and '*C*' represents the subtype-specific emissions factor.

SO_2 Prices

We note here the distinction between the SO_2 allowance price and the sulphur price associated with the combustion of a specific fuel. The allowance price represents the average monthly market price associated with the emission of one ton of SO_2, whereas the fuel-specific emissions price depends on the firm's technology and the specific fuel combusted, as well as the allowance price, and is measured in cents per mmBtu. We calculated this latter value using the actual permit price, fuel-specific emissions values as above, and fuel-specific Btu and quantity data from the FERC Form 423. We aggregated this data to the firm level, and missing values were replaced with a fuel-specific state average sulphur price. Thus, for example:

$$SO_2 \text{ Price of Coal} = (100 \times (\text{Permit Price/PPI}) \times \text{Emissions from Coal}) \div \text{Q of Coal Combusted},$$

and if this value was missing, it was assigned the average SO_2 price for coal from the state in which the firm operated for the appropriate month.

Total Fuel Price

The fuel price that later appears in the cost frontier/functions is the *total* fuel price, i.e. the sum of the SO_2 and Btu price components for each fuel aggregate. For oil and gas, this is just the sum of the delivered fuel price and fuel's SO_2 price. Some plants, however, have installed scrubbers as a means of CAAA compliance, reducing required permit quantities associated with coal combustion. We account for this in the total coal price calculation by including the percentage of coal capacity covered by scrubbers as follows:

$$\text{Total Coal Price} = \text{Btu price of coal} + (1 - \text{\% Capacity Scrubbed}) \times SO_2 \text{ Price of Coal}.$$

Capacity

As noted, all firms in our dataset have the capacity to burn coal, oil, and natural gas, implying that a means of determining fuel-burning ability was required. Several boilers listed on the Form EIA-860 are dual-fired units capable of burning more than one fuel. In these cases, we counted the unit's capacity in both fuels' categories, but count it only once in the firm's total capacity. For example, if a unit was capable of burning either DFO or BIT, the unit's capacity was counted both as oil and as coal capacity, but the firm-level total reflects only the unit's nameplate capacity.

4.3 Descriptive Statistics

Descriptive statistics for the relevant final variables are presented in Table 1 below, which includes the main cost function variables. Fuel cost shares are depicted over time in Figures 2–5,[43] and Figure 6 portrays mean delivered fuel costs over time. Finally, Table 2 presents variable cost and cost share values reflecting the different input definitions for Models 1 and 2.

Table 1: Cost Function/Frontier Variables: All Firms, All Years

Variable	Units	Mean	Median	Standard Deviation	Min	Max
Total Coal Price	¢/mmBtu	181.70	183.75	44.22	61.19	385.15
Total Gas Price	¢/mmBtu	415.15	356.02	195.96	40.72	2527.93
Total Oil Price	¢/mmBtu	520.93	515.13	177.67	133.42	1343.60
Btu Coal Price	¢/mmBtu	173.62	174.77	45.26	61.19	363.81
Btu Gas Price	¢/mmBtu	415.15	356.02	195.96	40.72	2527.93
Btu Oil Price	¢/mmBtu	518.73	511.76	176.97	133.42	1342.47
Permit Price	$/ton	115.57	130.00	111.91	0[44]	705.95
Generation	1000's MWh	580.58	238.16	625.76	1.02	3426.04
Total Capacity	kW	1,768,266	1,285,800	1,669,586	74,599.97	6,506,999

[43] Note that the values presented in these Figures reflect the case in which the SO_2 and Btu prices are included in the total fuel price. The general trend would be consistent regardless of SO_2 price inclusion.
[44] Note that zero values have been converted to $1.0e^{-10}$ because of the logarithmic nature of the variable's appearance in the inefficiency model.

Figure 2: Mean Fuel Cost Shares

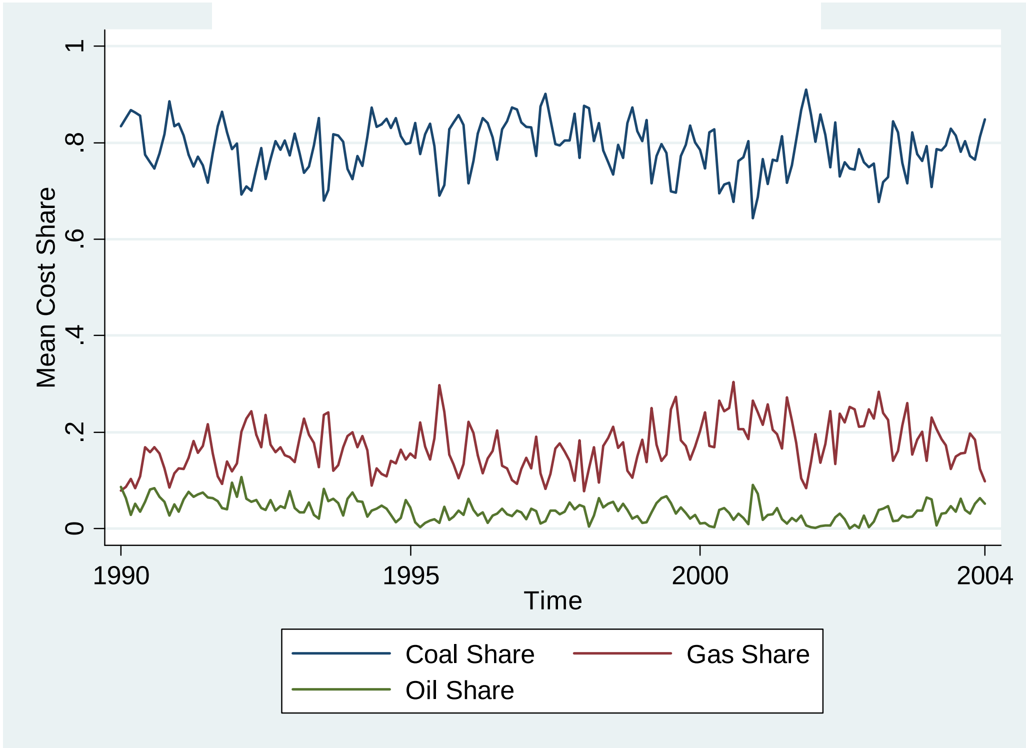


Figure 3: Mean Coal Cost Share

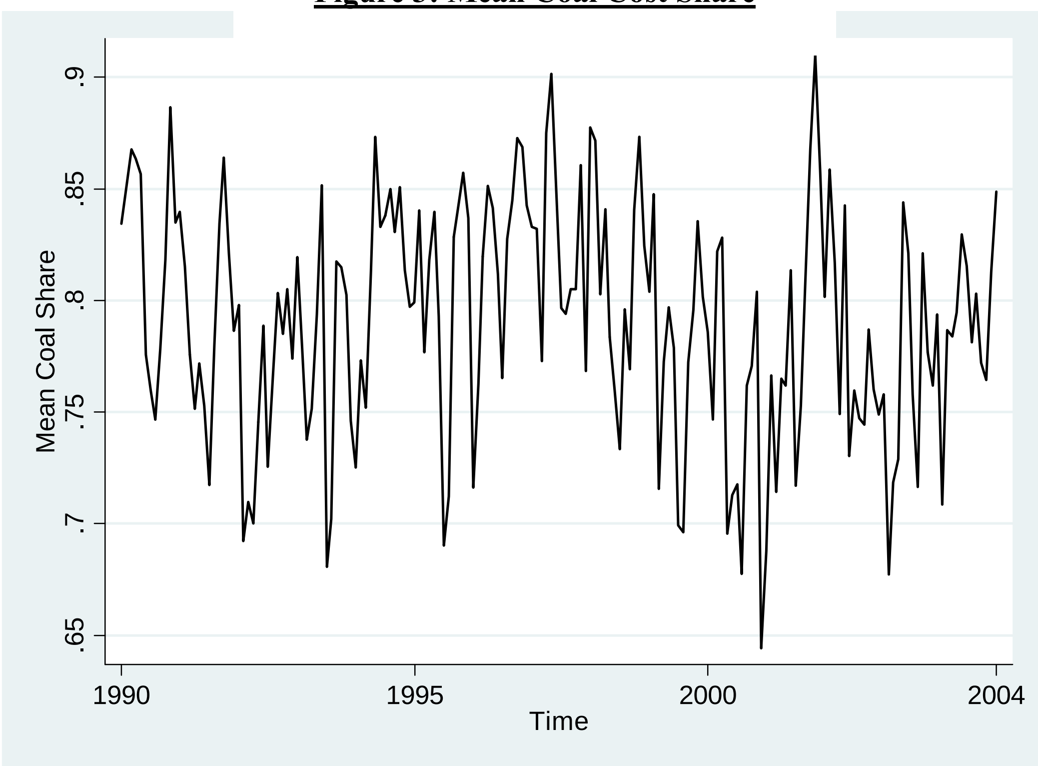


Figure 4: Mean Gas Cost Share

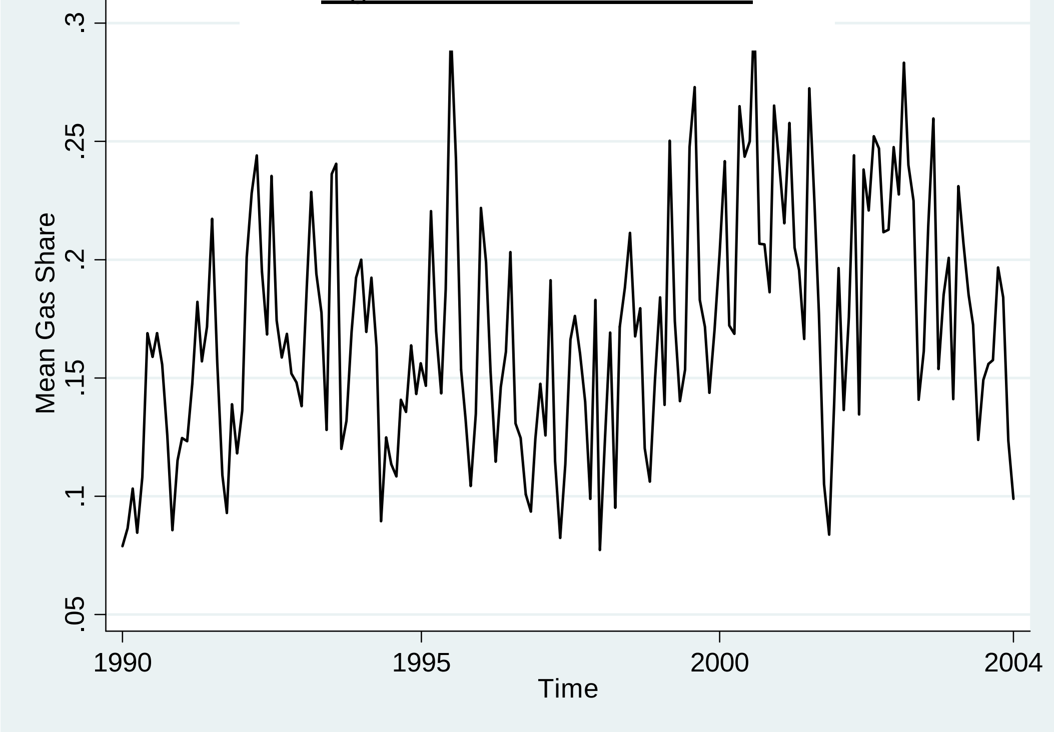


Figure 5: Mean Oil Cost Share

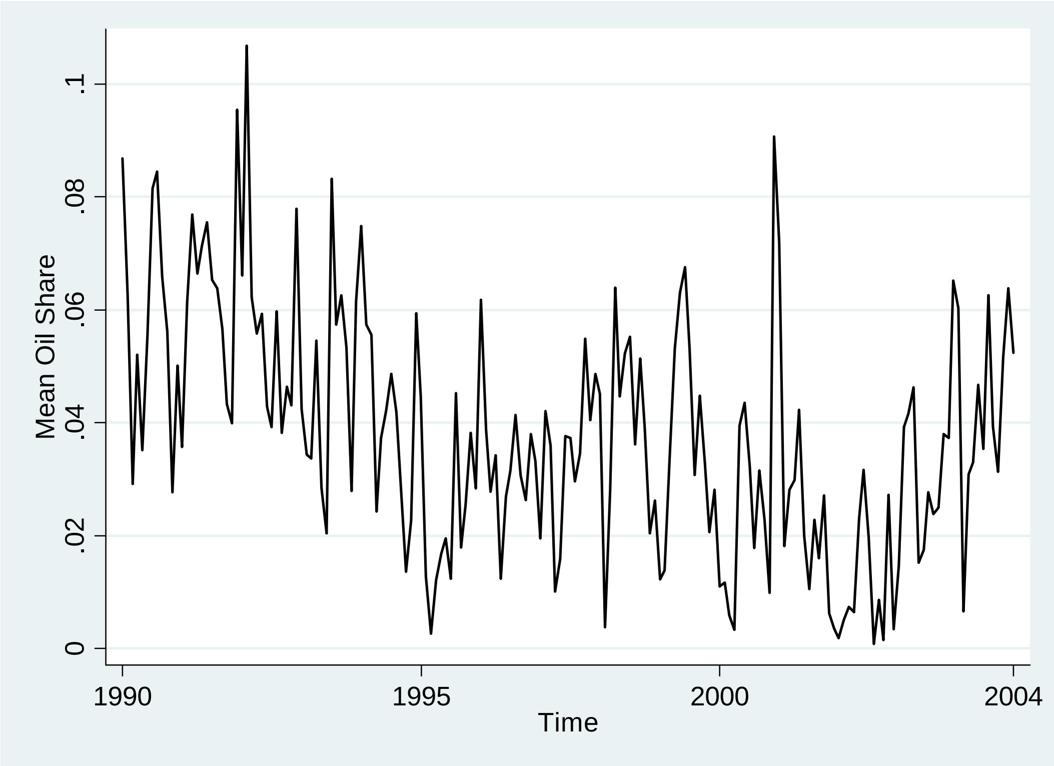


Figure 6: Mean Btu Fuel Prices

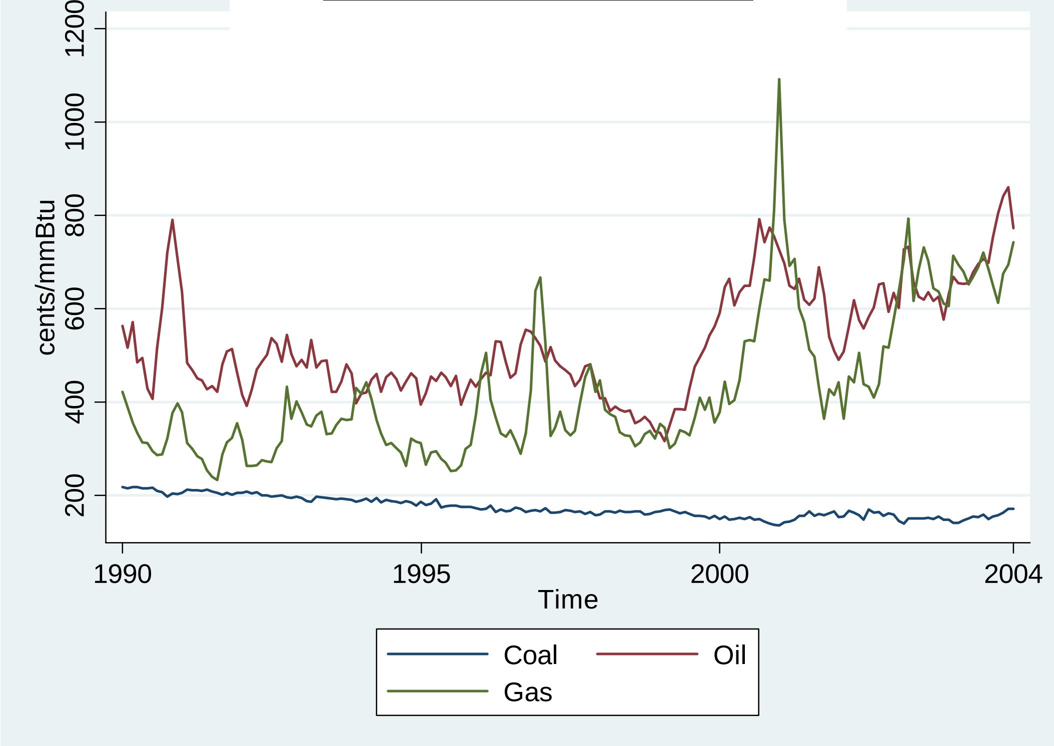


Table 2: Variable Costs And Cost Share Values Reflecting Different Input Definitions: All Firms, All Years

Variable	Units	Mean	Median	Standard Deviation	Min	Max
Total Variable Costs* (SO_2+Btu)	Millions Dec. 2004 $	11.8287	6.6745	13.3545	0.00005	223.1613
Coal Cost Share (SO_2+Btu)	%	0.7914	0.9163	0.2616	0	1
Gas Cost Share (SO_2+Btu)	%	0.1699	0.0432	0.0387	0	1
Oil Cost Share (SO_2+Btu)	%	0.0387	0[59]	0.1031	0	1
Total Variable Costs* (4 inputs)	Millions Dec. 2004 $	11.4427	6.3888	13.0420	0.00005	223.1613
Coal Cost Share (4 inputs)	%	0.7818	0.8904	0.2619	0[59]	1.00
Gas Cost Share (4 inputs)	%	0.1716	0.0458	0.2475	0[59]	1.00
Oil Cost Share (4 inputs)	%	0.0387	0[59]	0.1058	0[59]	1.00

*Note that these values are slightly different for the SO_2 + Btu case and the four input case because of the role played by percentage of scrubbed capacity in the calculations. The former does not separate SO_2 cost contributions by fuel type, while the latter does.

5 The Models

5.1 *Description and Explanation*

We present three potential fossil fuel cost function models for electric utilities operating under the tradable sulphur allowance scheme. Each is a representation of the general restricted cost function:

Total Fossil Fuel Cost = $f(P, J, Y, K, E, T, A)$,

where P is a vector of fuel input prices, J is a vector of input quantities, Y is total electricity output, K is a quasi-fixed capital variable represented by generating capacity, E is the emissions price, T is the time period, and A is a vector of firm-specific characteristics. This restricted variable cost function (Lau (1976)) includes K as a quasi-fixed input, and we assume firms choose variable fossil fuel inputs optimally given their fixed capital stock,[45] implying, as noted, that our analysis is short run in nature. All three models assume a single-output technology, and in Models 1 and 2, emissions are interpreted in different ways as an input to the production process.[46,47] Model 3 does not include the SO_2 price at all, and represents the situation in which firms ignore the sulphur price in their input selection and cost-minimizing decisions.

The models therefore differ in their representation of the inputs and the incorporation of the sulphur price. Model 1 assumes three fossil fuel inputs (coal, oil, and natural gas), where each fuel price has two components: one accounting for the market price of the fuel (the 'Btu price') and one associated with the emissions created by the fuel's combustion (the 'SO_2 price'). The assumption is that the allowance price affects the relative fuel prices in a manner determined by the differing sulphur contents of the fuels, thereby causing substitution amongst the fuels under cost-minimizing behaviour.

As explained in Section 4, the SO_2 component of the total fuel price accounts for both the permit price and the quantity of emissions generated through the specific fuel's combustion, and its calculation includes information on both the firm's inclusion in the SO_2 scheme and its installed scrubber capacity. Because scrubbers are installed on coal-fired units only, we assume scrubbed capacity affects the SO_2 price of coal alone, while programme inclusion affects the SO_2 price of all fuels.

Model 2 treats allowances as a fourth and separate input to the production process in a manner similar to Considine and Larson (2006). Here, in addition to the Btu market prices of coal, oil, and natural gas, the permit price also appears separately on the right hand side of the restricted variable cost function.

[45] Other examples of the use of a restricted cost function in the absence of full input price data availability include Halvorsen and Smith (1986), Lee (2007), Lee and Ma (2001), and Lundmark (2005).

[46] It is possible to model emissions as a second 'bad' output, as Färe et al. (1993). These models are based on input distance functions, which are dual to the cost function. Kolstad and Turnovsky (1998) note that endogenous explanatory variables, and the fact that the distance function is unobservable, may cause econometric problems, but distance functions are still prevalent in the applied literature, particularly in papers concerned with marginal abatement cost calculations. See, e.g., Färe et al. (1993), Coggins and Swinton (1996), and Hailu and Veeman (2000).

[47] Considine and Larson (2006) also model emissions as a production factor calling it an 'environmental input'.

Model 3, in contrast, does not include the sulphur price at all. Like Model 1, Model 3 assumes three fossil fuel inputs, but it assumes that fuel prices are not affected by the allowance price, and that firms did not account for the SO_2 price in their cost-minimizing input decisions. Model 3 is therefore included to justify our assumption that the SO_2 allowance price did, in fact, affect firm's cost-minimizing behaviour.

5.2 Empirical Specification and SUR Estimation

We estimated each of the models with a translog specification (see discussion in Section 3.2, Christensen et al. (1975), and Söderholm (1998, 1999)). Its basic form is:

$$\begin{aligned}\ln VC = \beta_0 + \sum_{i=1}^{n}\beta_i \ln P_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij}\ln P_i \ln P_j + \beta_K \ln K + \beta_Y \ln Y + \beta_{KY}\ln K \ln Y \\ \frac{1}{2}\beta_{KK}(\ln K)^2 + \frac{1}{2}\beta_{YY}(\ln Y)^2 + \sum_{i=1}^{n}\beta_{Ki}\ln K \ln P_i + \sum_{i=1}^{n}\beta_{Yi}\ln Y \ln P_i + \\ \beta_T Time + \frac{1}{2}\beta_{TT}Time^2 + \beta_{TY}Time\ln Y + \sum_{i=1}^{n}\beta_{Ti}Time\ln P_i + \varepsilon\end{aligned}$$ **Equation 4**

where *VC, P_i, K,* and *Y* are variable cost, the price of input *i*, capacity and output, respectively.[48] The β's are the parameters to be estimated, ε is the stochastic error term, and both *n* (the number of inputs) and P_i change to incorporate the assumptions of Models 1–3.

Using Shephard's Lemma, the *n* cost-minimizing variable cost share equations can be obtained by differentiating the log of the cost function with respect to the log of the price of input *i*:

$$\mathrm{S_i} = \frac{\partial \ln VC}{\partial \ln P_i} = \beta_i + \sum_{j=1}^{n}\beta_{ij}\ln P_j + \beta_{Ki}\ln K + \beta_{Yi}\ln Y + \beta_{Ti}Time + \varepsilon$$ **Equation 5**

[48] We exclude time's interaction with capacity for two reasons: (1) our focus is on disembodied technical change because of our short run focus and the associated assumption that capital is fixed and (2) our capital variable measures generating capacity and excludes scrubbers and other non-combustion capital that would presumably have contributed to capital-augmenting technical change over the period.

where n is the number of inputs for the model and S_i is the cost share for input i.

In Models 1 and 3, n = 3 with coal, oil, and natural gas input prices including or excluding the allowance price as described above. In Model 2, n = 4 where allowances are the fourth input with a price equal to the permit price.

We note also that differences in state regulation affect firms' investment options and fuel-use decisions. Some utilities, for example, are constrained to burn local coal or discouraged from installing scrubbers on coal-fired units.[49] Our models do not account for state/regional differences, which may blur (but should not change) the overall results, though the firm fixed effects discussed later are presumably correlated with state regulatory characteristics, and may help account for state effects.

All three models are estimated both with and without firm fixed effects (FE), where for the FE estimation we add (F – 1) firm-specific dummy variables,[50] D_i, each with a parameter to be estimated, such that the term $\delta_i D_i$ is appended to Equation 4. Note that the firm dummies do not appear in the share equations, as the share equations derive, by definition, from the partial derivative of the variable cost function with respect to the fuel prices. These issues are discussed further in Section 7. As in the standard least squares dummy variable (LSDV) model, the remaining error term is assumed iid $N(0, \sigma^2_{\varepsilon})$. (Baltagi (2001))

We impose the following standard symmetry and homogeneity restrictions[51] in all models to ensure that the cost functions are well-behaved (see Chambers (1988), Greene (1997), Cornes (1992)):

$$\beta_{ij} = \beta_{ji} \; ; \sum_{i=1}^{n} \beta_i = 1; \; \sum_{i=1}^{n} \beta_{ij} = 0 \;\; \forall j; \\ \sum_{i=1}^{n} \beta_{Yi} = 0; \; \sum_{i=1}^{n} \beta_{Ki} = 0; \; \sum_{i=1}^{n} \beta_{Ti} = 0 \quad .$$

Equation 6

[49] Thanks to Malcolm Keay for pointing this out.
[50] F = the number of firms. One dummy is dropped to avoid the problem of multicollinearity.
[51] The homogeneity restrictions ensure linear homogeneity of the cost function with respect to input prices, and do not imply linear homogeneity of the underlying production function with respect to input quantities. The symmetry restriction derives from Shephard's Lemma and Young's Theorem (see Chambers (1988) and Thompson (2006)).

For all three models, we estimate the variable cost function (Equation 4) jointly with $n - 1$ of the cost share equations[52] (Equation 5) in a Seemingly Unrelated Regression (SUR) framework in order to take advantage of the cross-equation error term correlation, and to incorporate the cross-equation parameter restrictions as implied by the duality characteristics.[53,54] The SUR model is estimated via feasible generalized least squares (FGLS), which corrects the error covariance matrix for contemporaneous correlation. Following Greene (2003),[55] the SUR model can be written as:

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \cdot \\ \cdot \\ \cdot \\ \mathbf{y}_M \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & \mathbf{0} \ldots \mathbf{0} \\ \mathbf{0} & \mathbf{X}_2 \ldots \mathbf{0} \\ & \cdot \\ & \cdot \\ & \cdot \\ \mathbf{0} & \mathbf{0} \ldots \mathbf{X}_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \cdot \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_M \end{bmatrix}$$

. **Equation7**

$$= \mathbf{X}\beta + \varepsilon$$

In Models 1 and 3, $M = 3$ and in Model 2, $M = 4$, with y_1 corresponding to the cost function, and $y_{2,\,3,\,4}$ corresponding to the cost share equations as required. Generalized Least Squares (GLS) is therefore the efficient estimator, as it allows for cross equation restrictions and results in β estimates with a smaller generalized variance than those given by ordinary least squares performed on the individual equations (see Zellner (1962) and Greene (2003)). The covariance matrix of the error terms for the t^{th} observation is

[52] Because $\sum_{i=1}^{n} \frac{\partial \ln VC}{\partial \ln P_i} = 1$, the inclusion of all n share equations results in a singular covariance matrix and one must therefore be dropped.

[53] Breusch–Pagan test results confirming correlation of the error terms of the estimated equations are presented in Section 5.5.1.

[54] We provide a brief description of the ITSUR methodology below. See Zellner (1963), Greene (2003), Wooldridge (2002), Kmenta and Gilbert (1968), Conniffe (1982), and Revankar (1974) for further details.

[55] This exposition assumes a fixed T for ease of presentation. See Schmidt (1977) and Im (1994) for an exposition with unequal observation numbers.

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \dots \sigma_{2M} \\ & . & \\ & . & \\ & . & \\ \sigma_{M1} & \sigma_{M2} & \dots \sigma_{MM} \end{bmatrix}. \qquad \textbf{Equation8}$$

The disturbances for the system given in Equation5 can then be written[56]

$$E\left[\varepsilon\varepsilon'\right] = \mathbf{V} = \Sigma \otimes \mathbf{I} \qquad \textbf{Equation 9}$$

so that

$$\mathbf{V}^{-1} = \Sigma^{-1} \otimes \mathbf{I}\,, \qquad \textbf{Equation 10}$$

and the GLS estimator is

$$\begin{aligned} \hat{\beta} &= \left[\mathbf{X}'\mathbf{V}^{-1}\mathbf{X}\right]^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{y} \\ &= \left[\mathbf{X}'\left(\Sigma^{-1} \otimes \mathbf{I}\right)\mathbf{X}\right]^{-1}\mathbf{X}'\left(\Sigma^{-1} \otimes \mathbf{I}\right)\mathbf{y} \end{aligned}. \qquad \textbf{Equation11}$$

Because **Σ** is generally unknown, the FGLS estimator is used instead, and the residuals from the separate OLS estimation of the individual SUR equations are used to estimate the elements of Σ consistently, as follows:

$$\hat{\sigma}_{ij} = \frac{\mathbf{e}_i{}'\mathbf{e}_j}{T}. \qquad \textbf{Equation 12}$$

Thus, the covariance matrix of the error terms is estimated in the first stage as

---

[56] Note that $\otimes$ denotes the Kroenecker product, such that $A \otimes B = \begin{pmatrix} a_{11}B & \dots & a_{1n}B \\ \vdots & \ddots & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{pmatrix}$.

$$\mathbf{S} = \begin{bmatrix} \hat{\sigma}_{11} & \hat{\sigma}_{12} & \dots & \hat{\sigma}_{1M} \\ \hat{\sigma}_{21} & \hat{\sigma}_{22} & \dots & \hat{\sigma}_{2M} \\ & . & & \\ & . & & \\ & . & & \\ \hat{\sigma}_{M1} & \hat{\sigma}_{M2} & \dots & \hat{\sigma}_{MM} \end{bmatrix} \qquad \textbf{Equation 13}$$

and the corresponding FGLS estimator is

$$\hat{\beta}_{FGLS} = \left[\mathbf{X}'\left(\mathbf{S}^{-1} \otimes \mathbf{I}\right)\mathbf{X}\right]^{-1} \mathbf{X}'\left(\mathbf{S}^{-1} \otimes \mathbf{I}\right)\mathbf{y}. \qquad \textbf{Equation 14}$$

This procedure is iterated in an iterated seemingly unrelated regression procedure. FGLS estimates are consistent and efficient in large samples, and because the SUR model meets the Oberhofer–Kmenta (1974) conditions ensuring monotonicity of the sequential procedure, the iterated FGLS estimates converge to Maximum Likelihood estimates (see Biørn (2004), Beck and Katz (1995) and Greene (2003)).

6 Model Selection

This section addresses the selection between Models 1–3 described in Section 4 above. We present both the Akaike Information Criterion (AIC) (Akaike (1973)) and the Bayesian Information Criterion (BIC) (Schwarz (1978)) as model selection criteria (see also Buckland et al. (1997) and Greene (2003)). Both the AIC and BIC are based on an information criterion as follows:

$I_j = -2\log(L_j) + q_j$ **Equation15**

where L_j represents the likelihood function evaluated with the maximum likelihood parameters for model j, and q_j is a penalty for increased parameters and/or observations. For the AIC, $q = 2k$, while for the BIC, $q = k\log(n)$ such that

AIC = $-2\log(\text{L}) + 2k$ **Equation16**

and

BIC = $-2\log(L) + k\log(n)$ **Equation 17**

where n is the number of observations, and k is the number of the model's parameters. These measures reward goodness fit as measured by the value of the maximized likelihood function, but penalize losses of degrees of freedom, with the penalty for additional parameters being greater for the BIC. The AIC is an asymptotically efficient criterion, while the BIC is asymptotically consistent,[57] and the 'best' model by either criterion has the lowest value information criterion.

[57] As $N\rightarrow\infty$, efficient criteria will select the 'best' finite-dimensional model when the true model is infinite-dimensional, while consistent criteria select the 'true' finite-dimensional model from a group of models with probability approaching 1. See Shi and Tsai (2002).

In addition to the AIC and BIC, we present the R^2 and adjusted R^2 values[58] for the pooled and fixed effects estimation of the three models.[59] The values in Table 3 result from the constrained estimation of the cost function for the respective models,[60] and should be compared by model and estimation type for each individual statistic. We note first that Model 3 is inferior to Models 1 and 2 by all criteria, indicating that the SO_2 price did, indeed, affect firm behaviour. This indicates that the allowance price should not be excluded from the model, and we are left with the question of how it should be incorporated.

Table 3: Model Selection Criterion					
		R^2	**Adjusted R^2**	**AIC**	**BIC**
Model 1: *n* = 5128 *k* = 27, 63	**Pooled**	0.8284	0.8275	12389.07	12519.92
	FE	0.8452	0.8433	11934.61	12300.98
Model 2: *n* = 5128 *k* = 34, 70	**Pooled**	0.8285	0.8274	12383.32	12559.96
	FE	0.8453	0.8432	11927.18	12339.35
Model 3: *n* = 5128 *k* = 27, 63	**Pooled**	0.8264	0.8255	12446.19	12577.04
	FE	0.8420	0.8401	12038.55	12404.93

The BIC and adjusted R^2 values indicate the superior fit of Model 1 for both pooled and FE estimation, while the AIC and R^2 values favour Model 2.[61] Because the R^2 value contains more information than the R^2 measure, and because the BIC has the quality of consistency (as opposed to the AIC's efficiency), we consider these measures preferential in this case, and they indicate the slight superiority of Model 1's fit to the available data. This, combined with our objective of estimating interfuel (rather than fuel-allowance) substitution elasticities, leads us to abandon Model 2 and its assumption that permits should be interpreted as a fourth and separate input to the electricity production process, as suggested by Considine and Larson (2006). Rather, we proceed with the assumption that firms, given our single-output

[58] The adjusted R^2 value is calculated as follows: $AdjR^2 = 1 - \frac{n-1}{n-K}\left(1-R^2\right)$ so that the standard R^2 coefficient of determination is adjusted for losses in degrees of freedom as parameters are added to the model. See, e.g., Greene (2003).

[59] The relevant parameter estimates from Models 2 and 3 are presented in Tables A1 and A2 in the Appendix.

[60] Constraints as given in the previous section.

[61] Note also that the AIC and BIC both favour fixed effects over pooling for all three models. This is discussed further in the following section.

model, incorporate the allowance price into individual fuel prices, and choose inputs accordingly. The remainder of our analysis is therefore based on Model 1, and the relevant descriptive statistics for Model 1's variables for each of the five-year time subsets discussed below are provided in Tables A3–A5 in Appendix 1.

7 Panel Issues: Fixed Effects vs Pooling

Before presenting results based on Model 1's estimation, we consider several issues related to specification and estimation techniques. This section and the next address panel and estimation issues, while Section 9 tests various technology-related hypotheses. As noted in the literature review, a majority of previous studies on interfuel substitution in the electricity generating industry have been done either with cross sectional or aggregate time series data. Of the few recent papers that employ panel data, most have focused on pooled analysis, have used data from prior to the tradable sulphur scheme, or have studied the behaviour of other industries or other nations.[62] The size of our panel allows us to model unobserved effects and test for firm heterogeneity in a way that is impossible with time-series and cross section data. Panel estimation also reduces multicollinearity issues and allows for efficiency gains in estimation. (Smith and Fuertes (2007))

With the large N, large T characteristics of our panel, two important issues must be addressed.[63] The first is stationarity, discussed in Section 8 below. The second, and the focus of this section, is that of orientation and heterogeneity, as briefly mentioned in Section 5. With a panel as large as ours, it is possible to treat the data as a set of time series, or a set of cross sections. When not assuming poolability, we interpret the panel as a set of firm-specific time series, leaving us with the question of firm heterogeneity. It is possible to allow for group-specific heterogeneity in all parameters by estimating the model separately for each firm such that the cost function looks as follows:

[62] See Söderholm (1998), Söderholm (2000), and Ko and Dahl (2001) for a summary of previous studies, and see Bjørner and Jensen (2006) and Arnberg and Bjørner (2006) for panel studies of Danish interfuel and interfactor demand. Considine and Larson (2006) is a panel study covering the same period and industry as ours. See the literature review in section 3.3 for further details.

[63] Heteroskedasticity is a third. We do not discuss it here explicitly because (1) the slope parameter estimates themselves are of greater importance to our research than the standard errors, and (2) SUR estimation is based on FGLS, which was proposed by Parks (1967) and Kmenta (1986) as a means for dealing with non-spherical error terms in panel data estimation. Panel corrected standard errors (PCSEs), proposed as superior to Parks' (1967) GLS approach by Beck and Katz (1995), are not available for SUR estimation, as they are based on a correction of OLS residuals. Note also that the estimates of the β parameters (our main concern, given our focus on elasticity estimates) remain unbiased in the presence of heteroskedasticity, and only their standard errors will be imprecise.

$\vec{y}_{it} = \alpha_i + \vec{\beta}_i \vec{x}_{it} + u_{it};\;\; u_{it} \sim iid\, N(0, \sigma_i^2)$. **Equation 18**

In Equation 18, $\vec{y}_{it}$ contains the variable fuel cost observations and $\vec{x}_{it}$ is a vector of the right hand side variables from Equation 4. Given our objective of national-level policy analysis, however, this level of heterogeneity is unnecessary,[64] and we impose the restriction of equal slope parameters, i.e. $\beta_i = \beta, \forall i$.[65]

The remaining heterogeneity is in the intercept term of the variable cost function, and can be modelled as either fixed effects (FE) or random effects (RE). RE estimation requires the assumption that the individual effects are distributed independently from the regressors. It is likely, however, that firm-specific characteristics are correlated with our right hand side variables, particularly capacity and output quantities,[66] and we therefore proceed with the FE approach.

Firm fixed-effects can be incorporated equivalently by including cross section-specific dummy variables or via within- estimation. Both focus solely on within- (rather than between-) group variation, meaning that we focus on changes in variables across time for each firm, not on changes in variables between firms. We opt for the dummy variable (DV) approach to FE estimation which, as mentioned above, looks as follows:

$y_{it} = \alpha + \delta_i D + \beta x_{it} + u_{it}$, **Equation 19**

where *y* is a vector of independent variables for a general regression, *x* is a matrix of independent variables, *D* is a vector of firm dummies, and β and δ_i are parameters to be estimated. The intercept for each firm is then equal to $\alpha + \delta_i$.[67] We apply the DV technique

[64] We thank Søren Arnberg for a useful conversation about this issue.
[65] Note that we do not assume firm heterogeneity outright, but report results for both the homogeneous-parameter pooled model and the FE model, and test for poolability as noted later in this section.
[66] Delivered fuel prices may be correlated with firm characteristics as well, as delivered fuel prices depend on firm location. Capacity and output may be correlated with firm characteristics, as they may reflect management ability and/or location.
[67] One of the firm dummies must be dropped to avoid multicollinearity issues. The intercept for that firm is just α, meaning that all other intercepts are relative to that of the dropped firm.

by adding firm-specific dummy variables to the cost function Equation 4.[68] (See Baltagi (2001), Baum (2006), and Wooldridge (2002) for more on FE estimation.)

We then estimate the three-input SUR Model 1 described in Section 5 with firm-specific heterogeneity (the 'FE model') and without heterogeneity (the 'pooled model') on the full dataset and on three time subsets 1990–1994, 1995–1999, and 2000–2004, corresponding respectively to the period prior to the CAAA's SO_2 trading scheme, Phase I of the scheme, and Phase II. To test for poolability in each of the time periods, we use an F-test as follows:

$$F = \frac{(R_{FE}^2 - R_{pooled}^2)\big/(n-1)}{(1-R_{FE}^2)\Big/\left(\sum_i nT_i - n - k\right)} \quad \text{with } F \sim \chi^2(n-1, \sum_i nT_i - n - k) \qquad \textbf{Equation 20}$$

where n is the number of groups (here, firms), T_i is the number of observations available for firm i, and k is the number of parameters to be estimated in the FE model. The results for the F tests, given the calculated R^2 values from the constrained estimation cost function in Stata are presented in Table 4. The F-tests support the AIC and BIC results from Table 3 in the previous section, indicating that firm effects are present and significant. In the sections that follow, we therefore present results and interpretations for the FE estimation of Section 5's three-input Model 1 for the relevant time subsets, implying a focus on within-firm variation. The corresponding estimates from pooled estimation for all subsections can be found in Appendix 1.

Table 4: Test for the Presence of Firm Fixed Effects

	1990–2004	1990–1994	1995–1999	2000–2004
FE				
R^2	0.8452	0.8677	0.8467	0.8603
N	37	35	37	35
$\sum_i nT_i$	5128	1763	1898	1467
k	54	52	54	52
Pooled				
R^2	0.8284	0.8454	0.8282	0.8360
N	37	35	37	35
$\sum_i nT_i$	5128	1763	1898	1467

[68] We had originally included firm dummies in the cost function *and* the corresponding cost share equations, but from Shephard's Lemma, the intercept parameters of the share equations derive from the homogenous β parameters in the cost function.

k	18	18	18	18
F-value	15.1848*	8.3088*	6.0574*	7.0601*
* Denotes value exceeds 5 per cent critical F value. NB: 5 per cent critical value for F with 30 df in the numerator and ∞ df in the denominator is 1.46, and for 40 df in the numerator is 1.39.				

7.1 SUR vs Single Equation Estimation

In order to validate our choice of the SUR modelling approach over single-equation estimation, we present the results of the Breusch–Pagan (B–P) test for single equation OLS estimation versus simultaneous FGLS estimation of the system. The B–P test statistic is distributed $\chi^2(3)$ in our case, and the results in Table 5 indicate that the null of no contemporaneous correlation of the equations' residuals is strongly rejected. The SUR method using the cost function and two cost share equations as described in Section 5.2 above is thus more efficient, and yields lower standard errors than the separate estimation of three OLS regressions. (See Greene (2003) and Zellner (1962).) The corresponding residual correlation matrices are presented in Tables A8–A11 in Appendix 1.

Table 5: Breusch–Pagan Test for Correlation of Equation Residuals

	All Years	**1990–1994**	**1995–1999**	**2000–2004**
B–P Test Value	7956.82 (0.0000)	2895.03 (0.0000)	3574.51 (0.0000)	2264.85 (0.0000)
NB: p-value in parentheses. The 5 per cent critical $\chi^2(3)$ value is 7.815.				

Slope parameter estimates for the FE–SUR estimation of Model 1 are presented in Table 6 below.[69] Because we are interested in the parameter estimates primarily for their role in the calculation of demand and substitution elasticities (discussed in Section 8), and because the parameters themselves have little economic meaning (see Binswanger (1974)), we do not discuss them in any detail. We note only that (1) most parameter estimates have the expected sign and (2) most of the fuel-related parameters (i.e. those that are important for elasticity calculations) are significant at the 5 per cent level.

[69] Firm-dummy and intercept parameters from the FE model are available in Table A6 in the Appendix.

Table 6: Parameter Estimates from 3-input FE model, 4 Time Subsets				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
β_K	–4.4524** (1.0869)	–0.2117 (2.0413)	2.9379 (–0.9919)	–13.0495** (3.1821)
β_Y	–0.3457 (0.4755)	–1.9801** (0.7714)	–0.2408 (0.1969)	1.7938 (1.1991)
β_{KK}	0.3173** (0.0892)	–0.0868 (0.1624)	–0.2408 (0.1969)	1.0370** (0.2589)
β_{KY}	0.0592 (0.0430)	0.1963** (0.0695)	0.1126* (0.0606)	–0.1445 (0.1110)
β_{YY}	0.0453* (0.0208)	0.0116 (0.0459)	0.0604 (0.0391)	0.1020 (0.0719)
β_C	0.9095** (0.0843)	1.3269** (0.1352)	0.7769** (0.1340)	0.4485** (1.1851)
β_O	–0.2667** (0.0326)	–0.2732** (0.0590)	–0.2821** (0.0471)	–0.3134** (0.0631)
β_G	0.3572** (0.0791)	–0.0537 (0.1237)	0.5052** (0.1258)	0.8649** (0.1762)
β_{CC}	–0.0458** (0.0081)	–0.0876** (0.0149)	–0.0826** (0.0122)	–0.0222 (0.0156)
β_{CO}	0.0337** (0.0035)	0.0506** (0.0069)	0.0427** (0.0053)	0.0051 (0.0064)
β_{CG}	0.0121* (0.0069)	0.0371** (0.0123)	0.0398** (0.0103)	0.0171 (0.0064)
β_{OO}	–0.0850** (0.0035)	–0.1311** (0.0063)	–0.0688** (0.0051)	–0.0372** (0.0075)
β_{OG}	0.0513** (0.0034)	0.0806** (0.0063)	0.0261** (0.0047)	0.0321** (0.0066)
β_{GG}	–0.0634** (0.0069)	–0.1176** (0.0122)	–0.0659** (0.0100)	–0.0492** (0.0138)
β_{KC}	–0.0254** (0.0082)	–0.0730** (0.0132)	–0.0164 (0.0130)	0.0230 (0.0184)
β_{KO}	0.0319** (0.0032)	0.0345** (0.0057)	0.0329** (0.0045)	0.0317** (0.0063)
β_{KG}	–0.0065 (0.0077)	0.0385** (0.0095)	–0.0164 (0.0122)	–0.0548** (0.0184)
β_{YC}	0.0408** (0.0060)	0.0774** (0.0095)	0.0393** (0.0095)	–0.0070 (0.0176)
β_{YO}	–0.0134** (0.0060)	–0.0094** (0.0041)	–0.0184** (0.0033)	–0.0155** (0.0047)
β_{YG}	–0.0274** (0.0057)	–0.0681** (0.0084)	0.0210** (0.0090)	0.0225* (0.0131)
β_T	–0.0019** (0.0008)	0.0037 (0.0038)	–0.0057 (0.0036)	0.0077* (0.0042)
β_{TT}	0.00003** (0.00001)	–0.0002 (0.0001)	0.0002** (0.0001)	–0.0002 (0.0001)
β_{TQ}	0.00007 (0.0001)	0.0015** (0.0005)	–0.0001 (0.0005)	–0.0012* (0.0007)
β_{TC}	–0.0004** (0.0001)	–0.00002 (0.0004)	–0.0009** (0.0003)	0.0006 (0.0004)
β_{TO}	–0.0002* (0.0001)	–0.0023** (0.0005)	0.0003 (0.0005)	0.0012* (0.0007)
β_{TG}	0.0005** (0.0001)	0.0009** (0.0003)	0.0006** (0.0003)	–0.0007* (0.0004)

** Indicates significance at the 5 per cent level. * Indicates significance at the 10 per cent level.

8 Panel Unit Roots and Stationarity

The final panel issue we address is that of stationarity. In long panels such as ours, stationarity becomes a question, as regression in levels with non-stationary variables can introduce problems of spurious regression (see Greene (2003), Newbold and Granger (1974) and Philips (1986)). Our panel is not long temporally, but because of its monthly nature we have a large T (max T=180). We therefore briefly discuss the issue of panel stationarity and present the results of the Fisher test for the residuals from the constrained OLS estimation of the cost function and share equations.

The Augmented Dickey–Fuller (ADF) test serves as the basis for the panel unit root test we use below. It tests the null hypothesis of a time series unit root and augments the standard Dickey–Fuller test (Dickey and Fuller (1979)) to guard against serial correlation of the error term by including lags of Δy_t as follows:

$$\Delta y_t = \alpha + b y_{t-1} + \sum_{j=1}^{k-1} \phi \Delta y_{t-j} + \varepsilon_t \ . \qquad \textbf{Equation 21}$$

Here, k represents the lag-order of the AR(p) process that y_t follows and must be chosen by the researcher, and $b = (\rho - 1)$, such that the null hypothesis, $b = 0$, is equivalent to the hypothesis that $\rho = 1$. While alternative time series unit root tests exist (e.g. the non parametric Phillips–Perron (PP) test (Phillips and Perron, 1988) and the KPSS test (Kwiatkowski et al., 1992) which maintains the null hypothesis that the series is in fact I(0)),[70] the ADF is the most prominent in the literature and, as noted, serves as the basis for the Fisher panel unit root test discussed below.

The low power of time series unit root tests (see, e.g., Metes (2005)) has spurred a literature beginning with the papers by Levin and Lin (1992 and 1993) on panel unit root tests, with the objective of increasing the power of unit root tests generally through the additional data available when a cross section dimension is included. Much of this literature has focused on

[70] See Metes (2005), Greene (1997) and Smith and Fuertes (2007).

the question of purchasing power parity (PPP)[71] and other similarly macro-oriented problems, but the large T characterization of our dataset makes the insights relevant here as well.

The null and alternative hypotheses are slightly different for panel data than they are in a strictly time series setting. In the ADF equation 21 above, for example, the hypotheses are as follows:

H_0: $\rho_1 = 1$ against H_1: $\rho_1 < 1$

where ρ's subscript refers to the data's single cross section. In the panel setting, the null must incorporate all cross sections:

H_0: $\rho_i = 1$ against H_1: $\rho_i < 1$, for $i = 1, 2, \ldots, N$.

The panel unit root test we employ here is the Fisher test, originally proposed by Fisher (1932), and promoted by Maddala and Wu (1999) as superior to the IPS (Im, Pesaran, and Shin (1996, 2002)) and LL (Levin and Lin (1992, 1993)) tests for its simplicity and applicability to unbalanced panels such as ours.[72] The Fisher test allows for heterogeneity, and, like the IPS test, begins with individual ADF tests for each cross section. The test statistic for the ρ parameter is based on the significance levels (p-values) of the ADF tests, p_i, where p_i is the significance level of the i^{th} test. These p-values are independent uniform (0, 1) variables when the ADF test statistics are continuous, and Fisher (1932) shows that $-2 \ln p_i$ is distributed $\chi^2(2)$. Maddala and Wu (1999) suggest summing these p-values over N for the test statistic:

$$\lambda = -2\sum_{i=1}^{N} \ln p_i \qquad \textbf{Equation 22}$$

where $\lambda \sim \chi^2(2N)$.

[71] See, for example, Oh (1996), Wu (1996), and MacDonald (1996).
[72] Note that the IPS test is more powerful than the LL test (Im, Pesaran, and Shin (2003), Maddala and Wu (1999), and Smith and Fuertes (2007)) because it does not assume a constant ρ_i for all i. The IPS test (which compares individual unit root test statistics) requires balanced panel data, but was found by Maddala and Wu (1999) to be less powerful than the Fisher test (which compares individual unit root tests' significance levels) at detecting panel unit roots.

The results of the Fisher panel unit root tests are presented in Table 7. In order to apply the Fisher tests, the trend inclusion and lag-number decision must be made. Metes (2005) notes both the importance of the lag-number decision and the multitude of methods for optimal lag selection.[73] Some suggest starting with many lags and sequentially removing the longest lag when it produces an insignificant t-value, while others recommend using the Akaike Information Criterion or Bayes Information Criterion to select the optimal lag value, *k**, from several models with a range of *k* values.[74] Because getting the lag-length correct is crucial to the validity of the unit root test, and because of the controversy over selection methods, we present results for the Fisher panel test and the individual ADF tests for lag values 1–4, with and without a trend for each variable. This allows us to draw conclusions about the stationarity of the data, and minimizes concern over the correct time series specification. Thus, the ADF model we use looks as follows:

$$\Delta y_{it} = \alpha_i + \delta t + \rho_i y_{i,t-1} + \sum_{j=1}^{4} \theta_{ij} y_{i,t-j} + \varepsilon_{it} \qquad \textbf{Equation 23}$$

where y represents the natural log of variable y, and $\delta = 0$ for the model without trend.

The results in Table 7 show that the residuals reject the Fisher test's unit root null with and without a trend at all lags at the 5 per cent level.[75] This, combined with the measurement error and subsequent parameter bias concerns when combining first differences with fixed effect estimation (see Tauchmann (2006), and Griliches and Hausman (1986)), the difficulty of parameter interpretation for models estimated in first differences, and the fact that 428 observations are lost when the data is transformed into first differences, leads us to conclude that estimation in levels is both sufficient and superior. Fisher test results for unit roots in the individual variables are presented in Table A12 in Appendix 1.

[73] See also Hall (1994).
[74] Other methods have been suggested (e.g. Schwert (1989) suggests a rule for determining a maximum lag value based on the number of observations in the sample), but the ones mentioned above are the most prevalent and straightforward.
[75] Note that this does not necessarily prove that all series are stationary, as rejection of the null (i.e. $b_i = 0$ for all i) could occur if even one of the b_i is non-zero. This is a problem with all panel unit-root tests, and we chose the Fisher test as the best available.

Table 7: Fisher Panel Unit Root Tests for Residuals				
	Variable Cost Equation	Coal Share Equation	Gas Share Equation	Oil Share Equation
1 lag	1025.765* (0.0000)	727.292* (0.0000)	314.978* (0.0000)	756.882* (0.0000)
2 lags	787.341* (0.0000)	603.271* (0.0000)	228.770* (0.0000)	543.312* (0.0000)
3 lags	573.340* (0.0000)	487.170* (0.0000)	168.345* (0.0000)	442.378* (0.0000)
4 lags	434.542* (0.0000)	360.979* (0.0000)	139.689* (0.0000)	302.569* (0.0000)
1 lag, trend	956.205* (0.0000)	696.221* (0.0000)	364.665* (0.0000)	690.983 (0.0000)
2 lags, trend	746.102* (0.0000)	585.617* (0.0000)	252.458* (0.0000)	491.481* (0.0000)
3 lags, trend	530.240* (0.0000)	466.913* (0.0000)	172.014* (0.0000)	392.612* (0.0000)
4 lags, trend	396.359* (0.0000)	370.589* (0.0000)	130.8935* (0.0001)	278.733* (0.0000)

* Signifies rejection of the null of a unit root at the 5 per cent level. NB: p-values in parentheses.

9 Technology Hypothesis Tests

Because the translog function does not impose any restrictions on the underlying production technology, we test for various characteristics in this section in order to justify our cost function and its resulting parameter estimates. We do so by imposing restrictions related to various technology assumptions upon the translog cost function, and test each with a Wald test.

We first test the Cobb–Douglas restrictions in order to validate the use of the more general translog cost function. The Cobb–Douglas functional form, which implies unitary input substitution elasticities, is reasonable if the following holds:

$$\beta_{KK} = \beta_{KY} = \beta_{YY} = \beta_{ff} = \beta_{Yf} = \beta_{Kf} = \beta_{Tm} = 0 \qquad \textbf{Equation24}$$

where *f* stands for each of the fuels, and *m* for each of the variables interacted with time. The restrictions in Equation 24 are rejected (see Table 8), indicating that the flexible translog cost function is preferable to the Cobb–Douglas technology, and implying substitution elasticities are not equal to one. Next, the translog cost function exhibits strong separability of capital from the fossil fuel inputs if

$$\beta_K = \beta_{KK} = \beta_{KY} = \beta_{KC} = \beta_{KO} = \beta_{KG} = 0\,. \qquad \textbf{Equation 25}$$

If the hypothesis represented by Equation 25 can be rejected, capital is not strongly separable from the fossil fuel inputs in the production process, and excluding the capital variable from the cost function would result in biased parameter estimates. (See Lee (2007).)
The production function associated with our restricted variable cost function is linearly homogeneous in all inputs if the following restrictions hold:[76]

$$\beta_Y = 1 - \beta_K\,;\ \beta_{xY} = -\beta_{xK} \qquad x = K, Y, P_c, P_o, P_g\,. \qquad \textbf{Equation 26}$$

[76] See Halvorsen and Smith (1986), Ellis and Halvorsen (2002), and Lee (2007).

If Equation 26 can be rejected, the production process is not linearly homogenous, and scale effects are present in the production process. A related characteristic is that of homotheticity, which we test for by imposing the restriction

$$\beta_{KY} = \beta_{KC} = \beta_{KO} = \beta_{KG} = 0. \qquad \textbf{Equation 27}$$

If Equation 27 can not be rejected, input prices and output are separable in the cost function, meaning that $VC(y, \boldsymbol{p})$ can be written as $h(y)VC(\boldsymbol{p})$ (see Ball and Chambers (1982) and Chambers (1988)). If Equation 27 can be rejected, factor proportions are not equal at the cost-minimizing points for all output levels, and the expansion path is not linear.

Finally, we test for neutrality of technical change, as discussed further in Section 10. Technical change is Hicks-neutral in the fossil fuel inputs if

$$\beta_{TC} = \beta_{TO} = \beta_{TG} = 0 \qquad \textbf{Equation 28.}$$

Conditional on Equation 28 holding, the complete absence of technical change can be tested with the additional restriction:

$$\beta_{T} = \beta_{TT} = \beta_{TQ} = 0 \qquad \textbf{Equation 29}$$

The results for the Wald tests of the restrictions shown in Equations 24–29 on the FE estimation of Model 1 for the whole period are presented below in Table 8. All restrictions are rejected at the 1 per cent significance level. The technology, then, is not strongly separable in inputs K, C, O, and G, and estimating a cost function without the capacity variable would lead to biased parameter estimates. The technology is neither linearly homogenous in inputs[77] nor homothetic, implying the presence of scale economies and the non-separability of output from the input prices in the cost function. The tests associated with technical change (Equations 28 and 5.29) indicate that technical change *was* indeed present, and that it was not Hicks-neutral over the period. This will be discussed further in Section 10. Overall, the results in Table 8 serve to support the use of the unrestrictive cost function presented in Equation 4.

[77] Note that this is different from the linear homogeneity in input prices that is imposed via restrictions on the cost function and resulting share. This restriction is required for downward sloping input demand curves.

Table 8: Technology Hypothesis Tests		
Hypothesis	Wald Test Statistic	Critical χ^2 value
Cobb–Douglas	1283.98	37.57
Separability of K from fossil fuel inputs	155.78	11.34
Linear Homogeneity	413.86	16.81
Homothetic Technology	66.62	13.28
Hicks-Neutral Technical Change	18.55	11.34
No Technical Change	25.81	11.34
NB: Critical χ^2 values are reported at the 1 per cent significance level.		

10 Elasticities of Demand and Substitution

Having tested for alternative specifications and considered the issues of stationarity and firm heterogeneity, we use the parameters from the FE estimation of our Model 1 to assess fuel elasticities in this section. We provide estimates for input demand elasticities, as well as Allen–Uzawa, Morishima and Shadow elasticities of substitution for the entire period and for each of the five-year subsets in an effort to characterize short run fuel use and substitution possibilities for the firms in our dataset. Before presenting the results themselves, we briefly discuss each of the elasticities, their calculations and their interpretations.

10.1 Input Demand Elasticities

Recall Property X.3 from Section 3.1 which states that, given linear homogeneity, concavity and twice differentiability of the cost function, changes in pairs of input prices have symmetric effects on input demand, i.e.

$$\partial x_i / \partial p_j = \partial x_j / \partial p_i \text{ . } \quad \textbf{Equation 30}$$

Thus the marginal effect of a rise in the price of input *i* on the demand for input *j* is symmetric to that of a rise in the price of input *j* on the demand for input *i* (see Chambers (1988) p.65). Derived demand *elasticities,* however, measure the relative changes in the demand for two inputs for a relative change in their prices, and are not necessarily symmetric.

For a general cost function, the derived demand elasticity for factor *i* with respect to the price of factor *j* is defined as

$$\eta_{ij} \equiv \frac{p_j}{x_i} \frac{\partial x_i}{\partial p_j} \quad \textbf{Equation 31}$$

where $i = j$ refers to the own-price elasticity of demand, $i \neq j$ refers to the cross-price elasticity of demand, and by Shephard's Lemma and the definition of the cost share,[78] $x_i = \partial C / \partial p_i = \frac{C}{p_i} S_i$ is the derived demand for factor *i.* It can be shown that the symmetry of the cross-price effects from Equation 30 implies

$$\eta_{ij} = \eta_{ji}(S_j / S_i) \qquad \textbf{Equation 32}$$

where S_i refers to the cost share of factor *i,* meaning that the cross-price elasticities are related by the ratio of factor cost shares.[79]

For the translog case, the elasticities of factor demand are written as follows:

$$\eta_{ij} = \frac{\beta_{ij}}{S_i} + S_j \qquad \textbf{Equation 33}$$

$$\eta_{ii} = \frac{\beta_{ii}}{S_i} + S_i - 1 \qquad \textbf{Equation 34}$$

where η_{ij} is the cross-price elasticity and η_{ii} is the own-price elasticity of factor demand. (See Binswanger (1974).) The elasticities of demand provide information about relative-price-induced factor demand changes, but they do not provide information about the ease of substitution. For that we must turn to substitution elasticities. The three substitution elasticities we consider here are the Allen (or Allen–Uzawa) partial elasticity of substitution (AES), the Morishima elasticity of substitution (MES), and the shadow elasticity of substitution (SES). We discuss each in turn below.

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[78] By Shephard's Lemma, $\frac{\partial C}{\partial p_i} = x_i$ and $\frac{\partial \ln C}{\partial \ln p_i} = S_i$ where x_i is the derived demand for input *i* and S_i is the cost share of input *i*. The cost share is by definition: $S_i = \frac{x_i p_i}{C}$, where *C* is total cost, or, in our case, variable cost.

[79] It is for this reason that the Allen–Uzawa cross-price elasticities of substitution are symmetric. See Chambers (1988, Chapter 2).

10.2 The Allen–Uzawa Partial Elasticity of Substitution

The AES was proposed as a generalization of Hicks' concept of substitution elasticity[80] for multi-input technologies. As shown below, the AES can be written as a derived demand elasticity divided by a cost share, and it is therefore a one-price-one-factor elasticity of substitution (OOES) (Mundlak (1968)) that expresses the percentage change in the demand for one factor given a percentage change in the price of another, holding output and other factor prices constant. Allen originally proposed the AES between factors *i* and *j* in terms of the production function as follows:

$$\sigma_{ij}^{A} = \frac{F_{ji}}{|F|} \frac{\sum_{i=1}^{n} \left(\partial f(x) / \partial x_i \right) x_i}{x_i x_j} \qquad \textbf{Equation 35}$$

where $f(x)$ is the production function, $|F|$ is the determinant of the bordered Hessian, F_{ji} is the cofactor associated with f_{ji}, and x_i is quantity of input *i*.

Uzawa (1962) used the duality between cost and production functions to show that an equivalent representation of Equation 35 using the cost function for constant returns to scale technologies is:

$$\sigma^{AU} = \frac{CC_{ij}}{C_i C_j} \qquad \textbf{Equation 36}$$

where *C* denotes the cost function, and subscripts represent partial derivatives. Behar (2004) proves that this equivalence holds for all technologies. Meanwhile, the symmetric cross-price property of well-behaved demand functions (see Equation 28) implies that $C_{ij} = C_{ji}$, which, when combined with Equation 36 implies that the AES is a symmetric measure, i.e. $\sigma_{ij}^{AU} = \sigma_{ji}^{AU}$. An alternative representation of Equation 36 is[81]

$$\sigma^{AU} = \frac{\eta_{ij}}{S_j} \qquad \textbf{Equation 37}$$

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[80] Hicks (1932) defined the elasticity of substitution for a two-input technology as the ratio of the proportionate change in factor proportions to proportionate changes in the marginal rate of technical substitution, meaning that the Hicksian elasticity of substitution is meant to summarize the shape of the isoquant.

[81] See Chambers (1988) and Binswanger (1974).

where η_{ij} is the cross-price elasticity of demand and S_j is the cost share of the j^{th} input, meaning the AES is simply a weighted measure of the cross-price elasticity of demand.

In the translog case, the AES are written as

$$\sigma_{ij}^{AU} = \frac{\beta_{ij}}{S_i S_j} + 1 \qquad \forall i, j;\ i \neq j \qquad \textbf{Equation 38}$$

$$\sigma_{ii}^{AU} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i^2} \qquad \forall i \qquad \textbf{Equation 39}$$

where σ_{ij}^{AU} refers to the cross-price Allen–Uzawa elasticity of substitution, σ_{ii}^{AU} refers to the own-price Allen–Uzawa elasticity of substitution, and the β's are the own- and cross-price parameters from the estimated translog cost function presented in Table 6.

The AES is the most often-cited substitution elasticity in the applied literature, probably because of its relative ease of calculation and the fact that it is unaffected by the magnitude of changes in factor prices. That said, it does not actually measure the curvature of the isoquant in a multi-factor setting, nor does it provide information about relative factor shares, and it is therefore inconsistent with the original Hicksian definition of substitution elasticity. In addition, it assumes that the input factor changes are invariant to which of the input prices change, which appears unrealistically restrictive. (See Blackorby and Russell (1989).) Chambers (1988) also notes that the AES could easily be ignored as a measure of substitution, as one could argue that η_{ij} is in fact the interesting measure, while σ^{AU} just disguises this by dividing it by the cost share as shown in Equation37. We report the AES nonetheless, partly out of convention and for ease of comparison to previous studies, and partly because they are at least proportional to $\partial \ln x_i / \partial \ln p_j$ when output and other input prices are held constant, and thus contain simple (if unrealistic) information about substitution possibilities.

10.3 The Morisihima Elasticity of Substitution

The Morishima elasticity of substitution (MES) is a two-factor-one-price elasticity of substitution (TOES) (Mundlak (1968)) that expresses the percentage change in relative factor demands (accounting for own- *and* cross-price elasticity effects) for a percentage change in factor prices.[82] It therefore a truer measure of the ease of substitution and the curvature of the isoquant, but it is reported with much less frequency.

The Morishima elasticity of substitution can be written as[83]

$$\sigma_{ji}^{M} = \frac{p_i C_{ij}}{C_j} - \frac{p_i C_{ii}}{C_i} \qquad \textbf{Equation 40}$$

or, equivalently,

$$\sigma_{ji}^{M} = \eta_{ji} - \eta_{ii} \qquad \textbf{Equation 41}$$

where subscripts on C represent partial derivatives with respect to price, and η_{ji} and η_{ii} are the cross- and own-price elasticities of demand given in Equations 31 and 32 for the translog case. It is clear from Equation 41 that the Morishima elasticities need not be symmetric[84] (see Koizumi (1976)) and that a pair of factors found to be Allen complements ($\sigma_{ij}^{AU} < 0$) may be found to be substitutes by the Morishima measure ($\sigma_{ij}^{M} > 0$).[85] It should be noted also that the value (and even the sign) of σ^{M} depends on which input price is changing (see Chambers (1988)). Thus, as Blackorby and Russell (1989) note, the Morishima elasticity is more suitable than the AES for determining the effects of a change in the ratio of input prices on the ratio of input quantities, and we report Morishima values for these reasons.

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[82] TOES elasticities generally take the form $(\hat{x}_i - \hat{x}_j)/\hat{p}_j$ where '^' indicates a percentage change. See Chambers (1988).

[83] See Blackorby and Russell (1989).

[84] The Morishima substitution elasticity is symmetric only if the technology exhibits a constant elasticity of substitution, if the cost function is Cobb–Douglas, or if there are only two inputs. (See Chambers (1988) or Blackorby and Russell (1989).) None of these properties holds here.

[85] Since $\eta_{ij} < 0$, $\sigma_{ij}^{M} > 0$ iff $|\eta_{ji}| > |\eta_{ii}|$.

10.4 The Shadow Elasticity of Substitution

The shadow elasticity of substitution is a member of the class of two-factor-two-price elasticities of substitution (TTES) (Mundlak (1968)), which consider changes in input ratios for changes in input price ratios. Following Chambers (1988), if the price of two factors, p_i and p_j change, we have

$$\hat{x}_i(p,y) = \eta_{ii}\hat{p}_i + \eta_{ij}\hat{p}_j \quad and \quad \hat{x}_j(p,y) = \eta_{ji}\hat{p}_i + \eta_{jj}\hat{p}_j \qquad \textbf{Equation 42}$$

where the circumflex denotes a percentage change or logarithmic derivative. Subtracting these, we get

$$\begin{aligned}\hat{x}_i(p,y) - \hat{x}_j(p,y) &= (\eta_{ii} - \eta_{ji})\hat{p}_i + (\eta_{ij} - \eta_{jj})\hat{p}_j \\ &= \sigma_{ij}^M \hat{p}_j - \sigma_{ji}^M \hat{p}_i\end{aligned}. \qquad \textbf{Equation 43}$$

Because all TTES elasticities are of the form $\frac{\hat{x}_i(p,y) - \hat{x}_j(p,y)}{\hat{p}_j - \hat{p}_i}$, it is clear from Equation 43 that the resulting TTES is:

$$\frac{\hat{x}_i(p,y) - \hat{x}_j(p,y)}{\hat{p}_j - \hat{p}_i} = \sigma_{ij}^M \frac{\hat{p}_j}{\hat{p}_j - \hat{p}_i} - \sigma_{ji}^M \frac{\hat{p}_i}{\hat{p}_j - \hat{p}_i}. \qquad \textbf{Equation 44}$$

Thus, a TTES measures relative changes in input demand for a relative change in input prices, and can be written generally as a weighted average of the relevant Morishima elasticities[86] which, as noted, measure changes in input ratios for changes in individual input prices.

The SES is a special case of TTES originally introduced by McFadden (1963), and restricts attention to a given factor price frontier, thereby assuming constant cost. It incorporates more information into its measure of input substitutability than the Morishima measure, and is also symmetric. The SES, which is effectively a cost-share weighted average of the Morishima elasticity pairs, can be written

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[86] See Koizumi (1976).

$$\sigma_{ij}^{S} = \sigma_{ij}^{M} \frac{S_i}{S_i + S_j} + \sigma_{ji}^{M} \frac{S_j}{S_i + S_j}$$ **Equation 45**

where S_i refers to the cost share for input i.

10.5 Elasticity Estimates

Demand elasticities and substitution elasticities, each evaluated at mean cost shares, are presented in Tables 9 and 10 respectively, for the three-input FE model, as estimated on the full dataset and the three time subsets. Standard errors are reported in parentheses, and the corresponding estimates from the pooled estimation can be found in Appendix 1.

Table 9: Demand Elasticities – FE model

	All Years	**1990–1994**	**1995–1999**	**2000–2004**
Own-Price Elasticity of Demand				
η_{CC}	–0.2665 (0.0102)	–0.3191 (0.0188)	–0.2960 (0.0151)	–0.2569 (0.0202)
η_{OO}	–3.1594 (0.0915)	–3.4277 (0.1193)	–3.0149 (0.1518)	–2.2919 (0.2652)
η_{GG}	–1.2033 (0.0406)	–1.6010 (0.0786)	–1.2521 (0.0626)	–1.0464 (0.0691)
Cross-Price Elasticity of Demand				
η_{CO}	0.0813 (0.0044)	0.1167 (0.0087)	0.0866 (0.0065)	0.0348 (0.0083)
η_{OC}	1.6637 (0.0905)	1.7482 (0.1301)	2.0781 (0.1570)	0.9528 (0.2260)
η_{CG}	0.1852 (0.0087)	0.2023 (0.0155)	0.2094 (0.0128)	0.2221 (0.0179)
η_{GC}	0.8627 (0.0406)	1.0301 (0.0791)	1.0553 (0.0644)	0.8574 (0.0690)
η_{OG}	1.4957 (0.0880)	1.6795 (0.1207)	0.9369 (0.1413)	1.3390 (0.2323)
η_{GO}	0.3406 (0.0200)	0.5709 (0.0410)	0.1967 (0.0297)	0.1890 (0.0328)

Table 10: Substitution Elasticities – FE model

	All Years	1990–1994	1995–1999	2000–2004
Allen				
σ^{AU}_{CC}	–0.3367 (0.1289)	–0.4031 (0.0238)	–0.3789 (0.0194)	–0.3328 (0.0261)
σ^{AU}_{OO}	–81.6765 (2.3643)	–64.8426 (2.2576)	–89.7353 (4.5470)	–81.2224 (9.3992)
σ^{AU}_{GG}	–7.0832 (0.2390)	–10.2952 (0.5052)	–7.8249 (0.3914)	–5.2341 (0.3457)
σ^{AU}_{CO}	2.1021 (0.1144)	2.2083 (0.1643)	2.5770 (0.1947)	1.2344 (0.2928)
σ^{AU}_{CG}	1.090 (0.0513)	1.3012 (0.0999)	1.3087 (0.0799)	1.1108 (0.0893)
σ^{AU}_{OG}	8.8045 (0.5178)	10.8003 (0.7760)	5.8551 (0.8832)	6.6980 (1.1619)
Morishima				
σ^{M}_{OC}	0.3478 (0.0131)	0.4358 (0.0249)	0.3826 (0.0195)	0.2917 (0.0251)
σ^{M}_{CO}	4.8230 (0.1593)	5.1759 (0.2185)	5.0930 (0.2746)	3.2447 (0.4346)
σ^{M}_{GC}	0.4517 (0.0184)	0.5214 (0.0334)	0.5054 (0.0272)	0.4790 (0.0372)
σ^{M}_{CG}	2.0660 (0.0787)	2.6311 (0.1522)	2.3074 (0.1235)	1.9038 (0.1341)
σ^{M}_{GO}	4.6551 (0.1549)	5.1072 (0.2017)	3.9518 (0.2477)	3.6309 (0.4444)
σ^{M}_{OG}	1.5439 (0.0495)	2.1719 (0.0972)	1.4488 (0.0739)	1.2354 (0.0834)
Shadow				
σ^{S}_{CO}	5.0158 (0.1598)	5.3928 (0.2204)	5.3093 (0.2755)	3.4692 (0.4345)
σ^{S}_{CG}	2.2127 (0.0818)	2.8142 (0.1575)	2.4633 (0.1280)	2.0303 (0.1415)
σ^{S}_{OG}	5.6441 (0.1576)	6.4270 (0.2147)	5.0754 (0.2485)	4.5350 (0.4423)

10.6 Discussion

All elasticity measures indicate that all three fuels were substitutes for all other fuels during the entire period and during each time subset, supporting our claim that short run interfuel substitution is indeed possible in US electricity generation, and that this phenomenon is important in understanding the short run effects of market-based environmental policy. Before discussing the individual elasticities, we note the role that cost shares (and, as such, capital stock) play in all elasticity calculations.[87] Smaller shares of a particular fuel imply a greater capital stock in other fuels for a given firm,[88] and an accompanying inclination to switch out of the small-share fuel and into larger-share fuels. It is not therefore surprising that

[87] See also Frondel and Schmidt (2002).
[88] Recall that the capital stock is treated here as fixed at its firm-specific long run optimal value, implying that firms with a greater share of, say, coal-burning capital are better-equipped for and more efficient at burning coal.

we find oil (which has the smallest cost share) was the most own-price responsive, followed by gas and then coal, nor is it surprising that the largest substitution elasticities by all measures were associated with changes in oil prices.

The own-price elasticities (η_{ii} and σ_{ii}^{AU}) are significant and have the expected negative signs, with oil having been the most own-price responsive, followed by gas and then coal; findings consistent with those of Dahl and Ko (1998). The own-price coal elasticities indicate coal demand was relatively inelastic, and became more so over the periods analysed. This is presumably due to a combination of several things: (1) a large coal cost share, indicating a large proportion of coal-fired capital, (2) substitution from high- to low-sulphur coal not captured by our model, (3) the increased cost-effectiveness of scrubbers (which operate on coal-fired capacity) at higher permit prices as seen in later periods, and (4) the role of coal-units as base-load power. This last point is partly the result of the long start-up time for coal-fired units (particularly relative to gas), which leads firms to continue with coal combustion even as demand falls, as the shut-down and restart of these units is not economical if demand is expected to rise again within a couple of hours.

To place our estimates in context, we compare them to those reported by Ko and Dahl (2001), who used a translog cost function (without capital or a time variable) with pooled monthly data on 185 electric utilities during 1993. Our dataset covers a longer period and includes the SO_2 scheme's price effects, and our model focuses on within-unit variation while accounting for capital stock. Despite these differences, some elasticity estimates are quite similar, and generally supported Ko and Dahl's (2001) findings that firms have become more responsive to oil and gas prices, and less responsive to coal.[89] We also compare our results to the mean elasticities from previous cross-sectional and panel estimates reported by Ko and Dahl (2001).[90] Ko and Dahl (2001) provide only demand elasticities, though, as shown above, these are related to each of the substitution elasticity measures.

Our own-price elasticity estimates for oil were similar to Ko and Dahl's (–3.05) (though slightly larger in the 1990–1994 period) and larger than the mean from previous studies

[89] Ko and Dahl (2001) attribute these fuel-price sensitivity findings to industry deregulation.
[90] The average elasticity estimates for cross sectional and panel data interfuel substitution papers using three fossil fuel inputs reported by Ko and Dahl (2001) are based on estimates from Griffin (1977), Haimor (1981), and Bopp and Costello (1990). These studies are described in our literature review.

(–2.43). Our own-price estimates for coal and gas, however, were slightly smaller than those reported by Ko and Dahl (–0.57 and –1.46, respectively). Our coal elasticities were smaller than the reported mean of previous cross-sectional and panel studies (–0.58), and our gas elasticities were similar to or slightly larger than the average from previous studies (–1.05). These last findings thus do not support Dahl and Ko's (1998) prediction of increased gas demand elasticities resulting from the deregulation of the gas market in 1990, probably because of the (partly endogenous) increase in the natural gas price across the period.

As for our cross-price elasticities of demand, those involving coal were lower than Ko and Dahl's (2001), possibly for reasons associated with high- to low-sulphur coal switching. Our η_{OC} was larger than the mean reported from previous cross-sectional and panel studies (0.69), while our other coal-related cross-price elasticities were similar to the mean from previous studies. Our oil and gas cross-price elasticities (η_{OG} and η_{GO}) were larger than those reported by Ko and Dahl (–0.15 and –0.08, respectively), and had an opposite sign. Previous cross sectional and panel studies found positive signs, but had a much smaller mean for η_{OG} (0.20) and a comparable mean for η_{GO} (0.33). Overall, then, we find greater oil share sensitivity, and lesser coal and gas share sensitivity than previous studies.

It is worth noting that our reported elasticities are based on estimation with data on fuel purchases (as were those of Ko and Dahl (2001)). Because coal can be stored and combusted at a later date, our elasticities involving coal are, if anything, possibly under-estimates of actual demand and substitution elasticities. This serves as further support for the argument that short run fuel substitution does, indeed, occur in the industry.

By the symmetric Allen–Uzawa measure, oil and gas were the greatest substitutes, followed by coal and oil and then coal and gas, which is unsurprising given the relative cost shares. Oil and gas saw a decline and a recovery in substitutability during the periods corresponding to Phase I and Phase II, respectively, while coal and oil saw a small rise in substitutability during the Phase I period and a decline during Phase II. As noted, however, these Allen measures account only for a change in a single input for a change in a single input price, holding output and other prices constant, and are therefore limited in their usefulness.

The Morishima measure, quantifying changes in an input ratio for changes in a given input price, is not symmetric and is sensitive to which fuel price changes. From Table 10, for example, a 1 per cent change in the price of oil led to a 4.82 per cent change in the coal-to-oil input ratio, whereas a 1 per cent change in the price of coal led to a 0.35 per cent change in the oil-to-coal (using parameter values from the entire dataset, and evaluating the elasticity at mean cost shares). By the Morishima measure, oil price changes led to the largest input-factor ratio changes, while coal price changes led to the smallest factor price ratio changes, again presumably due to reasons associated with capital stock and cost shares, as well as to relative fuel prices.

In all but the last period, the increase in the coal-to-oil ratio was largest for a change in the oil price, while in the 2000–2004 period, the increase in the gas-to-oil ratio was larger. Changes in the gas price led to larger increases in the coal-to-gas ratio than the oil-to-gas ratio in all periods, indicating a preference for switching toward coal when moving away from gas. Gas-to-oil substitutability declined across the periods, while gas-to-coal substitutability rose during Phase I, probably due to access to lower-sulphur western coal, and declined again during Phase II, possibly as a result of exhausting high-to-low sulphur coal switching opportunities.

These Morishima elasticities indicate that substitution out of oil and into coal was easiest in the first two periods, while from 2000 onwards, substitution from oil to gas was easier (possibly because of the exhaustion of oil-to-coal possibilities). They also indicate that factor ratios saw the smallest changes for changes in the coal price (the oil-to-coal ratio being slightly less responsive to a change in the coal price than the gas-to-coal ratio). The high proportion of coal-burning generating capacity no doubt contributed to this phenomenon, as did the low Btu price of coal, but it was also probably due to the within-fuel coal-switching that occurred as rail deregulation allowed for greater access to lower-sulphur western coal by the electricity industry. Thus, even as coal's price rose relative to that of natural gas and oil, as a result of the SO_2 allowance prices, some firms were able to switch from dirty eastern sub-bituminous coal to cleaner-burning western bituminous coal, in order to reduce their emissions.[91] Indeed, this was unexpectedly the largest source of emissions-reduction under the SO_2 scheme (see, e.g., Ellerman and Dubroeucq (2004)).

[91] Note that CO_2 emissions factors vary by coal-type as well, with bituminous coal generally emitting more SO_2 and CO_2 per ton of coal combusted than sub-bituminous coal. (EPA (2000))

The Shadow Elasticity estimates make explicit the percentage change in the ratio of input quantities for a percentage change in the *ratio* of their prices.[92] Thus, for example, a 1 per cent change in the coal-price to gas-price ratio led to a 2.21 per cent change in the gas-to-coal input ratio using the parameters from the full period estimation. By the SES measure, oil and gas show the greatest substitutability for the overall period, the period prior to the SO_2 scheme's onset, and for Phase II, but during the period corresponding to Phase I, coal and oil exhibited
greater substitutability.

All three fuel pairs (with the exception of coal–gas, which saw a slight increase in substitutability during the Phase I period) saw a decline in their input ratio changes as their relative input prices changed over time, as may have been expected given the general decline in substitution elasticities by the Morishima measure. This is probably due, again, to the high-to-low sulphur coal substitution in combination with the exhaustion of interfuel substitution possibilities, and increased use of permits for emission coverage as firms became more comfortable with the buying, using, and banking of SO_2 allowances.

We note that the Allen measure indicates a greater degree of substitutability between oil and gas, and a lesser degree of substitutability between coal and gas than any other measure, but does not incorporate the information about relative input demand changes (as the Morishima measure does) nor information about relative input prices (as the SES measure does). These latter two elasticities are, therefore, more valuable in this setting, as the demand for all fuels is likely to respond to changes in both individual and relative input prices in the electricity generating industry.

Overall, each of the substitution elasticity measures indicates the greatest fuel-share sensitivity to changes in the price of oil, and the presence of both across- and within-unit substitution.[93] A general trend of declining fuel substitutability across time is also present in all measures, presumably because of capital constraints and exhaustion of fuel-switching opportunities.

[92] Recall that the SES assumes a constant variable cost. (See Chambers, 1988.)
[93] Most dual-fired units come in the form of combined-cycle gas turbines (CCGTs) combining gas and coal combustion or dual-fired coal/oil burners (Hansen, 1998).

11 Technical Change

Recall from Section 9 that the restrictions on the underlying production technology associated with neutral technical change and the absence of technical change (Equations 28 and 29) were both rejected by the Wald test at the 1 per cent significance level. Thus, technical change was, indeed, present across the 1990–2004 period, and was non-neutral. We discuss further particulars in this section.

We included time as a fixed input to the production process to account for the fact that technology is generally not constant even in a short run context, and that it generally requires the passage of time to occur. Chambers (1988) notes that this is a passive technique that basically measures the researcher's ignorance, as it does not explicitly define technical change nor explain how it comes about. A potentially viable explanation in the electricity generating industry is Hicks' (1963) 'induced innovation' hypothesis which claims that market forces (e.g. relative input price changes) guide innovation and technical change. (See also Lundmark (2005) and Chavas et al. (1997).) Because technical change can be defined as changes in the production process that alter the input/output ratio, it can be described as either progressive or regressive. Progressive technical change allows fewer inputs to produce the same output (or greater output to be made with the same inputs), whereas the opposite is true of regressive technical change. Progressive technical change can, then, reduce problems associated with resource scarcity (or high relative input prices), though the causality can also, as first noted by Hicks (1932), run in the opposite direction, i.e. resource scarcity (or high relative input prices) can lead to 'induced innovation', thereby guiding the direction of technical change. As noted by Lundmark (2005) and Chavas et al. (1997), the induced innovation hypothesis is usually couched in terms of bias in technical change, where technical change that is biased toward a particular factor ('factor-using') results in an increase in its relative use, and the opposite is true of technical change that is biased *against* a particular factor ('factor-saving').

Induced technical change has been claimed to reduce the cost of emissions reductions (see Gerlagh (2007)), with some authors arguing that induced technical change can lead to a large reduction in costs (Gerlagh and van der Zwaan (2003), Manne and Richels (2004), and Gerlagh (2006)), or a double dividend (Carraro and Galcotti (1997)). Others argue that the impact of factor substitution will play a greater role than induced technical change in reducing emissions reduction costs for a given technology (Goulder and Schneider (1999) and Nordhaus (2002)). It is not our objective to make claims about the relative importance of interfuel substitution and technical change, but we do note and describe the bias of technical change in our dataset without explicitly noting causality.

Note that technical change can be embodied in a particular technological innovation, input, or investment (e.g. a new boiler or an additive that increases the combustion efficiency of a fuel) or disembodied, in the sense that it is not the direct result any particular input or investment (capital or otherwise). Our short run focus and the corresponding assumption of fixed capital imply that we are concerned with disembodied technical change.[94] The minimum costs associated with the more expansive input requirement set found under progressive technical change can not be greater than those for the original input requirement set, and the opposite is true for regressive technical change.[95] Thus, for the dual cost function:

$$\left.\frac{\partial \ln VC}{\partial t}\right|_{P,Y,t} \equiv \theta \leq 0 \quad \text{when technical change is progressive, and}$$

$$\left.\frac{\partial \ln VC}{\partial t}\right|_{P,Y,t} \equiv \theta \geq 0 \quad \text{when technical change is regressive.}$$[96]

These partial derivatives with respect to time show the impact of technical change on the cost function and look as follows:

$$\frac{\partial \ln VC}{\partial t} = \beta_T + \beta_{TT} Time + \beta_{TY} \ln Y + \sum_{i=1}^{3} \beta_{Ti} \ln p_i \qquad \textbf{Equation 46}$$

[94] See Binswanger (1974), Lundmark (2005), and Chavas et al. (1998) for more on embodied and induced technical change. Note also that our capital variable, capacity, does not account for scrubber or other non-combustion capital, further supporting our focus on disembodied technical change.
[95] This is because under progressive technical change, the old input set is still feasible, while under regressive technical change the original input bundle may be eliminated.
[96] See Chambers (1988) for more detail.

where i denotes the three fossil fuel inputs. Following Altunbas et al. (1999) and using Baltagi and Griffin's (1988) terminology, the impact of technical change on the cost function in our case can be broken into two components:

(1) pure technical change ($\beta_T + \beta_{TT}Time + \beta_{TY}\ln Y$) and

(2) non-neutral technical change $\left(\sum_{i=1}^{3} \beta_{it} \ln p_i\right)$.

The former accounts for total cost reductions possible while holding the cost share ratios constant, and the latter accounts for factor bias in technical change and variable cost sensitivity to changes in input prices. Before discussing the results, we note that the size of all technical change estimates were not very large, meaning that even for the significant estimates, the impact was quite small.

Estimates of factor augmentation in technical change are listed in the bottom of Table 11.[97] Non-neutral technical change in the Hicksian sense occurs when the isoquant does not shift homothetically inward and the factor ratio does not stay constant at constant factor prices (Binswanger (1974)). When using the time trend approach, technical change is said to be factor-i using (saving) if the cost share of input i rises (declines) with time when factor prices are held constant, i.e. if $\left.\frac{\partial \ln S_i}{\partial t}\right|_{p=\bar{p}} > 0 \;\; (< 0)$ where S_i is the cost share for input i.

We find evidence of coal- and oil- saving and gas-using technical change when the model is estimated over the full time period. For the 1990–1994 period, prior to Phase I of the SO_2 programme, we find a similar pattern, though the insignificant β_{TC} parameter indicates coal-neutrality in technical change. For the 1995–1999 period, during Phase I, we find technical change was coal-saving, gas-using, and oil-neutral, whereas for the final period, during Phase II, we find evidence of technical change that was gas-saving, oil-using, and coal-neutral. The switch from coal-saving to coal-neutral technical change is presumably due to the list of explanations for coal demand stability given above. These things, along with the rise in natural gas prices in the later years of the dataset, would also explain the gas-saving characteristics of technical change for the final period, as combined-cycle gas turbine (CCGT) units operating with both natural gas and coal represent a large portion of the nation's dual-fired capacity (Hansen (1998)). The oil-saving characteristics of technical

[97] Results from the pooled model are presented in Table A15 in the Appendix.

change for the whole dataset seem heavily affected by the experience in the 1990–1994 period. Indeed, technical change appears to switch from oil-saving to oil-using by Phase II of the SO_2 scheme. This could again be explained by the switch from high- to low-sulphur coal, as dual-fired coal/oil units (Hansen (1998)) were used more heavily as western coal became cheaper.

In addition to results on pure and factor-augmenting technical change, we also present results pertaining to economies of scale[98] and scale bias in technical change. For our variable cost function, scale economies are measured as[99]

$$\varsigma = \frac{\partial \ln VC}{\partial \ln Y} \qquad \textbf{Equation 47}$$

and are reported as estimated at mean values in Table 11. Scale bias in technical change which leads to a change in the range over which a certain degree of scale economies can be realized, and may therefore change the cost-minimizing output level, is measured as[100]

$$\gamma = \frac{\partial \varsigma}{\partial T} = \beta_{YT} \qquad \textbf{Equation 48}$$

(See Stevenson (1980b).)

[98] Recall that linear homogeneity of the production function (Equation 26) was rejected in Section 9, indicating the presence of scale effects.
[99] $\varsigma < 1$ indicates economies of scale, while $\varsigma > 1$ indicates diseconomies of scale, and $\varsigma = 1$ indicates constant returns to scale.
[100] $\gamma < 0$ indicates an increase in the minimum efficient size (MES), while $\gamma > 0$ indicates a reduction in MES, and $\gamma = 0$ indicates no change in MES.

Table 11: Technical Change Estimates – Fixed Effects Model				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
Rate of cost Reduction	0.00046* (0.00028)	–0.00287** (0.00128)	0.00222* (0.00121)	0.00347** (0.00137)
Pure Technical Change	0.00065 (0.00085)	0.00660** (0.00337)	0.00090 (0.00314)	–0.00341** (0.00478)
Non-Neutral Technical Change	–0.00019 (0.00076)	–0.00948** (0.00312)	0.00132 (0.00289)	0.00688* (0.00434)
Economies of Scale	–0.1337 (0.6053)	–1.9477** (0.9856)	–0.6830 (0.8606)	2.3909 (1.5847)
Scale Bias in Technical Change	0.00006 (0.00012)	0.00150** (0.00051)	–0.00011 (0.00048)	–0.00118* (0.00066)
FACTOR USE				
$\partial^2 \ln VC \big/ \partial P_C \partial Time = \beta_{TC}$	–0.00036** (0.00009)	–0.00002 (0.00036)	–0.00086** (0.00032)	0.00064 (0.00040)
$\partial^2 \ln VC \big/ \partial P_O \partial Time = \beta_{TO}$	–0.00024* (0.00013)	–0.00234** (0.00053)	0.00034 (0.00049)	0.00121* (0.00068)
$\partial^2 \ln VC \big/ \partial P_G \partial Time = \beta_{TG}$	0.00053** (0.00008)	0.00086** (0.00033)	0.00063** (0.00030)	–0.00067* (0.00038)
* Indicates significance at the 10 per cent level. ** Indicates significance at the 5 per cent level.				

We find some evidence of scale economies, though our results are generally insignificant. The results on scale bias in technical change indicate that the minimum efficient size (as measured by output) may have increased over the period, particularly after the onset of the SO_2 scheme, though the effect of output on technical change was small, and of an order comparable to the factor augmentation effects.

Our results on overall rate of cost reduction are mixed, and indicate regressive disembodied technical change in all periods post-SO_2 regulation, driven more by non-neutral technical change than by shifts in the production function. Non-neutral technical change was regressive after the SO_2 scheme's onset, even as the production function apparently shifted neutrally outward in the Phase II period. The regressive nature of the non-neutral technical change post SO_2 regulation is presumably due to the fixed capital stock having been chosen optimally for operation in a market without SO_2 prices. Prior to the scheme, technical change apparently led to reductions in variable costs driven by non-neutral technical change.

12 Input Demand Responsiveness to Hypothetical Policy Scenarios

Using the demand elasticities from Section 9, it is possible to estimate what the effects of alternative emissions policies on fuel shares would have been, relative to the actual share effects of the observed SO_2 scheme. We do so in this section by estimating the percentage change in the fuel cost shares for a hypothetical policy-induced percentage change in fuel prices, to give some indication of the SO_2 scheme's fuel share effects relative to those of hypothetical alternative policies. We note that our elasticity estimates are evaluated at a single point, and may not represent elasticities evaluated at cost shares other than the mean.[101] We also acknowledge that our estimates are not able to account for complexities such as intra-fuel substitution (particularly for coal) or policy-induced endogenous price changes, but the results below provide some insight into the impact of different environmental policies on changes in each fuel's use relative to those observed under the CAAA's SO_2 scheme. By selecting hypothetical values for a particular regulatory variable and calculating its effects on the overall fuel prices, it is possible to calculate how fuel shares may have looked under regulatory schemes other than the one actually observed. We address two policy scenarios, each with three levels of stringency. In one, we assume permit prices were 20 per cent, 50 per cent or 100 per cent higher than those actually observed, and in the other we assume that in addition to the observed SO_2 scheme, scrubber installation was mandated on 20 per cent, 50 per cent or 80 per cent of each firm's coal capacity.

Because emissions regulations alter the prices of all of the fuel inputs and because the percentage change in the use of each fuel must reflect the *relative* price change effects, the hypothetical percentage change in each fuel's cost share was calculated to be:

$\eta_{ii} \times$ % change in $P_i + \eta_{ij} \times$ % change in $P_j + \eta_{ik} \times$ % change in P_k,

where the η's represent the requisite own- or cross-price demand elasticity from Table 9. Table 12 presents the results of these calculations using the parameter estimates from the FE model on the full dataset, giving an indication of how fuel shares would have differed had these alternative policies been implemented instead. Because the general relationships

[101] This will be particularly true if the fuel inputs exhibit kinked demand curves.

appeared to hold across all periods, estimates from the FE model's time subsets are relegated to Tables A16–A18 in Appendix 1 in order to save space.

As indicated by the negative percentage change estimates, increasing the price of SO_2 allowances would have led to a reduction in the cost shares of both coal and oil relative to the shares actually observed. Because coal and oil have the highest sulphur contents, their prices would have risen relative to gas, making gas use more appealing, and coal and oil combustion less so. It appears that coal's cost share would have been more responsive to increases in the allowance price, as indicated by the slightly larger absolute value of the share changes for coal than for oil.

Table 12: Hypothetical Policy Responses
Fixed Effects Model: All Years

	% Change Coal Share	% Change Oil Share	% Change Gas Share
20 % Permit Price Increase	–0.00983 (0.00027)	–0.00822 (0.00027)	0.01238 (0.00027)
50 % Permit Price Increase	–0.01517 (0.00035)	–0.01263 (0.00040)	0.01909 (0.00035)
100 % Permit Price Increase	–0.02409 (0.00050)	–0.01998 (0.00065)	0.03027 (0.00052)
20 % Scrubber Mandate	0.01344 (0.00026)	–0.00410 (0.00008)	–0.00934 (0.00018)
50 % Scrubber Mandate	0.00745 (0.00018)	–0.00227 (0.00005)	–0.00518 (0.00012)
80 % Scrubber Mandate	0.00146 (0.00013)	–0.00045 (0.00004)	–0.00102 (0.00009)

As compared to increasing allowance prices, increasing a firm's capacity covered by scrubbers under the SO_2 scheme would have had the opposite effect on the total coal price. By increasing scrubber coverage, a firm's overall emissions are reduced, making the combustion of all fossil fuels relatively less expensive. Coal, being the cheapest but also the dirtiest fuel, would have been the most appealing had scrubber capacity increases been mandated.[102] Given the results in Table 12 and the elasticity estimates from Tables 9 and 10, it appears that firms would have switched from oil and gas to coal had scrubber capacity coverage been mandated, and coal's share would have increased while the shares of oil and gas decreased, relative to the share results observed for the CAAA 1990's SO_2 policy.

[102] Recall our model's assumption that scrubbers are fully efficient. If they are not, all effects under the scrubbed capacity scenario would be smaller in absolute value, but maintain the same sign.

Table 12 shows that the gas share would have been the most responsive to permit price increases (relative to observed prices), while the coal share would have been most responsive to scrubber mandates. The coal and oil shares would have seen nearly equivalent percentage reductions for the hypothetical SO_2 price policies, relative to the shares induced by the SO_2 prices actually observed. The gas share would have been slightly more responsive to the scrubber mandates than the oil share.

13 Conclusions

This paper investigated the fuel use and technical change effects of relative fossil fuel price changes, as determined by both the standard market Btu prices of the fuels and the implied 'SO_2 price' associated with the tradable SO_2 allowance price. We presented three alternative specifications for the inclusion of the sulphur price in the cost function: one in which the SO_2 allowance price was incorporated into the total fuel price, one in which SO_2 allowances were treated as a separate input to the production process, and a third that excluded SO_2 prices from the firm's input decision problem. We showed that the data fit the first of these models best, indicating that firm behaviour was, in fact, affected by allowance prices in the short run, and that these allowance prices are more appropriately modelled as affecting relative fuel prices rather than being treated as a separate input.

We considered the presence of firm heterogeneity, finding that our model was more appropriately estimated with firm fixed effects than with pooled data. We went on to test for panel stationarity, concluding that our data does not appear to exhibit non-stationarity, and thus does not suffer from problems associated with spurious regression. The results we presented are therefore related to the 3-input (coal, oil, gas) fixed-effects SUR model that incorporates the SO_2 price into the total price of each fuel.

Having justified our model, we then presented demand and substitution elasticity estimates (Allen–Uzawa, Morishima, and Shadow) that indicate short run interfuel substitution was, indeed, possible over the period studied. This signifies that, even with our model's inability to account for intra-coal switching, the putty-clay hypothesis does not appear to hold strictly in the electricity generating industry. The elasticities, which show the greatest degree of substitutability between oil-and-gas and oil-and-coal, indicate the role of both across- and within-unit substitution in response to relative fuel price changes. Oil use exhibited the greatest flexibility, presumably because of its low cost share, high relative Btu price and the industry's experience in switching away from its use during the 1970s. Coal saw the least flexibility, presumably because of its large cost share (indicating a high proportion of coal-fired capacity), the presence of scrubbers on some coal-fired units, and the prevalence of high-to-low sulphur coal switching in response to the SO_2 scheme.

We briefly discussed technical change over the period, finding evidence of increasing costs over the period, as well as small but significant non-neutral technical change and evidence of scale diseconomies. We note that technical change over the full dataset appeared gas-using and coal- and oil-saving, though these characteristics were not consistent over the time subsets. Finally, we noted the implication of the demand elasticity calculations for the effects of alternative hypothetical environmental policies, suggesting that relative to the fuel shares observed under the CAAA 1990, the coal share would have been the most (positively) responsive to changes in scrubbed capacity mandates, while the gas share would be most (positively) responsive to increases in the emissions price (due, for example, to a reduced emissions cap or an increased emissions tax). Oil use would have declined as the result of either policy change relative to the status quo, presumably due to its high Btu price and low cost share.

Several extensions to this research would be interesting, including estimation with a larger dataset and the incorporation of firms with other combustion technologies (i.e. firms having capacity with less than three of the fossil fuels, or with the capability to generate with hydro or nuclear). It might also be interesting to address technical change with a capital vintage variable to see if results differ significantly, and to incorporate state regulation into the cost function, possibly via the inclusion of state-specific dummies. Finally, estimation with data on the fuels' carbon contents and hypothetical carbon allowance prices could provide useful information about fuel share response to potential cap-and-trade CO_2 regulation.

Appendix 1: Data Descriptions and Additional Estimates

Parameter estimates from Models 2 and 3:

Table A1: Parameter Estimates *Model 2: Four Inputs*					
Parameter	**Pooled**	**FE**	**Parameter**	**Pooled**	**FE**
β_K	2.7863** (0.6956)	–3.0432** (1.2731)	β_{GE}	–0.0118** (0.0042)	–0.0086** (0.0028)
β_Y	0.6673 (0.4303)	–0.6358 (0.5579)	β_{EE}	0.0029 (0.0028)	0.0015 (0.0028)
β_{KK}	–0.1901** (0.0638)	0.1575 (0.1038)	β_{YC}	–0.0569 (0.0527)	0.0086 (0.0541)
β_{KY}	–0.0044 (0.0396)	0.1194** (0.0498)	β_{YO}	0.1961** (0.0517)	0.0661 (0.0549)
β_{YY}	0.0611** (0.0285)	–0.0226 (0.0325)	β_{YG}	–0.1427** (0.0497)	–0.0790 (0.0503)
β_C	5.2482** (0.7334)	6.8531** (0.8214)	β_{YE}	0.0035** (0.0017)	0.0043** (0.0016)
β_O	2.8838** (0.7569)	1.3051 (0.8624)	β_{KC}	–0.2387** (0.0710)	–0.3999** (0.0770)
β_G	–7.1447** (0.6953)	–7.1247** (0.7497)	β_{KO}	–0.3122** (0.0715)	–0.1348* (0.0802)
β_E	0.0126 (0.0457)	–0.0334 (0.0459)	β_{KG}	0.5516** (0.0662)	0.5339** (0.0692)
β_{CC}	–0.6202** (0.1166)	–0.9382** (0.1294)	β_{KE}	–0.0007 (0.0021)	0.0008 (0.0021)
β_{CO}	–0.3231** (0.0895)	0.0790 (0.0998)	β_T	0.0117** (0.0032)	0.0121** (0.0031)
β_{CG}	0.9334** (0.0965)	0.8485** (0.0973)	β_{TT}	–0.0002** (0.00003)	–0.0002** (0.00003)
β_{CE}	0.0098** (0.0046)	0.0107** (0.0045)	β_{TY}	–0.0023** (0.0002)	–0.0034** (0.0003)
β_{OO}	0.6449** (0.1219)	0.0627 (0.1266)	β_{TC}	–0.0084** (0.0014)	–0.0083** (0.0014)
β_{OG}	–0.3209** (0.0883)	–0.1380 (0.0881)	β_{TO}	–0.0004 (0.0012)	0.0021* (0.0012)
β_{OE}	–0.0009 (0.0040)	–0.0037 (0.0039)	β_{TG}	0.0106** (0.0014)	0.0091** (0.0013)
β_{GG}	–0.6007** (0.1018)	–0.7019** (0.1016)	β_{TE}	0.0005** (0.0001)	0.0005** (0.0001)
** Indicates significance at the 5 per cent level. * Indicates significance at the 10 per cent level.					

Table A2: Parameter Estimates *Model 3: No SO_2 Price Effects*					
Parameter	**Pooled**	**FE**	**Parameter**	**Pooled**	**FE**
β_K	3.2887** (0.6904)	–2.0813 (1.2703)	β_{GG}	–0.6329** (0.1017)	–0.6441** (0.1021)
β_Y	0.3456 (0.4267)	–0.7100 (0.5591)	β_{YC}	–0.0719 (0.0504)	0.0310 (0.0522)
β_{KK}	–0.2324** (0.0639)	0.0788 (0.1041)	β_{YO}	0.1923** (0.0519)	0.0580 (0.0553)
β_{KY}	0.0128 (0.0397)	0.1150** (0.0503)	β_{YG}	–0.1204** (0.0480)	–0.0889* (0.0491)
β_{YY}	0.0608** (0.0287)	–0.0165 (0.0328)	β_{KC}	–0.2056** (0.0673)	–0.3767** (0.0737)
β_C	4.6040** (0.6836)	6.1761** (0.7796)	β_{KO}	–0.3112** (0.0718)	–0.1423* (0.0809)
β_O	2.9244** (0.7540)	1.5335* (0.8638)	β_{KG}	0.5168** (0.0629)	0.5190** (0.0668)
β_G	–6.5284** (0.6497)	–6.7096** (0.7111)	β_T	–0.0015 (0.0010)	–0.0018* (0.0010)
β_{CC}	–0.5214** (0.1113)	–0.7646** (0.1236)	β_{TT}	–0.00002 (0.0010)	–0.000001 (0.00001)
β_{CO}	–0.3487** (0.0885)	0.0210 (0.0989)	β_{TY}	–0.0016** (0.00016)	–0.0022** (0.0002)
β_{CG}	0.8701** (0.0840)	0.7436** (0.0949)	β_{TC}	–0.0060** (0.0009)	–0.0053** (0.0009)
β_{OO}	0.5860** (0.1221)	0.0786 (0.0949)	β_{TO}	–0.0004 (0.0008)	0.0010 (0.0008)
β_{OG}	–0.2373** (0.0876)	–0.0995 (0.0877)	β_{TG}	0.0079** (0.0009)	0.0065** (0.0009)
** Indicates significance at the 5 per cent level. * Indicates significance at the 10 per cent level.					

Descriptive statistics for Model 1's variables for the 5-year time subsets:

Table A3: Model 1 Cost Function Variables: All Firms, 1990–1994						
Variable	**Units**	**Mean**	**Median**	**Standard Deviation**	**Min**	**Max**
Total Coal Price	¢/mmBtu	198.78	205.70	39.94	83.97	344.27
Total Gas Price	¢/mmBtu	329.15	303.13	118.94	40.72	2116.09
Total Oil Price	¢/mmBtu	484.42	508.81	162.95	133.42	1066.11
Btu Coal Price	¢/mmBtu	198.78	205.70	39.94	83.97	344.27
Btu Gas Price	¢/mmBtu	329.15	303.13	118.94	40.72	2116.09
Btu Oil Price	¢/mmBtu	484.42	508.81	162.95	133.42	1066.11
Permit Price	$/ton	13.39	0	42.1234	0	149.0000
Generation	1000's MWh	548.7799	279.7950	576.7458	1.0870	2393.07
Total Capacity	kW	1,769,999	1,178,688	1,708,416	76,500	6,507,000
Total Variable Costs* (SO_2+Btu)	Millions Dec. 2004 $	12.4059	6.9106	15.0927	0.0002	226.1613
Coal Cost Share (SO_2+Btu)	%	0.7916	0.8954	0.2664	0	1
Gas Cost Share (SO_2+Btu)	%	0.1555	0.0364	0.2479	0	1
Oil Cost Share (SO_2+Btu)	%	0.0529	0	0.1289	0	1

Table A4: Model 1 Cost Function Variables: All Firms, 1995–1999						
Variable	**Units**	**Mean**	**Median**	**Standard Deviation**	**Min**	**Max**
Total Coal Price	¢/mmBtu	172.61	171.49	40.60	77.46	321.21
Total Gas Price	¢/mmBtu	359.76	324.75	163.80	80.73	2440.66
Total Oil Price	¢/mmBtu	443.00	440.38	124.22	162.47	913.85
Btu Coal Price	¢/mmBtu	166.68	166.67	41.43	77.46	306.48
Btu Gas Price	¢/mmBtu	359.76	324.76	163.80	80.73	2440.66
Btu Oil Price	¢/mmBtu	442.09	439.02	124.36	162.57	913.85
Permit Price	$/ton	135.11	128.33	44.96	74.00	213.50
Generation	1000's MWh	617.4655	313.0590	647.1100	1.0230	2887.41
Total Capacity	kW	1,845,967	1,338,438	1,697,422	74,600	6,507,000
Total Variable Costs* (SO_2+Btu)	Millions Dec. 2004 $	11.6271	7.1076	11.8640	0.00005	63.1553
Coal Cost Share (SO_2+Btu)	Percentage	0.8064	0.9260	0.2479	0	1
Gas Cost Share (SO_2+Btu)	Percentage	0.1600	0.0386	0.2316	0	1
Oil Cost Share (SO_2+Btu)	Percentage	0.0336	0	0.0890	0	0.8050

Table A5: Model 1 Cost Function Variables: All Firms, 2000–2004						
Variable	**Units**	**Mean**	**Median**	**Standard Deviation**	**Min**	**Max**
Total Coal Price	¢/mmBtu	172.95	175.37	47.45	61.19	385.15
Total Gas Price	¢/mmBtu	590.16	584.27	197.65	136.70	2527.93
Total Oil Price	¢/mmBtu	665.64	676.09	167.60	149.43	1343.60
Btu Coal Price	¢/mmBtu	152.36	156.00	41.54	61.19	363.81
Btu Gas Price	¢/mmBtu	590.16	584.27	197.65	136.70	2527.93
Btu Oil Price	¢/mmBtu	659.11	672.37	169.89	148.76	1342.47
Permit Price	$/ton	213.08	165.38	128.39	130.00	705.95
Generation	1000's MWh	571.0757	526.2590	651.5956	1.3450	3426.04
Total Capacity	kW	1,665,654	938,200	1,579,251	76,700	5,626,000
Total Variable Costs* (SO_2+Btu)	Millions Dec. 2004 $	11.3958	6.1961	12.9289	0.0005	115.6143
Coal Cost Share (SO_2+Btu)	%	0.7719	0.9171	0.2718	0	1
Gas Cost Share (SO_2+Btu)	%	0.1999	0.0582	0.2604	0	1
Oil Cost Share (SO_2+Btu)	%	0.0282	0	0.0938	0	0.9700

Table A6: Constant and Dummy Variable Parameters – FE model, 3-input SUR

Data	**const.**	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	δ_7	δ_8	δ_9	δ_{10}	δ_{11}	δ_{12}	δ_{13}	δ_{14}	δ_{15}	δ_{16}	δ_{17}	δ_{18}
all	24.400* (6.878)	omitted	–0.596* (0.106)	–2.734* (0.285)	–2.387* (0.177)	0.512* (0.153)	–1.131* (0.260)	–2.607* (0.268)	–0.758* (0.212)	0.057 (0.150)	0.352* (0.179)	–2.306* (0.233)	–0.277* (0.127)	–0.973* (0.158)	–1.295* (0.122)	–0.914* (0.195)	–0.361* (0.176)	–0.439* (0.088)	–0.888* (0.220)
1990–1994	3.395 (13.26)	omitted	–0.349* (0.184)	–3.661* (0.556)	–3.252* (0.335)	0.906* (0.324)	–0.100 (0.526)	–3.390* (0.503)	0.551 (0.429)	0.257 (0.292)	0.111 (0.124)	–2.291* (0.460)	–0.236 (0.240)	–1.632* (0.368)	–1.923* (0.219)	–0.094 (0.412)	0.225 (0.333)	–0.029 (0.441)	n/a
1995–1999	–25.52* (15.81)	omitted	–0.351 (0.262)	–0.117 (0.630)	–0.956* (0.382)	0.951* (0.489)	–0.551 (0.871)	–0.979 (0.572)	–0.474 (0.695)	0.915* (0.462)	0.901* (0.118)	–0.667 (0.498)	–0.225 (0.354)	0.182 (0.351)	–0.153 (0.217)	–0.391 (0.614)	0.032 (0.573)	–0.083 (0.133)	–0.333 (0.703)
2000–2004	77.45* (20.14)	omitted	–1.133* (0.280)	–4.532* (0.653)	–3.222* (0.438)	0.616* (0.357)	–1.509* (0.687)	–4.475* (0.671)	–1.335* (0.559)	–0.111 (0.359)	–0.111 (0.158)	–4.275* (0.647)	–0.217 (0.340)	–1.971* (0.297)	–2.331* (0.247)	–1.301* (0.523)	–0.802 (0.498)	–0.762* (0.161)	–1.255* (0.598)

	δ_{19}	δ_{20}	δ_{21}	δ_{22}	δ_{23}	δ_{24}	δ_{25}	δ_{26}	δ_{27}	δ_{28}	δ_{29}	δ_{30}	δ_{31}	δ_{32}	δ_{33}	δ_{34}	δ_{35}	δ_{36}	δ_{37}
all	–0.649* (0.209)	0.456* (0.087)	–0.253* (0.117)	–2.415* (0.238)	–0.126 (0.169)	–0.670* (0.090)	–0.093 (0.109)	–1.093* (0.285)	–0.379* (0.142)	–0.764* (0.099)	0.257* (0.078)	–0.484* (0.113)	–0.319 (0.242)	0.003 (0.229)	–0.763* (0.092)	–0.432* (0.082)	–0.392* (0.121)	–0.159 (0.114)	–1.004* (0.130)
1990–1994	0.235 (0.417)	0.014 (0.130)	–0.834* (0.219)	–2.701* (0.469)	–0.034 (0.309)	–0.634* (0.147)	0.493* (0.193)	0.142 (0.576)	–0.094 (0.270)	–0.692* (0.147)	–0.075 (0.122)	–0.267 (0.217)	0.506 (0.493)	0.565 (0.445)	n/a	–0.515* (0.129)	–1.158* (0.216)	–0.295 (0.179)	–1.582* (0.248)
1995–1999	–0.244 (0.663)	1.222* (0.157)	0.898* (0.232)	–1.293* (0.522)	–0.067 (0.486)	–0.491* (0.175)	0.393 (0.343)	–0.304 (0.949)	–0.275 (0.405)	–0.220 (0.276)	0.591* (0.124)	–0.324 (0.316)	0.296 (0.781)	0.569 (0.745)	–0.333* (0.138)	–0.015 (0.161)	0.651* (0.234)	–0.151 (0.324)	0.295 (0.285)
2000–2004	n/a	0.436* (0.237)	–0.987* (0.208)	–3.830* (0.567)	–0.142 (0.475)	–1.096* (0.213)	–0.741* (0.238)	n/a	–0.365 (0.372)	–1.269* (0.254)	0.031 (0.163)	–0.605* (0.255)	–0.339 (0.631)	0.021 (0.626)	–1.154* (0.152)	–0.828* (0.175)	–0.997* (0.278)	0.030 (0.286)	–1.915* (0.271)

* Indicates significance at the 10 per cent level.

Table A7: Parameter Estimates from Pooled 3-Input Model				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
β_K	4.6814** (0.6184)	0.8102 (0.9530)	10.5631** (0.9921)	2.3386* (1.3351)
β_Q	0.0397 (0.3835)	2.2204** (0.5791)	–3.2018** (0.6045)	1.7664** (0.8895)
β_{KK}	–0.3360** (0.0578)	0.0041 (0.0887)	–0.8670** (0.0918)	–0.0767 (0.1288)
β_{KY}	0.0257 (0.0362)	–0.1799** (0.0549)	0.3094** (0.0562)	–0.1448* (0.0866)
β_{YY}	0.3297** (0.0794)	0.2492** (0.0412)	–0.0503 (0.0402)	0.1594** (0.0639)
β_C	0.9449** (0.0847)	1.3648** (0.1356)	0.7582** (0.1347)	0.4252** (0.1865)
β_O	–0.2747** (0.0326)	–0.2482** (0.0957)	–0.2914** (0.0472)	–0.3207** (0.0631)
β_G	0.3297** (0.0794)	–0.1166 (0.1485)	0.5332** (0.1262)	0.8954** (0.1776)
β_{CC}	–0.0747** (0.0083)	–0.1020** (0.0149)	–0.1095** (0.0131)	–0.0334** (0.0168)
β_{CO}	0.0332** (0.0035)	0.0466** (0.0097)	0.0440** (0.0053)	0.0018 (0.0064)
β_{CG}	0.0415** (0.0072)	0.0554** (0.0129)	0.0655** (0.0113)	0.0317** (0.0152)
β_{OO}	–0.0823** (0.0035)	–0.2012** (0.0219)	–0.0638** (0.0051)	–0.0369** (0.0075)
β_{OG}	0.0491** (0.0034)	0.0881** (0.0111)	0.0198** (0.0048)	0.0352** (0.0067)
β_{GG}	–0.0906** (0.0073)	–0.1383** (0.0121)	–0.0853** (0.0112)	–0.0669** (0.0155)
β_{KC}	–0.0291** (0.0083)	–0.0764** (0.0132)	–0.0164 (0.0130)	0.0247 (0.0185)
β_{KO}	0.0325** (0.0032)	0.0350** (0.0057)	0.0337** (0.0045)	0.0321** (0.0062)
β_{KG}	–0.0034 (0.0078)	0.04143** (0.0121)	–0.0173 (0.0122)	–0.0568** (0.0177)
β_{YC}	0.0434** (0.0061)	0.0790** (0.0096)	0.0405** (0.0096)	–0.0078 (0.0138)
β_{YO}	–0.0137** (0.0024)	–0.0095** (0.0041)	–0.0190** (0.0033)	–0.0159** (0.0047)
β_{YG}	–0.0297** (0.0057)	–0.0695** (0.0088)	–0.0215** (0.0090)	0.0237* (0.0132)
β_T	–0.0034** (0.0008)	–0.0011 (0.0043)	–0.0020 (0.0041)	0.0080* (0.0046)
β_{TT}	–0.0004** (0.000001)	–0.0001 (0.0001)	–0.0001 (0.0001)	–0.0002 (0.0001)
β_{TY}	0.0007** (0.0001)	0.0014** (0.0006)	0.0007 (0.0006)	0.0001 (0.0007)
β_{TC}	–0.0005** (0.0001)	–0.0001 (0.0004)	–0.0010** (0.0003)	0.0005 (0.0004)
β_{TO}	–0.0008** (0.0001)	–0.0023** (0.0006)	–0.0005 (0.0006)	–0.0001 (0.0007)
β_{TG}	0.0007** (0.0001)	0.0010** (0.0003)	0.0007** (0.0003)	–0.0006 (0.0004)

Residual Correlation Matrices for Breusch–Pagan Test of Equation Independence:

Table A8: Correlation Matrix of Residuals: All Years			
	Variable Cost	Coal Share	Gas Share
Variable Cost	1.0000		
Coal Share	0.5554	1.0000	
Gas Share	–0.6233	–0.9245	1.0000

Table A9: Correlation Matrix of Residuals: 1990–1994			
	Variable Cost	Coal Share	Gas Share
Variable Cost	1.0000		
Coal Share	0.6211	1.0000	
Gas Share	–0.7032	–0.9016	1.0000

Table A10: Correlation Matrix of Residuals: 1995–1999			
	Variable Cost	Coal Share	Gas Share
Variable Cost	1.0000		
Coal Share	0.6844	1.0000	
Gas Share	–0.7313	–0.9382	1.0000

Table A11: Correlation Matrix of Residuals: 2000–2004			
	Variable Cost	Coal Share	Gas Share
Variable Cost	1.0000		
Coal Share	0.5455	1.0000	
Gas Share	–0.5989	–0.9421	1.0000

Table A12: Fisher Panel Unit Root Test Results for Model Variables									
	Ln(P_C)	**Ln(P_O)**	**Ln(P_G)**	**Ln(Y)**	**Ln(K)**	**Ln(VC)**	**Coal Share**	**Oil Share**	**Gas Share**
No lags	385.121* (0.0000)	645.367* (0.0000)	477.260* (0.0000)	1177.113* (0.0000)	58.158 (0.9120)	1367.248* (0.0000)	1097.282* (0.0000)	1495.370* (0.0000)	919.204* (0.0000)
1 lag	184.796* (0.0000)	309.104* (0.0000)	253.099* (0.0000)	976.086* (0.0000)	55.984 (0.9413)	805.492* (0.0000)	804.940* (0.0000)	899.719* (0.0000)	602.683* (0.0000)
2 lags	126.863* (0.0001)	200.137* (0.0000)	211.162* (0.0000)	785.395* (0.0000)	53.631 (0.9643)	624.751* (0.0000)	680.736* (0.0000)	666.752* (0.0000)	487.045* (0.0000)
3 lags	107.485* (0.0067)	146.575* (0.0000)	165.412* (0.0000)	527.861* (0.0000)	61.798 (0.8384)	507.583* (0.0000)	440.451* (0.0000)	477.432* (0.0000)	426.175* (0.0000)
4 lags	78.609 (0.3353)	107.103* (0.0072)	123.590* (0.0003)	348.168* (0.0000)	57.516 (0.9215)	404.447* (0.0000)	380.816* (0.0000)	413.832* (0.0000)	325.627* (0.0000)
Trend, no lag	504.005* (0.0000)	685.196* (0.0000)	686.136* (0.0000)	1187.903* (0.0000)	41.973 (0.9990)	1341.204* (0.0000)	1112.248* (0.0000)	1344.159* (0.0000)	965.895* (0.0000)
Trend, 1 lag	222.007* (0.0000)	301.054* (0.0000)	374.594* (0.0000)	1027.090* (0.0000)	36.622 (0.9996)	775.118* (0.0000)	817.220* (0.0000)	813.481* (0.0000)	647.838* (0.0000)
Trend, 2 lags	137.042* (0.0001)	204.760* (0.0000)	289.767* (0.0000)	865.522* (0.0000)	43.149 (0.9984)	635.682* (0.0000)	690.272* (0.0000)	584.545* (0.0000)	531.242* (0.0000)
Trend, 3 lags	109.906* (0.0043)	140.325* (0.0000)	213.515* (0.0000)	592.956* (0.0000)	51.545 (0.9782)	504.771* (0.0000)	457.594* (0.0000)	425.220* (0.0000)	453.307* (0.0000)
Trend, 4 lags	80.964 (0.2710)	94.817* (0.0519)	165.225* (0.0000)	396.786* (0.0000)	55.986 (0.9413)	408.913* (0.0000)	412.962* (0.0000)	368.396* (0.0000)	353.554* (0.0000)

* Unit root rejected at the 5 per cent confidence level or better. *P* values provided in parentheses.

Elasticity estimates from pooled model:

Table A13: Demand Elasticities – Pooled model				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
Own Price E of D				
η_{CC}	–0.3029* (0.0105)	–0.3373* (0.0188)	–0.3294* (0.0163)	–0.2714* (0.0217)
η_{OO}	–3.0890* (0.0918)	–4.7534* (0.4143)	–2.8651* (0.1517)	–2.2809* (0.2664)
η_{GG}	–1.3633* (0.0429)	–1.7336* (0.0778)	–1.3728* (0.0698)	–1.1345* (0.0775)
Cross-price E of D				
η_{CO}	0.0806* (0.0044)	0.1117* (0.0122)	0.0882* (0.0066)	0.0305* (0.0083)
η_{OC}	1.6296* (0.0910)	1.6734* (0.1830)	2.1166* (0.1579)	0.8339* (0.2260)
η_{CG}	0.2223* (0.0091)	0.2255* (0.0163)	0.2412* (0.0141)	0.2409* (0.0197)
η_{GC}	1.0355* (0.0423)	1.1480* (0.0830)	1.2157* (0.0709)	0.9303* (0.0761)
η_{OG}	1.4394* (0.0889)	1.8228* (0.2093)	0.7475* (0.1426)	1.4470* (0.2357)
η_{GO}	0.3278* (0.0203)	0.6196* (0.0712)	0.1572* (0.0299)	0.2042* (0.0333)
* Indicates significance at the 5 per cent level.				

Table A14: Substitution Elasticities – Pooled model				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
Allen				
$\sigma_{A\text{–}U,CC}$	–0.3827* (0.0132)	–0.4260* (0.0237)	–0.4085* (0.0202)	–0.3517* (0.0282)
$\sigma_{A\text{–}U,OO}$	–79.8584* (2.3723)	–89.9212* (7.8379)	–85.2762* (4.5145)	–80.8348* (9.4421)
$\sigma_{A\text{–}U,GG}$	–8.0252* (0.2527)	–11.1481* (0.5000)	–8.5796* (0.4361)	–5.6750* (0.3878)
$\sigma_{A\text{–}U,CO}$	2.0843* (0.1147)	2.1139* (0.2312)	2.6248* (0.1959)	1.0803* (0.2929)
$\sigma_{A\text{–}U,CG}$	1.3084* (0.0534)	1.4502* (0.1048)	1.5075* (0.0879)	1.2052* (0.0986)
$\sigma_{A\text{–}U,OG}$	8.4723* (0.5236)	11.7218* (1.3460)	4.6776* (0.8909)	7.2381* (1.1791)
Morishima				
$\sigma_{M,OC}$	0.3852* (0.0133)	0.4490* (0.0272)	0.4176* (0.0205)	0.3019* (0.0263)
$\sigma_{M,CO}$	4.7387* (0.1594)	6.4268* (0.3551)	4.9818* (0.2749)	3.1148* (0.4343)
$\sigma_{M,GC}$	0.5252* (0.0191)	0.5628* (0.0330)	0.5706* (0.0287)	0.5124* (0.0407)
$\sigma_{M,CG}$	2.3988* (0.0827)	2.8817* (0.1518)	2.5885* (0.1374)	2.0648* (0.1500)
$\sigma_{M,GO}$	4.5285* (0.1563)	6.5762* (0.5982)	3.6136* (0.2484)	3.7279* (0.4494)
$\sigma_{M,OG}$	1.6911* (0.0522)	2.3533* (0.1128)	1.5300* (0.0801)	1.3388* (0.0919)
Shadow				
$\sigma_{S,CO}$	4.9685* (0.1600)	6.6664* (0.3578)	5.2300* (0.2760)	3.3579* (0.4343)
$\sigma_{S,CG}$	2.5580* (0.0860)	3.0675* (0.1557)	2.7565* (0.1423)	2.1948* (0.1579)
$\sigma_{S,OG}$	5.6856* (0.1605)	8.0046* (0.05749)	4.8838* (0.2523)	4.7087* (0.4508)
* Indicates significance at the 5 per cent level.				

Table A15: Technical Change Estimates – Pooled Model				
	All Years	**1990–1994**	**1995–1999**	**2000–2004**
$\theta = d\ln VC/dt$ = rate of cost reduction	–0.00029 (0.00025)	–0.00536* (0.00127)	0.00204* (0.00114)	0.00188 (0.00119)
Pure Technical Change	0.00342* (0.00084)	0.00346 (0.00378)	0.00577 (0.00353)	0.00312 (0.00453)
Non Neutral Technical Change	–0.00371* (0.00075)	–0.00882* (0.00355)	–0.00373* (0.00334)	–0.00124 (0.00427)
Economies of Scale	0.44249 (0.50897)	3.57679** (0.77601)	–3.51415** (0.80020)	2.70795** (1.2305)
Scale Bias in Technical Change	0.00066** (0.00012)	0.00140** (0.00058)	0.00074 (0.00055)	0.00009 (0.00065)
FACTOR USE				
$\partial^2 \ln VC / \partial P_C \partial Time = \alpha_{TC}$	–0.00054** (0.00009)	–0.00011 (0.00036)	–0.00099* (0.00033)	0.00053 (0.00040)
$\partial^2 \ln VC / \partial P_O \partial Time = \alpha_{TO}$	–0.00083** (0.00013)	–0.00227* (0.00060)	–0.00048 (0.00056)	–0.00007 (0.00067)
$\partial^2 \ln VC / \partial P_G \partial Time = \alpha_{TG}$	0.00071** (0.00008)	0.00098* (0.00033)	0.00072* (0.00031)	–0.00056 (0.00039)
** Indicates significance at the 5 per cent level. * Indicates significance at the 10 per cent level.				

HYPOTHETICAL POLICY RESPONSES

Fixed Effects Models, Time Subsets:

Table A16: Hypothetical Policy Responses Fixed Effects Model: 1990–1994			
	% Change Coal Share	% Change Oil Share	% Change Gas Share
20%Permit Price Increase	–0.00332 (0.00033)	–0.00014 (0.00022)	0.00281 (0.00026)
50%Permit Price Increase	–0.00415 (0.00042)	–0.00017 (0.00027)	0.00351 (0.00033)
100% Permit Price Increase	–0.00554 (0.00056)	–0.00023 (0.00036)	0.00468 (0.00044)
20% Scrubber Mandate	0.00188 (0.00019)	–0.00069 (0.00007)	–0.00119 (0.00012)
50% Scrubber Mandate	0.00106 (0.00013)	–0.00039 (0.00005)	–0.00067 (0.00008)

80% Scrubber Mandate	0.00024 (0.00011)	–0.00009 (0.00004)	–0.00015 (0.00007)

Table A17: Hypothetical Policy Responses
Fixed Effects 1995–1999

	% Change Coal Share	% Change Oil Share	% Change Gas Share
20% Permit Price Increase	–0.02174 (0.00067)	–0.01614 (0.00058)	0.02289 (0.00055)
50% Permit Price Increase	–0.02972 (0.00083)	–0.02112 (0.00072)	0.03098 (0.00066)
100% Permit Price Increase	–0.04303 (0.00110)	–0.02942 (0.00098)	0.044468 (0.00086)
20% Scrubber Mandate	0.01937 (0.00041)	–0.00567 (0.00012)	–0.01371 (0.00029)
50% Scrubber Mandate	0.01110 (0.00030)	–0.00325 (0.00009)	–0.00785 (0.00021)
80% Scrubber Mandate	0.00283 (0.00024)	–0.00083 (0.00007)	–0.00200 (0.00017)

Table A18: Hypothetical Policy Responses
Fixed Effects Model: 2000–2004

	% Change Coal Share	% Change Oil Share	% Change Gas Share
20%Permit Price Increase	–0.00561 (0.00014)	–0.00450 (0.00024)	0.00800 (0.00018)
50%Permit Price Increase	–0.01402 (0.00035)	–0.01125 (0.00060)	0.01999 (0.00046)
100% Permit Price Increase	–0.02804 (0.00070)	–0.02249 (0.00120)	0.03998 (0.00092)
20% Scrubber Mandate	0.01162 (0.00043)	–0.00294 (0.00008)	–0.01878 (0.00050)
50% Scrubber Mandate	0.00153 (0.00034)	–0.00158 (0.00006)	–0.01005 (0.00037)
80% Scrubber Mandate	0.02171 (0.00058)	–0.00021 (0.00005)	–0.00132 (0.00029)

Pooled Model Hypothetical Policy Results:

Table A19: Hypothetical Policy Responses Pooled Model: All Years			
	% Change Coal Share	% Change Oil Share	% Change Gas Share
20% Permit Price Increase	–0.0112 (0.0003)	–0.0080 (0.0003)	0.0136 (0.0003)
50% Permit Price Increase	–0.0173 (0.0004)	–0.0123 (0.0004)	0.0210 (0.0004)
100% Permit Price Increase	–0.0275 (0.0006)	–0.0194 (0.0006)	0.0332 (0.0006)
20% Scrubber Mandate	0.0153 (0.0003)	–0.0041 (0.0001)	–0.0112 (0.0002)
50% Scrubber Mandate	0.0085 (0.0002)	–0.0023 (0.0001)	–0.0062 (0.0001)
80% Scrubber Mandate	0.0017 (0.0002)	–0.0004 (0.00004)	–0.0012 (0.0001)

Table A20: Hypothetical Policy Responses Pooled Model: 1990–1994			
	% Change Coal Share	% Change Oil Share	% Change Gas Share
20% Permit Price Increase	–0.0035 (0.0004)	–0.0007 (0.0003)	0.0031 (0.0003)
50% Permit Price Increase	–0.0044 (0.0004)	–0.0009 (0.0004)	0.0039 (0.0004)
100% Permit Price Increase	–0.0059 (0.0006)	–0.0012 (0.0005)	0.0052 (0.0005)
20% Scrubber Mandate	0.0020 (0.0002)	–0.0007 (0.0001)	–0.0013 (0.0001)
50% Scrubber Mandate	0.0011 (0.0001)	–0.0004 (0.00005)	–0.0007 (0.0001)
80% Scrubber Mandate	0.0002 (0.0001)	–0.0001 (0.00004)	–0.0002 (0.0001)

Table A21: Hypothetical Policy Responses Pooled Model: 1995–1999			
	% Change Coal Share	% Change Oil Share	% Change Gas Share
20% Permit Price Increase	–0.0242 (0.0007)	–0.0149 (0.0006)	0.0239 (0.0006)
50% Permit Price Increase	–0.0332 (0.0009)	–0.0195 (0.0007)	0.0324 (0.0007)
100% Permit Price Increase	–0.0480 (0.0012)	–0.0271 (0.0009)	0.0466 (0.0010)
20% Scrubber Mandate	0.0216 (0.0005)	–0.0058 (0.0001)	–0.0158 (0.0003)
50% Scrubber Mandate	0.0124 (0.0003)	–0.0033 (0.0001)	–0.0090 (0.0002)
80% Scrubber Mandate	0.0031 (0.0003)	–0.0008 (0.0001)	–0.0023 (0.0002)

Table A22: Hypothetical Policy Responses Pooled Model: 2000–2004			
	% Change Coal Share	% Change Oil Share	% Change Gas Share
20% Permit Price Increase	–0.0059 (0.0001)	–0.0046 (0.0002)	0.0087 (0.0002)
50% Permit Price Increase	–0.0149 (0.0004)	–0.0113 (0.0006)	0.0217 (0.0005)
100% Permit Price Increase	–0.0297 (0.0007)	–0.0228 (0.0012)	0.0433 (0.0009)
20% Scrubber Mandate	0.0229 (0.0006)	–0.0026 (0.0001)	–0.0204 (0.0005)
50% Scrubber Mandate	0.0123 (0.0005)	–0.0014 (0.0001)	–0.0109 (0.0004)
80% Scrubber Mandate	0.0016 (0.0004)	–0.0002 (0.00004)	–0.0014 (0.0003)

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