Do price shocks change electricity consumption? Evidence from New Zealand industrial users

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April 2, 2013

Abstract

Recent concerns regarding climate change have led many policy makers to suggest the use of a carbon tax to reduce energy demand and reduce carbon emissions. This paper uses exogenous price changes in the New Zealand electricity market to study the effect of electricity prices on the electricity consumption of industrial users by estimating the short- and long-run price elasticity of demand for electricity. In the short run, industrial consumers are highly price inelastic. However, they appear to be more price elastic in the long run.

*The author would like to thank Professor Shaun McRae for his guidance throughout the entire project, without which this project would have been impossible. The author would also like to thank Professor Jeffrey Smith for his advice prior to this project, and various friends for their inputs.

1. Introduction

Concerns about climate change resulting from uncontrolled greenhouse gas emissions have led to increased interest in the use of price-based policies such as carbon taxes to reduce the consumption of energy derived from fossil fuels. Unfortunately, the efficacy of the current prescribed policies remains uncertain. Theory suggests that such price-based policies should be most effective at internalizing the externality of pollution (or in this case, greenhouse gas emissions). In particular, due to the heterogeneity in marginal cost of abatement across industries, price-based policies are less likely to produce huge deadweight losses compared to quantity-based policies (Weitzmann 1974). However, it is uncertain if price-based policies alone constitute the most cost-effective means of achieving sufficient significant reduction on greenhouse gas emissions. Most crucially, we do not have enough information on the extent of consumer response to such pricing policies.

Optimally, to evaluate the effectiveness of such policies, we would study the effect of an exogenous implementation of price-based regulations on the total energy usage by a community. Unfortunately, such an experiment is non-existent and improbable. In countries and regions that have already implemented an element of carbon taxation, regulations usually asymmetrically target different industries. For instance, in countries such as Norway or Sweden, carbon taxation policies usually target industries that are already the least polluting, and only minimally affect industries that are highly polluting. The rationale behind such an implementation of carbon taxation is to avoid inflicting undue economic distress on pollutive industries. Moreover, regions that are willing to implement just such a policy are usually already environmentally conscious. A case in point is Boulder, Colorado, which had unilaterally implemented a local carbon tax in November 2006. Any estimation of the effect of such policies on carbon emissions is unlikely to achieve external validity. For instance, we might underestimate its effect, since an environmentally conscious community would most probably already be polluting at a Pareto optimal level, and any additional policies would likely only have minimal effect. Conversely, an environmentally conscious community might react even more strongly to a carbon tax, and we might end up overestimating its effect.[1]

As a result, instead of directly studying the effect of extant carbon taxation policies, many have chosen to study the price response behavior of consumers. By estimating the price elasticity of demand for energy, policy makers are better able to decide the effectiveness of carbon taxation as a policy tool, and the extent to which carbon taxation can be used as a tool for reducing carbon emissions. For instance, if the price elasticity of demand is found to be highly inelastic across all industries, carbon taxation alone might be unsuitable as a policy tool in combating climate change. The huge amount of taxation required to produce

[1] Alcott and Mullainathan (2012) address some of the external validity issues that come with trying to estimate the effect of conservation policies.

the desired effect would most likely have drastic macroeconomic consequences. Moreover, such a policy will not likely pass public muster. Instead, subsidies and grants, or public pressures and education, leading to reduced energy use could be a more palatable option.[2] In particular, such policies could promote a gradual change in the capital stock of consumers and firms, leading to a eventual switch to more energy efficient appliances or machinery.[3] On the flip side, if price elasticities are found to be high across all industries, a low level of carbon taxation might suffice. Such a policy would then most likely be accepted by the public.

In my paper, I focus on the electricity market in New Zealand, and study the short and long term price elasticities across manufacturing sectors and individual firms. My reasons are two-fold. Firstly, the New Zealand electricity market was deregulated in 1996, and as a result, firms faced greater variation in the price of electricity they consume. This allows for more accurate estimation of the price elasticity of demand for electricity. Secondly, between 2000 and 2008, New Zealand faced four separate incidents where electricity production was severely constrained due to drought conditions, leading to huge increases in electricity prices. These price increases are arguably exogenous, as firms were unlikely to be able to predict the extent to which prices would rise. This exogenous variation allows for a more accurate statistical treatment of the data by avoiding simultaneous causality between prices and quantities . In addition, the huge supply shocks led to large price variations across years. This allows me to study both the price elasticities of firms at low price levels and higher price levels.

I estimate the price elasticities using two different models: a structural model of firm optimization, and a partial adjustment reduced-form model that is based on a structural model of electricity demand. The models differ strongly in their core assumption, with the former assuming that a firm is always behaving optimally in all time periods, and the latter assuming that firms are behaving sub-optimally. Both models are equally justifiable depending on the circumstances. Therefore, I estimated the price elasticity of electricity demand using both models in order to obtain a comparison of the resulting estimates.

I find in my estimation that firms are price inelastic in the short and medium run. This is largely unsurprising, since firms cannot spontaneously react to price variations in the short term. Moreover, there is no clear difference between the price elasticities estimated at different price levels. However, on a longer horizon, firms are generally price elastic. On average, the price elasticities across manufacturing sectors was -1.454. Moreover, some industrial users appear to be significantly more price elastic than others. This suggests that price-based policies, over a long run, can be very effective in cutting greenhouse gas emissions

[2]Price-based policies such as taxation are after all only a supply-side policy. If consumers are persistently overestimating the benefits they derive from inefficient energy use, then demand-side management is necessary to educate the public. Loughran and Kulick (2004), Auffhammer et al (2008) and Arimura et al (2011) provide evidence of the effectiveness of demand-side management and their long-run effects.

[3]Reiss and White (2008) and Alcott and Rogers (2012) give evidence of this gradual change in capital stock that comes from public "pressures" and education.

without substantially reducing consumer surplus. In addition, it also tells us that carbon taxes will affect industrial demand for electricity asymmetrically across sectors and firms, and that any imposition of such policies requires careful investigation as to which sectors are most strongly affected. Finally, it also tells us that carbon pricing policies are probably irrelevant in the short run, and that if we need a dramatic decrease in carbon production in the short term, other policies might be more effective.

The following parts of the paper are as follows. In Section 2, I give a background of the literature on electricity and energy demand. In Section 3, I provide a summary of the theoretical model of how firms respond to electricity price fluctuations in the short run and in the long run. Section 4 gives the empirical models that I will use, while Section 5 gives a brief description of the data. Section 6 explains my method of estimation, while Section 7 reports the results from my estimation. Section 8 reports the results and analysis of my estimation, while Section 9 concludes the paper and provides suggestions for future research. The attached appendices provide the estimation results.

2. Literature Review

The literature regarding electricity demand, especially that on estimating the price elasticity of electricity, is sizable. Much of the work started in the early 1970s, when there was intense interest in studying the price response of consumers. This was primarily necessitated by the need to be able to predict consumer behavior regarding electricity demand, thus allowing for more efficient production and distribution of electricity.

One of the most common ways of uncovering the price elasticity is to formulate a structural model of demand for electricity, and then derive the short-run and/or long run price elasticities from the coefficients on the right-hand side explanatory variables. Houthakker et al. (1974) were one of the first to estimate the price elasticities of residential consumers for electricity using such a method. In their partial adjustment model, the optimal quantity of electricity demanded was theorized to be a function of only per capita personal income and electricity prices. The observed quantity of electricity demand was then theorized to be a function of the optimal quantity of electricity demanded and the lagged (observed) quantity of electricity demanded. Using an error correction model to address the potential serial correlation in error terms (due to the presence of the lagged variable), they estimated price elasticities (at the national level) of -0.029 to -0.094 depending on the marginal prices faced by the consumer.

Much of the later work has generally been based on Houthakker's partial adjustment model with some improvements. For instance, Paul, Myers and Palmer (2009) based their model of electricity demand on the general theoretical structure of the partial adjustment model, but increasing the number of explanatory variables by taking into account of the weather explicitly (in the form of number of heating degree days, number of cooling degree days, the seasons, the number of daylight hours, and state-level fixed effects). This builds on the hypothesis that electricity demand is strongly correlated with the weather and seasons. They also take into account of the possibility of substitution between energy sources by including the price of natural gas into their regression. Unlike Houthakker (1975), they estimate their regressions at the state level. Moreover, in order to take into account of the potential serial correlation in error terms, Paul et al. chose a 2SLS estimation by using an instrumental variables technique to first estimate the lagged quantity of electricity demand. They obtained estimates of between -0.10 to -0.16 depending on consumer class and season.

Another work of interest is that by Bernstein (2005). Here, Bernstein estimates the price elasticity of electricity demand at three spatial levels (national, regional and state) for two consumer classes (residential and commercial). His explanatory variables included lagged values of observed electricity used, electricity and gas prices and their lagged values, population and per capita income (for residential consumers) / gross state product and new floor space (for commercial consumers) and their lagged values, and climatic variation along with state and time fixed effects. He estimated his model using OLS after testing for autocorrelation in the error terms, and finding no significant autocorrelation. Bernstein generally finds price elasticities of less than -0.2.

Instead of directly estimating the demand equation, another option would be for an economist to first postulate a certain firm production function that includes electricity use. Due to the duality in production and cost function, this initial assumption of a specific structural form of firm production function allows us to infer the structure of the cost function, from which we can then estimate the parameters of the cost function. One can then indirectly obtain the price elasticity for electricity demand from these parameters.

Berndt and Wood (1975) were one of the first to attempt a comprehensive assessment of industrial consumers using such a formulation. In their paper, Berndt and Wood assume a four-factor model: energy prices, material prices, capital and labor cost. Rather than measuring the price elasticity of electricity per se, Berndt and Wood estimated the elasticity of a basket of energy sources (including electricity) using an iterated 3SLS regression, and found a elasticity of about -0.47.

A primary weakness of the Berndt-Wood model is the lack of a temporal factor. Specifically, firms do not make decisions in only one time period, but rather choose a certain path of production based on rational expectations. Pindyck and Rotemburg (1983) take into account of this inter-temporal choice by modifying the Berndt-Wood model into a dynamic demand model. Using the same data set and method of estimation as Berndt and Wood, Pindyck and Rotemburg find short run elasticities of around -0.36 and long run elasticities of around -0.99.

Taking a different track, Patrick and Wolak (2001) also hypothesize a production / cost function, and estimate the price elasticity of demand for electricity for each type of industrial user in the U.K. Unlike the Berndt-Wood model, however, Patrick and Wolak do not directly estimate the function parameters from a system of equations arising from the factor share demand equations and cost function. Due to a lack of data on firm production for each specific industry, they proxied firm production using the quantity of electricity used. By recovering the cyclical component of electricity consumption using Fourier analysis, Patrick and Wolak estimated the expected costs associated with firm production, and proceeded to recover the parameters of the cost function.

3. Theory and Background

In order to derive the price elasticity of electricity demand, one might be tempted to do a straightforward regression of log quantity on log prices. Such a motivation is suggested by the log-linear inverse demand curve:

$$\ln Q^d = \alpha + \beta \ln P^d + \epsilon \tag{1}$$

where Q^d is the quantity of electricity demanded, P^d is the price of electricity, and ϵ is an unobservable error term. In this model, β would give the price elasticity of demand for electricity.

Such a model would, however, most likely suffer from the usual simultaneity and omitted variable biases. Firstly, the prices and quantities that we observe are simply the market-clearing prices and quantities, set by the simultaneous movements of both supply and demand curves. This model has the strong assumption that the demand curve stays exactly the same, as can be seen by the imposition by the constant α term. In reality, market-clearing prices and quantities are most probably set by simultaneous movements in both supply and demand curves. Depending on the extent to which each curve shifts, we might underestimate or overestimate the price elasticity. Secondly, the model necessitates that the error term is entirely uncorrelated with the prices paid. In reality, it is unlikely that the demand of electricity by firms is due solely to electricity prices. Instead, when considering the level of consumption of electricity, many confounding factors, such as the price of other inputs, and market demand for the firm's output, usually exist. These factors are very likely to be correlated with electricity prices. Indeed, taken to the extreme, a firm facing no demand for its product will consume no electricity, no matter how cheap it is, since it is making a loss by simply producing anything.

Therefore, in order to truly observe the price elasticity of demand, one would either have to isolate price movements due solely to a shift in the supply curve (i.e. an exogenous supply shock in the electricity market), or formulate a theory of firm demand for electricity that allows us to estimate the effect of the price of electricity on the quantity of electricity demanded conditioned on certain covariates that also affect electricity demand.

A common starting point in the literature is to assume a static model of electricity demand; that is, that the demand for electricity is only a function of the current price of factor inputs. Consider the static model with a firm that has many inputs and one output. The static production function of the firm is given by

$$y = f(\vec{x}; z) \tag{2}$$

where y represents the quantity of output, $\vec{x}$ represents a vector of quantity of inputs such as material, energy, labor and capital and z represents technology. Using the duality relation between cost and production functions, the firm's total cost function (which assumes the same shape as the production function) is given by

$$C = C(\vec{w}; y) \tag{3}$$

where $\vec{w}$ represents a vector of real prices of inputs such as material, energy, rental rate of capital, and real wages. If the firm is a price taker in both input and output markets, conditional on input costs, the firm will choose to maximize profits by minimizing its cost of production. Assume that the firm has already chosen an optimal level of output, y^*. Then, using Shepard's Lemma, we obtain the conditional factor demand function

$$\left(\frac{\partial C}{\partial w_i}\right)_{y=y^*} = x_i^* \tag{4}$$

where x_i^* represents the optimal amount of a certain input factor to produce the optimal output.

Given the complete set of conditional factor demand equations, along with the original cost function, we can then estimate obtain estimates of the parameters of the cost function, from which we can then calculate the price elasticity of electricity.

The static model, unfortunately, does not fully capture the dynamic decision making process of a firm. In particular, at any specific time t, a firm with rational expectations chooses to minimize the expected sum of discounted costs across time (after time t). The distinction between discounted and nominal cost is crucial: In a dynamic model, the same nominal cost incurred over time means that future costs are actually *lower* than current cost, and a firm would choose to consume more of a certain factor in the future than now. Moreover, a dynamic decision making process would also take into account of capital and labor depreciation over time, as well as the opportunity costs of capital and labor; a process which the static model is incapable of accommodating. Finally, the static model assumes that capital stock and labor are variable at all times. This is also unlikely to be true. Instead, both capital stock and labor are usually quasi-fixed. Therefore, one usually incurs a certain cost in changing capital stock or labor. For instance, in the case of capital stock, a company would have to take into account the loss incurred by condemning a machine that is still functional. Likewise, premature termination of labor contracts usually imposes some additional cost on a firm. Therefore, modifying the original static cost function, the total cost function a firm considers, at time t, becomes

$$\mathcal{C}_t = \mathbb{E}_t \left[\sum_{\tau=t}^{\infty} R^{\tau} \left(C(\vec{w}_{\tau}; K_{\tau}, L_{\tau}, y_{\tau}) + v_{\tau} K_{\tau} + u_{\tau} L_{\tau} + c_1(I_{\tau}) + c_2(H_{\tau}) \right) \right] \tag{5}$$

where $\mathbb{E}_t$ is the expectation operator (thus giving us the expected cost at time t) and R represents the discount rate. C is a modified version of the static cost function: It is now subject to the quasi-fixed levels of capital (K) and labor (L) input, along with a pre-determined level of output. $\vec{w}$ still represents input prices, but no longer includes the real rental rate of capital and real wage rate. Instead, v and u now represent the real rental rate of capital and real wage rate respectively, thus giving us the opportunity cost of capital and labor, I and H representing investment in new capital and net hiring respectively, as a result of capital depreciation and worker attrition, and c_1 and c_2 represents costs incurred due to capital and labour adjustment (i.e. costs incurred due to investment and new hirings). I and H are defined by

$$I_t = K_t - K_{t-1} \tag{6}$$

$$H_t = L_t - L_{t-1} \tag{7}$$

and R is defined by

$$R = \frac{1}{1+r} \tag{8}$$

where r is the real interest rate. Assuming that the firm is rational, and chooses to minimize its total discounted expected costs, we obtain the first order conditions:

$$
\begin{aligned}
\left(\frac{\partial C}{\partial w_{i,t}}\right)_{y=y^*} &= x^*_{i,t} & (9)\\
v_t + \frac{\partial c_1(I_t)}{\partial K_t} + \mathbb{E}_t\left[R\frac{\partial c_1(I_{t+1})}{\partial K_t}\right] &= 0 & (10)\\
u_t + \frac{\partial c_2(H_t)}{\partial L_t} + \mathbb{E}_t\left[R\frac{\partial c_2(H_{t+1})}{\partial L_t}\right] &= 0 & (11)
\end{aligned}
$$

where the first set of equations are the conditional factor demand equations as a result of Shepard's lemma, and the latter two are the Euler equations describing the expected time evolution of the quasi-fixed factors capital and labor. The latter two equations tells us that with perfect foresight, companies would perfectly compensate their capital and labor depreciation; i.e. observed total incurred capital and labor cost resulting from capital and labor input cost, depreciation, and investment/hiring (first two terms) exactly matches up with the expected savings from investing in capital and labor at time t, as opposed to say investing in the bond markets (last term, which is negative). Given the complete set of information needed in the preceding system of equations, we can solve for the structural parameters, and derive the price elasticity of demand of electricity. Since we assumed complete flexibility in input quantities, the structural parameters can in fact be interpreted as a long run price elasticity of electricity. Pindyck and Rotemberg (1983) considers just such a model, expanding the static translog model of Berndt and Wood (1975) into a dynamic model that takes into account of rational expectations.

One of the crucial assumptions in using the preceding firm production theories to estimate price elasticities is that firms are behaving optimally, that is firms are always producing at the point where they minimize production costs to maximize profits. This relies on a strong assumption that firms are able to switch between inputs effortlessly (i.e. unrestricted cross-price and own price elasticity of substitution), and that firms also have perfect information. In reality, firms are probably incapable of switching between inputs (or reduce their demand for a certain input) that easily. For instance, consider the conundrum of running huge data centers, where it is considered cheaper in the short run to keep a server running than to turn it off, even if there is no demand for storage space in the short run. Such a situation is not taken into account in the preceding model. Moreover, firms are unlikely to have perfect foresight. Taken together, firms are in fact usually behaving sub-optimally.

To take into account of such sub-optimal behavior, one could consider the partial adjustment model first proposed by Houthakker (1974), which assumes that consumers behave sub-optimally due to the lack of ability to optimally change their capital stock in a short time period. Specifically, Houthakker considers the following model:

$$\frac{Q_t}{Q_{t-1}} = \left(\frac{Q_t^*}{Q_{t-1}}\right)^\theta \tag{12}$$

where Q_t is the quantity of electricity consumed at time t, Q_t^* is the optimal quantity of electricity to be consumed at time t and θ is a parameter, between 0 and 1, that restricts the consumer from using the optimal amount of electricity, such that 1 represents perfect adjustment, and 0 reflects no adjustment capability.

Taking logs of both sides, we obtain

$$\ln Q_t = \theta \ln Q_t^* + (1-\theta) \ln Q_{t-1} \tag{13}$$

Assuming a functional form for the optimal demand of electricity with some factors P, X, Y, Z:

$$\ln Q^* = \alpha \ln P + \beta \ln X + \gamma \ln Y + \delta \ln Z \tag{14}$$

In this case, we obtain the equation:

$$\ln Q_t = \theta\alpha \ln P + \theta\beta \ln X + \theta\gamma \ln Y + \theta\delta \ln Z + (1-\theta) \ln Q_{t-1} \tag{15}$$

Rewriting, we obtain:

$$\ln Q_t = a \ln P + b \ln X + c \ln Y + d \ln Z + e \ln Q_{t-1} \tag{16}$$

The use of lagged quantity to proxy for input factors that cannot be easily changed or substituted reflects the situation where input factors are quasi-fixed. This corresponds, for instance, to the preceding scenario of data centers that cannot easily shut down servers even during times when supply greatly exceeds demand. Therefore, if P is the price of electricity, a can then be interpreted as the short-run price elasticity of electricity demand.

Bernstein (2005) and Paul et al (2009) uses a modified version of this model.

4. Models

In this paper, I estimate the price elasticity of electricity using both the structural model based on the cost function of the firm, and the partial adjustment model. This effort to perform two sets of estimation is motivated by two reasons.

Firstly, from a theoretical standpoint, it is hard for the econometrician to decide, *ex ante*, if a firm is behaving optimally or sub-optimally. As a result, one cannot definitively say which model is more appropriate for estimation, and I chose to estimate both models. Interestingly, if the partial adjustment model produces price elasticity estimates that do not differ significantly from that of the cost function model, this implies that firms are indeed behaving optimally.

Secondly, due to the availability of data at different levels of aggregation, it is extremely difficult to estimate the cost function accurately. Crucially, while electricity price and quantity data are available down to the half-hourly level, it is almost impossible to find cost or output data (just to name a few factors) at any level lower than the quarterly level. As a result, the cost function model was estimated on the annual level, and due to the sparse data, suffers from low statistical power. As a result, the partial adjustment model is a suitable augmentation to the cost function model, as it is estimated using only high frequency price and quantity information.

In this section, I proceed to explain and justify the models I estimate.

4.1 Structural cost function model

Here, I consider the translog production/cost function as my functional form for estimation. I consider four factors of production: electricity, materials, labor, and capital stock. Taken together, the dynamic translog cost function is

$$\begin{aligned}
\ln C_{tk} &= \alpha_0 + \beta_0 \ln y_{tk} + \sum_i \beta_i \ln x_{itk} + \frac{1}{2}\sum_{j\neq i}\sum_i \beta_{ij} \ln x_{itk} \ln x_{jtk} \\
&= \alpha_0 + \beta_0 \ln y_{tk} + \sum_i \beta_i \ln x_{itk} + \sum_{j>i}\sum_i \beta_{ij} \ln x_{itk} \ln x_{jtk} + \frac{1}{2}\sum_i \beta_{ii} \left(\ln x_{itk}\right)^2 \\
&\quad + \eta_t + \epsilon_k
\end{aligned} \tag{17}$$

where $i, j = 1, ..., 5$, indexes x as the real price of electricity (E), real price of materials (M), levels of labor (L), levels of capital stock (K) and levels of industrial output (y) respectively at time t for industrial sector k, η_t represents an exogenous time trend that varies production cost and might be correlated with previous shocks, ϵ_k represents an idiosyncratic shock uncorrelated with previous shocks, and we have assumed that the cost function is symmetric (so $\beta_{i,j} = \beta_{j,i}$).

Using the same motivation as Pindyck (1983), we let c_1 and c_2 assume the forms:

$$
\begin{aligned}
c_1(I_{tk}) &= \frac{1}{2}\gamma_{1,t} I_{tk}^2 && (18)\\
c_2(H_{tk}) &= \frac{1}{2}\gamma_{2,t} H_{tk}^2 && (19)
\end{aligned}
$$

from which I obtain the first-order conditions:

$$
\begin{aligned}
S_{E,tk} \equiv \frac{P_{E,t}E_t}{P_{E,t}E_t + P_{M,t}M_t} &= \beta_1 + \sum_j \beta_{1,j} \ln x_{jtk} + \nu_t + \mu_k && (20)\\
S_{M,tk} \equiv \frac{P_{M,t}M_t}{P_{E,t}E_t + P_{M,t}M_t} &= \beta_2 + \sum_j \beta_{2,j} \ln x_{jtk} + \nu_t + \mu_k && (21)\\
v_{tk} + \gamma_1 \left(K_{tk} - K_{t-1,k}\right) &= \mathbb{E}_t \left[R_t \gamma_1 \left(K_{t+1,k} - K_{tk}\right)\right] = R_t \gamma_1 \left(K_{t+1,k} - K_{tk}\right) + \nu_t + \mu_k \\
\implies \Delta_t K_{tk} &= \theta_{1,t}(R_t \Delta_{t+1} K_{t+1,k}) + v_{tk} + \nu_t + \mu_k && (22)\\
w_{tk} + \gamma_2 \left(L_{tk} - L_{t-1,k}\right) &= \mathbb{E}_t \left[R_t \gamma_2 \left(L_{t+1,k} - L_{tk}\right)\right] = R_t \gamma_2 \left(L_{t+1,k} - L_{tk}\right) + \nu_t + \mu_k \\
\implies \Delta_t L_{tk} &= \theta_{1,t}(R_t \Delta_{t+1} L_{t+1,k}) + w_{tk} + \nu_t + \mu_k && (23)
\end{aligned}
$$

where S represents factor shares, Δ_t represents first-differences at time t, $\theta_{1,t} = \frac{\gamma_{1,t+1}}{\gamma_{1,t}}$, $\theta_{2,t} = \frac{\gamma_{2,t+1}}{\gamma_{2,t}}$, and ν_t represents a time trend and μ_k represents an idiosyncratic shock. In addition, I have assumed perfect foresight and dropped the expectation operator. I then proceed to estimate equations 17, 20, 21, and 22, from which I obtain the price elasticity of electricity, at time t for each industrial sector k, using the formula:

$$
\hat{\mathcal{E}}_{E,tk} = \frac{\hat{\beta}_{11} + \hat{S}_{E,tk}^2 - \hat{S}_{E,tk}}{\hat{S}_{E,tk}} \tag{24}
$$

4.2 Partial adjustment model

Equation 20 from the cost function estimation motivates the consideration of electricity prices, material prices, labor costs, capital costs and industrial output as the explanatory factors for optimal electricity demand. One notes that industrial output is itself a proxy of macroeconomic conditions, since economic conditions are positively correlated with industrial output. Since macroeconomic conditions can be decomposed into a time trend and an exogenous variation, I consider the following specification:

$$
\ln Q_t = \alpha + \beta_1 \ln Q_{t-1} + \beta_2 \ln Q_t^*(\vec{X}) + f(t) + \epsilon_t + \mu \tag{25}
$$

where $\ln Q_t$ represents contemporaneous log quantities of electricity, $\ln Q_{t-1}$ represents one-period lagged log quantities of electricity, $Q^*(\vec{X})$ is the linear component of the demand function for optimal consumption of electricity, with $\vec{X}$ representing a vector of prices and other exogenous macroeconomic factors that affect industrial output, and $f(t)$ is the time-dependent component that affects the contemporaneous economic conditions (and hence industrial output) .

From the preceding motivation, $\ln Q_t^*$ assumes the following functional form:

$$\ln Q_t^* = a \ln P_{E,t} + b \ln P_{E,t-1} + \sum_{\text{all } k} c_k \ln P_{k,t} + \sum_{\text{all } k} d_k \ln P_{k,t-1} + \sum_{\text{all } l} e_l \ln M_{l,t} \tag{26}$$

where $P_{E,t}$ indicates price of electricity at time t, $P_{E,t-1}$ is the price of electricity one time period ago, $P_{k,t}$ indicates the prices of all other material and energy substitutes (indexed by k) at time t, $P_{k,t-1}$ are the corresponding lagged prices, and $M_{l,t}$ indicates other macroeconomic factors that might exogenously affect industrial output (indexed by l).

Finally, we let $f(t)$ be a flexible, non-linear function of time, which by itself probably provides a high degree of explanatory power regarding electricity demand. For instance, a firm would use more electricity during the day than at night simply due to a pre-determined 8-hour regular work day, and this amount is used regardless of other factors.[4]

My general regression specification thus reduces to:

$$\begin{aligned} \ln Q_t \quad = \quad & \alpha + \beta_1 \ln Q_{t-1} + \sigma_1 \ln P_t + \sigma_2 \ln P_{t-1} + \sum_{\text{all } k} \gamma_k \ln P_{k,t} + \sum_{\text{all } k} \delta_k \ln P_{k,t-1} \\ & + \sum_{\text{all } l} \zeta_l \ln M_{l,t} + \sum_{\tau} \lambda_\tau D_\tau + \epsilon_t \end{aligned} \tag{27}$$

5. Data

5.1 Structural cost function model data

Quarterly material, labor and capital costs were obtained from the Annual Enterprise Survey and the Economic Survey of Manufacturing from Statistics New Zealand. Quarterly capital, labor, material and energy price indices (aggregated and averaged over all industries), as well as the annual GDP deflator, were obtained from the Infoshare website run by Statistics New Zealand. Annual electricity prices and consumption, and

[4]Since we do not observe $f(t)$ directly, one immediately notices that a huge amount of the movement in energy demand comes from endogenous movement. Patrick and Wolak (2001) attempts to remove this endogenity by recovering the time trend using spectral (Fourier) analysis. In contrast, if one assumes that there is no structural break in the data generating process, one can also simply use a series of time-of-sample dummy variables to absorb the variation due solely to $f(t)$. I chose to use the latter method due to its greater simplicity in application.

annual gas prices and consumption were obtained from the Ministry of Economic Development. Finally, daily hydrology data was obtained from the Electricity Authority of New Zealand.

In order to create the relevant data set for estimation and analysis, I matched up the data from the Infoshare website with the data from the Ministry of Economic Development by year and sector. Where dollar-denominated volumes are used (for instance, sector output), all dollar-denominated values were deflated to year 2000 levels using the GDP deflator released by Statistics New Zealand. All quarterly data were aggregated within ANZSIC sectors to an annual level. Total costs for each sector and time were calculated by adding up the capital, labor, material and electricity costs. Factor shares for each sector and input were then created by calculating each input cost as a fraction of total cost.

5.2 Partial adjustment model data

Monthly aggregated world, aluminum and forestry producer price indices were obtained from ANZ, whilst monthly business confidence index and the NZX 50 stock index were obtained from Global Financial. Daily hydrological data, as well as half-hourly electricity quantities and prices, were obtained from the Electricity Authority of New Zealand. For this paper, I focused only on nine major industrial users with a direct connection to the transmission network. Electricity prices and quantities for these users are publicly available.

6. Method of estimation

6.1 Structural cost function estimation

With the creation of the set of factor shares and total cost data, I estimated equations 17, 20, 22 and 23 using a (three-stage least squares) seemingly unrelated regression estimation method, with the imposition of the constraints that all of the cross-price coefficients in each estimated equation sum up to unity in order to preserve the convexity of the cost function. That is,

$$\sum_j \beta_{i,j} = 1 \qquad \forall j \tag{28}$$

In addition, the factor share equation for materials was dropped to prevent perfect collinearity in the error terms (since by creation, the factor shares sum to unity). Finally, electricity prices were also instrumented with lake levels to avoid the endogenous setting of prices due to shifts in the demand curve.

6.2 Partial adjustment model

As mentioned in the preceding section, I obtained half-hourly price and quantity data for each firm. In order to investigate the very short, short and medium run price elasticities, I conducted my analysis on three levels of aggregation: half-hourly (i.e. disaggregated data), daily and monthly, each corresponding to the very short, short, and medium run price elasticity of electricity demand. This was done by calculating the total amount of electricity consumed at each level of aggregation, and calculating the volume-weighted average of prices for each level of aggregation. Equation 26 was then modified for each specific case as necessary.

At the half-hourly level, the exogenous variations in demand for electricity is most likely only a function of electricity prices; that is, after controlling for time effects, all other factors in the linear demand equation should drop out. It is a reasonable assumption. As the preceding cost function structural model suggests, firms have rational expectations about future economic conditions, and thus already have a general production plan in place. Specifically, a factory manager is most probably only given limited reign in altering energy use within the day, since his or her factory output would have already been set in place the preceding year. Therefore, such a manager would perhaps respond to excessive electricity use or excessively high prices by slight alterations to their factory processes, but is unlikely to dramatically change their electricity demand.

Due to the high-frequency nature of the data, it is unlikely that changes in electricity consumption are provoked by contemporaneous electricity prices. Rather, it is more likely that a factory manager reacts to preceding electricity prices. Therefore, I modify equation 26 by dropping the P_k and M_l terms. The D_τ terms are week of sample time dummies to control for time effects. Moreover, I also included a set of firm dummy variables to account for firm fixed effects. Here, σ_2 (the coefficient on the lagged price term) gives us the price elasticity of demand of electricity.

A serious problem arises from the preceding firm fixed-effect specification due to its assumption of homogeneity in price elasticities across companies. That is, by construction, I assume that, whilst companies have differing price elasticities of demand for electricity, they all asymptotically converge to the same average. This assumption might not be entirely true; for instance, steel mills might have a statistically and economically significant different price elasticity compared to a pulp mill. Therefore, I ran separate regressions on the data from each firm, and with σ_2 now giving us the price elasticity for each firm.

Another potential problem arises from the possibility of serial correlation in the error terms. Specifically, due to the inclusion of a lag quantity term, serial correlation in the residuals might bias our results. Therefore, I conducted first a sequential Box-Ljung test, and as a form of robustness check, a test for autocorrelation as suggested by Wooldrige and Drukker. Both tests show significant correlation in the error terms. As a result, the standard errors obtained for the preceding estimations were calculated using Newey-West standard errors to take into account of the serial correlation.

The daily level aggregation should most likely follow a similar data generating process as the half-hourly level: that is, daily changes in electricity use are unlikely to be a result of contemporaneous macroeconomic factors or prices. This is because factory managers are likewise unlikely to be able to respond to changes in contemporaneous macroeconomic factors or prices within a day, and are most probably reacting to price variations from the day before. However, due to the longer lag time in between observing a price change in the last period and the current period, it is most likely that price elasticities should be slightly larger in the short run.

Like the preceding estimation, I ran regressions for the full sample and at the firm level. D_τ here is now a set of month-of-sample dummies that control for fixed effects. σ_2 again gives us the price elasticities.

In order to perform some element of robustness checks, I tested the validity of assuming a lack of feedback from contemporaneous macroeconomics factors by using the NZX 50 stock index as a proxy for macroeconomic trends. The NZX 50, being the main stock market of New Zealand, should capture significantly the macroeconomic conditions of New Zealand. Therefore, I ran another batch of regressions on both the full sample and at the firm level with the inclusion of the NZX 50 index as a control variable.

In addition, I ran another set of regressions using quarter-of-sample dummy variables in place of the month-of-sample variables. This was done to reduce the number of dummy variables in my regression, and thus increase the number of degrees of freedom in my regression. By doing so, I am able to achieve greater statistical power. However, one cautions the use of these results, since the use of quarterly dummies would indicate that business conditions within the same quarter are homogenous, which is rather unlikely.

Finally, due to presence of autocorrelation in the error terms, all standard errors are obtained using Newey-West standard errors.

At the monthly level of aggregation, we should be able to observe the medium run price elasticity of electricity demand. However, at this point, contemporaneous economic factors should start exerting their effects. This is unsurprising, since a factory manager now has a whole month to observe and react to economic and price changes. As a result, I used a set of control covariates that included producer price indices for an aggregated world price index, for the forestry and related industries, and for the aluminum and related industries; a business confidence index; and finally the NZX 50 stock price index. The producer price indices are meant to controls for other input costs that would affect the demand of electricity. Specifically, increasing production cost, holding all other factors constant, would most likely decrease industrial output as factories attempt to reduce their cost. As a result, electricity demand will fall even with constant electricity prices. These price indices will control for such an effect. Forestry and aluminum price indices were chosen due to the large proportion of aluminum and forestry-related companies represented in this sample. The business confidence and NZX 50 indices, on the other hand, controls for output demand. Holding all else constant, better macroeconomics conditions would create higher demand for industrial output. To maximize profits, companies would therefore increase output even with electricity prices held constant. Therefore, both indices seek to control for this effect. Unlike the estimation done at the half-hourly or daily level, σ_1 here gives us the price elasticity of demand for electricity (that is, the coefficient on the contemporaneous price term). Moreover, it is most likely that these economic factors follow the exact same trend as industrial output. Like before, due to the presence of serial correlation in the error terms, all reported standard errors are Newey-West standard errors.

Another important consideration is that electricity prices themselves are not exogenous to the model; that is, there is feedback from contemporaneous and lagged electricity demand. As a result, the OLS estimates will most likely be biased. It can be justifiably argued that the variation in prices over the time period of interest are not spurred by the variation in quantity of electricity demanded. This is a particularly strong argument due to the fact that electricity production in New Zealand is dominated by hydroelectric production, such that electricity supply is largely out of the control of the producers. Therefore, price variations are usually a result of supply factors, in particular, hydrological levels. As a result, simultaneity bias is probably not a strong concern here, even though the estimates might be slightly downward biased. However, as a further form of robustness check, I used hydrological lake levels as an instrument to produce an exogenous change in electricity prices, and then use this predicted price values in the preceding regressions. This was done by first scaling the lake levels at Pukaki, Tekapo and Taupo to their highest observed lake levels (i.e. to a value between 0 and 1 inclusive), and then weighing them by their maximum storage values. Finally, I aggregated the values to obtain an aggregate measure of lake levels across the country, and use this as an instrument in predicting electricity prices. The two-stage least squares regression is as follows:

$$\ln P_t = \ln LakeLevels + \Gamma X + \mu_t \tag{29}$$

$$\ln Q_t = \alpha + \ln P_t + \Gamma X + \epsilon_t \tag{30}$$

where $LakeLevels$ is the aggregated measure of lake levels as mentioned in the preceding paragraph, and X are a vector of control covariates from the monthly regressions.

Finally, there might also be concerns that the imposition of a linear structure on logged prices unreasonably assumes a constant elasticity of demand at all price levels. Therefore, I modify each preceding regression specification to the following specification:

$$\ln Q_{t,i} = \alpha_i + \beta_{1,i}\ln Q_{t-1,i} + \sigma_{1,low,i}\ln P_{t,i} * I_{low} + \sigma_{1,high,i}\ln P_{t,i} * I_{high} + \sigma_{2,low,i}\ln P_{t-1,i} * I_{low} + \sigma_{2,high,i}\ln P_{t-1,i} * I_{high} + \Gamma_i X_i + \sum_i \gamma_i Firm + \epsilon_{i,t} \quad (31)$$

$$\ln Q_t = \alpha + \beta_1 \ln Q_{t-1} + \sigma_{1,high,i}\ln P_{t,i} * I_{high} + \sigma_{2,low,i}\ln P_{t-1,i} * I_{low} + \sigma_{2,high,i}\ln P_{t-1,i} * I_{high} + \Gamma X + \epsilon_t \quad (32)$$

where X represents a vector of control covariates relevant to the regression specification for each level of data aggregation, I_{low} is an indicator variable that evaluates to 1 when prices are low (arbitrarily set as any prices less than or equal to the price at the 90th percentile) and 0 otherwise, and I_{high} is an indicator variable that evaluates to 1 when prices are high (arbitrarily set as any prices more than the price at the 90th percentile) and 0 otherwise. This allows me to estimate the price elasticity of demand of a firm given that prices are high or low.

7. Results and analysis

7.1 Structural cost function model

Table 4 reports the estimated structural parameters, while table 5 reports the average price elasticities across sector and time, as well as the standard deviations, minimum, and maximum values. We see that the average price elasticity of all industry is -1.454. This indicates that a one standard deviation increase in electricity price will lead to a 65.6% decrease in electricity used. Such a decrease is economically significant. Moreover, for firms that are one standard deviation away from the mean, their price elasticity is -1.687, indicating that a one standard deviation increase in prices will lead to a 76.1% decrease in electricity consumed. As argued earlier in section 4, this price elasticity is a long run price elasticity. Therefore, I conclude using this evidence that the long run demand for electricity is in fact elastic.

A possible explanation for this price elastic behavior is due to the change in the type of capital stock over time as firms try to be more efficient in their energy use. Alcott and Rogers (2012), for instance, explore the possibility of consumers changing their capital stock over time as perceptions regarding energy efficiency changes, and find that consumers do significantly reduce their energy consumption over a long period of time. Indeed, by holding capital stock quasi-fixed, as my model does, it suggests that while firms are unable to respond much to price changes in the short run, in the longer term, firms could invest in more energy efficient machinery and processes as they replace their depreciated capital stock, and thus reduce their energy use. This explains the price elastic behavior in the long run.

Unfortunately, the estimated structural parameters are not statistically significant, suffering low statistical power due primarily to the small number of observations. Moreover, my proposed model is a very watered-down version of a cost function model that does not take into account of substitution effects from other fuel sources, thereby suggesting that the estimates might be biased by omitted variable bias. In addition, the use of aggregated price indices, rather than prices that directly relate to the material, capital and labor input of each sector, suggest the glossing over of heterogeneity between sectors. Finally, my estimation assumes that the structural parameters stay constant throughout all 20 years. This is highly implausible. Therefore, while the estimated price elasticities are huge and worthy of note, I advise the reader to be cautious when interpreting these results. On a more positive note, the estimates parallel that of the literature. Pindyck and Rotemberg (1983), for instance, report that firms are generally unit elastic (or slightly more than unit elastic) in the long run. However, more work definitely needs to be done here.

7.2 Partial Adjustment Model

Table 8 reports the estimation results at the daily level when all the data are pooled together. The estimated price elasticities (the coefficient on the lagged price term) ranged from -0.103 to -0.123, depending on the extent of time controls used. Interestingly, the point estimates do not significantly differ from each other (as suggested by their standard errors). Table 9 also reports the pooled regression results at the daily level, but taking into account the non-linearities in firm behavior at different price levels. It shows that firms are generally price inelastic at both price levels, but are slightly more elastic at higher price levels (estimates range from -0.0712 to -1.39) than at lower price levels (estimates range from -0.0776 to -0.0976). There is, however, no statistical difference between the two. Taken together, this suggests that, as a whole, the nine firms are collectively price inelastic in the short run. Indeed, a one standard deviation increase in prices would lead to a decrease of between 4.3% to 7.5%, a marginally economically significant result.

Tables 10 to 12 report the estimation done at the firm level for daily prices. The regression results reflect the previous findings of inelastic demand. Price elasticities range from effectively 0 to -0.331 depending on the extent of time controls used. Firm 4 (a wood product manufacturing plant) appears to be the most price elastic of all nine firms, reporting estimates from -0.193 to -0.335.

Tables 13 to 15 report the same estimation while allowing for non-linearities in price behavior. Like the preceding results, it reports generally inelastic demand for electricity. In addition, there does not appear to be a statistical difference between the two.

Table 15 reports the estimation done at the monthly level with all data pooled together. When estimated using an OLS method, the point estimate (on the contemporaneous price term) comes up to -0.0700, whilst the use of a 2SLS specification reduces the point estimate to -0.0335. This implies that a one standard deviation increase in prices would lead to a decrease of between 2 to 4 percent. This is hardly economically significant. Moreover, neither values are statistically different from 0.

Table 16 reports the estimation done at the monthly level with pooled data while taking into of non-linearities in demand behavior. We see that at low price levels, the coefficient is not significantly different from 0. On the other hand, the price elasticity at high price levels at marginally significant at 10%. The point estimate, at -0.0718, tell us that a one standard deviation increase in prices lead to an approximately 4% decrease in electricity quantity demanded. This is not economically significant.

Finally, tables 18 and 19 report monthly regressions by firm, the former using an OLS specification, the latter with a 2SLS specification. The 2SLS specification produces estimates of magnitude that are consistently larger than the estimates produce by the OLS specification, suggesting that simultaneity bias might have played a strong part in depressing the OLS estimates. The 2SLS estimates reports only two values that are statistically significant at the 5% level: -0.184 for firm 1 (a wood product manufacturing plant), and -0.0435 for firm 8 (a metal manufacturing plant). For firm 1, a one standard deviation increase in prices leads to a 13.8% percent decrease in electricity used. This is economically significant. For firm 8, a one standard deviation increase in prices leads to a 3.3% decrease in electricity used. This is not economically significant.

As mentioned earlier in section 3, the partial adjustment model gives us an estimation of the short run price elasticity of electricity; that is, it estimates the price elasticity of demand for electricity given quasi-fixed inputs. We can therefore conclude that, taken together, the short run price elasticities of firms are highly inelastic.

8. Conclusions and further research

The results from my estimation tells us that, whilst short-run electricity demand is highly inelastic, long-run demand is generally elastic. Therefore, a price-based policy is suitable if our intention is to reduce carbon emissions in the long run. If our intentions are to dramatically cut electricity demand in the short term, policies based entirely on prices will be very costly for achieving significant carbon reduction. Therefore, carbon taxes should not be seen as a short run solution.

Unfortunately, the long run price elasticity estimation suffer from numerous strong assumptions, namely the assumption of no structural break in the data generating process, no accounting for substitution effects from alternate energy sources, and the assumption of homogeneity across sectors. Due to the short term nature of this project, I was unable to collect sufficient data to address these issues. I suggest further research into this issue taking account of the preceding factors.

Appendix 1: Summary Statistics

Table 1: Summary Statistics for data used in estimation of cost function structural parameters

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
year	240	2,001	6.937	1,989	2,012
sales_	210	4.433e+06	4.311e+06	309,272	2.236e+07
salaries_	210	694,665	561,079	51,945	2.391e+06
stocks_	210	732,409	613,478	50,451	2.729e+06
finished_	210	1.469e+06	2.086e+06	70,396	1.331e+07
p_wageALL	210	1,080	146.9	889.7	1,340
p_capitalALL	240	1,073	138.2	875.1	1,305
p_manuALL	190	1,189	243.6	914.6	1,618
p_elec_deflated	230	92,751	41,844	58,487	185,348
Q_electricity	240	15,294	24,142	0.0182	91,804
capitalhat	190	1.665e+09	1.243e+09	7.295e+08	7.720e+09
agr_lakelevel	210	612,130	129,038	344,007	822,959
C_electricity	230	1.494e+09	2.791e+09	1,265	1.617e+10
C_materials	210	7.324e+08	6.135e+08	5.045e+07	2.729e+09
C_labor	210	6.947e+08	5.611e+08	5.195e+07	2.391e+09
C_capital	190	1.665e+09	1.243e+09	7.295e+08	7.720e+09
Cost	240	3.998e+09	3.640e+09	1,384	1.876e+10
S_electricity	230	0.316	0.370	4.38e-07	1
S_materials	210	0.210	0.135	0.0328	0.745
S_labor	210	0.205	0.130	0.0120	0.702
S_capital	190	0.421	0.160	0.0471	0.749
logP_electricity	230	11.35	0.403	10.98	12.13
logP_materials	190	7.061	0.200	6.818	7.389
logP_labor	210	6.976	0.134	6.791	7.201
logP_capital	240	6.970	0.126	6.774	7.174
logsales	210	14.97	0.798	12.64	16.92
loglake	210	13.30	0.224	12.75	13.62
investmentcost_t1	179	3.690e+07	5.604e+08	-2.737e+09	3.665e+09
investmentcost_t0	179	3.874e+07	5.884e+08	-2.874e+09	3.848e+09
laborcost_t1	200	1.136e+06	2.117e+08	-1.559e+09	1.175e+09
laborcost_t0	200	1.193e+06	2.223e+08	-1.637e+09	1.234e+09

Table 2: Summary statistics for data used for partial adjustment model, daily level

VARIABLES	N	mean	sd	min	max
price	24,216	52.47	31.89	0.00980	228.7
quantity	24,216	4.891e+11	1.269e+12	5.226e+06	4.453e+12
nz50	24,216	2,403	864.8	1,241	4,333
logNZX	24,216	7.726	0.334	7.123	8.374
gdpdeflator	24,216	93.60	7.288	84	109.5
count	24,216	1,351	785.0	1	2,801

Table 3: Summary statistics of data for partial adjustment model, monthly level

VARIABLES	N	mean	sd	min	max
gxp	1,157	5.025	2.601	1	9
price	1,157	52.75	32.65	9.704	235.2
quantity	1,157	1.481e+13	3.855e+13	7.623e+09	1.374e+14
nz50	1,157	2,414	861.9	1,288	4,285
businessconfidence	1,157	99.47	1.606	96.32	103.3
gdpdeflator	1,157	93.76	7.210	84	109.5
worldprice	1,157	145.4	19.95	111.3	190.7
forestry_products	1,157	122.0	15.92	90.75	171.8
aluminum	1,157	143.4	26.71	105.7	217.7
Pukaki_scaled	1,157	29,337	9,741	7,806	46,215
Tekapo_scaled	1,157	12,792	3,702	4,937	19,302
Taupo_scaled	1,157	10,170	3,684	1,872	17,469
agr_lakelevel	1,157	52,299	14,031	19,137	81,865
I_low	1,157	0.799	0.401	0	1
I_high	1,157	0.201	0.401	0	1
count	1,157	64.93	37.37	1	132

Appendix 2: Cost function structural parameters estimation results

Table 4: Estimated Structural Parameters Of Cost Function Model

	(1)	(2)	(3)	(4)	(5)
VARIABLES	S_electricity	S_materials	S_labor	investmentcost_t1	laborcost_t1
logP_electricity	-0.128	-0.237	-0.0915		
	(0.117)	(0.326)	(0.206)		
log_labor	0.464	-0.0271	0.288		
	(0.931)	(0.416)	(0.358)		
log_capital	0.943	1.019	0.128		
	(0.932)	(1.591)	(1.026)		
logsales	-0.0224	0.0245*	0.0379***		
	(0.0308)	(0.0130)	(0.0115)		
investmentcost_t0				-0.198***	
				(0.0724)	
laborcost_t0					0.0805
					(0.0718)
Constant	-5.866***	-3.479	-1.906	-1.575e+07	4.234e+06
	(0.682)	(6.238)	(3.908)	(4.261e+07)	(3.729e+06)
Observations	159	159	159	159	159
R-squared	0.032	-0.008	0.051	0.052	0.007
Standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Table 5: Summary statistics of estimated elasticities (as derived from structural parameters)

	No. of observations	mean	standard deviation	min	max
elasticity	180	-1.454	0.233	-2.167	-1.078

Table 6: Estimated price elasticities by year and sector

Year	Sector	Elasticity	Sector	Elasticity	Sector	Elasticity	Sector	Elasticities	Sector	Elasticities
1994	basicmetal	-1.769	fabricated metal	-1.844	meatanddairy	-2.166	minerals	-1.71824193	other	-2.112
1995	basicmetal	-1.672	fabricated metal	-1.742	meatanddairy	-1.991	minerals	-1.634057283	other	-1.945
1996	basicmetal	-1.590	fabricated metal	-1.665	meatanddairy	-1.878	minerals	-1.566716075	other	-1.823
1997	basicmetal	-1.579	fabricated metal	-1.655	meatanddairy	-1.849	minerals	-1.556162477	other	-1.795
1998	basicmetal	-1.582	fabricated metal	-1.654	meatanddairy	-1.868	minerals	-1.570262074	other	-1.800
1999	basicmetal	-1.495	fabricated metal	-1.549	meatanddairy	-1.717	minerals	-1.47853744	other	-1.668
2000	basicmetal	-1.492	fabricated metal	-1.563	meatanddairy	-1.751	minerals	-1.477302909	other	-1.676
2001	basicmetal	-1.467	fabricated metal	-1.528	meatanddairy	-1.725	minerals	-1.450656652	other	-1.645
2002	basicmetal	-1.409	fabricated metal	-1.472	meatanddairy	-1.635	minerals	-1.405521512	other	-1.571
2003	basicmetal	-1.355	fabricated metal	-1.421	meatanddairy	-1.552	minerals	-1.360225558	other	-1.504
2004	basicmetal	-1.299	fabricated metal	-1.353	meatanddairy	-1.467	minerals	-1.300658822	other	-1.426
2005	basicmetal	-1.312	fabricated metal	-1.368	meatanddairy	-1.481	minerals	-1.316897511	other	-1.438
2006	basicmetal	-1.265	fabricated metal	-1.315	meatanddairy	-1.427	minerals	-1.269727707	other	-1.380
2007	basicmetal	-1.171	fabricated metal	-1.212	meatanddairy	-1.305	minerals	-1.175941348	other	-1.265
2008	basicmetal	-1.301	fabricated metal	-1.344	meatanddairy	-1.482	minerals	-1.297493339	other	-1.414
2009	basicmetal	-1.088	fabricated metal	-1.122	meatanddairy	-1.217	minerals	-1.090293169	other	-1.169
2010	basicmetal	-1.092	fabricated metal	-1.124	meatanddairy	-1.221	minerals	-1.089435816	other	-1.170
2011	basicmetal	-1.141	fabricated metal	-1.174	meatanddairy	-1.286	minerals	-1.135270596	other	-1.226

Note: “Other” refers to an aggregation of the furniture, machinery and transport machinery manufacturing industries

Table 7: Estimated price elasticities by year and sector (continued)

Year	Sector	Elasticities	Sector	Elasticities	Sector	Elasticities	Sector	Elasticities	Sector	Elasticities
1994	petroleum	-1.836	print	-1.848	pulpandpaper	-1.841	textile	-1.871	wood	-1.863
1995	petroleum	-1.717	print	-1.753	pulpandpaper	-1.735	textile	-1.742	wood	-1.744
1996	petroleum	-1.630	print	-1.670	pulpandpaper	-1.636	textile	-1.647	wood	-1.651
1997	petroleum	-1.612	print	-1.648	pulpandpaper	-1.604	textile	-1.614	wood	-1.635
1998	petroleum	-1.600	print	-1.662	pulpandpaper	-1.612	textile	-1.619	wood	-1.645
1999	petroleum	-1.501	print	-1.550	pulpandpaper	-1.525	textile	-1.522	wood	-1.558
2000	petroleum	-1.535	print	-1.555	pulpandpaper	-1.545	textile	-1.532	wood	-1.569
2001	petroleum	-1.516	print	-1.528	pulpandpaper	-1.503	textile	-1.503	wood	-1.527
2002	petroleum	-1.447	print	-1.456	pulpandpaper	-1.439	textile	-1.443	wood	-1.475
2003	petroleum	-1.389	print	-1.398	pulpandpaper	-1.378	textile	-1.382	wood	-1.417
2004	petroleum	-1.322	print	-1.333	pulpandpaper	-1.311	textile	-1.312	wood	-1.351
2005	petroleum	-1.333	print	-1.345	pulpandpaper	-1.321	textile	-1.313	wood	-1.355
2006	petroleum	-1.268	print	-1.294	pulpandpaper	-1.273	textile	-1.264	wood	-1.308
2007	petroleum	-1.172	print	-1.193	pulpandpaper	-1.174	textile	-1.166	wood	-1.207
2008	petroleum	-1.308	print	-1.315	pulpandpaper	-1.298	textile	-1.277	wood	-1.328
2009	petroleum	-1.096	print	-1.107	pulpandpaper	-1.095	textile	-1.078	wood	-1.113
2010	petroleum	-1.099	print	-1.108	pulpandpaper	-1.100	textile	-1.077	wood	-1.118
2011	petroleum	-1.152	print	-1.156	pulpandpaper	-1.146	textile	-1.122	wood	-1.164

Appendix 3: Partial adjustment model results

Table 8: half-hourly data, full sample with fixed effects

	(1)
VARIABLES	logq
L.logq	0.976***
	(0.000578)
logp	0.00630***
	(0.000358)
L.logp	-0.00540***
	(0.000358)
Constant	0.190***
	(0.00463)
Observations	1,720,016
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Table 9: Daily data, full sample

	(1)	(2)	(3)
VARIABLES	logq	logq	logq
L.logq	0.816***	0.809***	0.804***
	(0.0160)	(0.0161)	(0.0160)
logp	0.129***	0.133***	0.140***
	(0.0251)	(0.0256)	(0.0254)
L.logp	-0.123***	-0.113***	-0.103***
	(0.0243)	(0.0239)	(0.0243)
logNZX	0.0394***	-0.206	-0.0824
	(0.0124)	(0.173)	(0.308)
Constant	3.321***	5.129***	4.209*
	(0.326)	(1.311)	(2.263)
Observations	24,697	24,697	24,697
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Note: (1) no time controls; (2) with quarter and year time controls; (3) with month and year time controls

Table 10: Daily data, full sample. Non-linear price behavior specification

	(1)	(2)	(3)
VARIABLES	logq	logq	logq
L.logq	0.713***	0.700***	0.695***
	(0.0203)	(0.0205)	(0.0202)
c.I_low#c.logp	0.116***	0.124***	0.129***
	(0.0190)	(0.0194)	(0.0198)
c.I_high#c.logp	0.154**	0.133**	0.122*
	(0.0645)	(0.0636)	(0.0661)
c.I_low#cL.logp	-0.0976***	-0.0884***	-0.0776***
	(0.0169)	(0.0167)	(0.0169)
c.I_high#cL.logp	-0.139**	-0.104	-0.0712
	(0.0649)	(0.0637)	(0.0673)
logNZX	0.0271**	-0.224	0.0469
	(0.0116)	(0.158)	(0.278)
Constant	5.438***	7.415***	5.330**
	(0.423)	(1.237)	(2.100)
Observations	24,207	24,207	24,207
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Note: (1) no time controls; (2) with quarter and year time controls; (3) with month and year time controls

Table 11: Daily data by firm, with NZX 50 and no time controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.858***	0.700***	0.597***	0.632***	0.889***	0.660***	0.868***	0.980***	0.730***
	(0.0262)	(0.0305)	(0.0662)	(0.0744)	(0.0187)	(0.0376)	(0.0296)	(0.00612)	(0.0582)
logp	0.0833***	-0.00143	0.201***	0.377***	0.0841	0.165*	0.127**	-0.00126**	0.0737
	(0.0302)	(0.0162)	(0.0703)	(0.139)	(0.0799)	(0.0854)	(0.0623)	(0.000616)	(0.0621)
L.logp	-0.0770**	-0.00186	-0.173***	-0.331***	-0.126	-0.0479	-0.128**	0.000417	-0.0696
	(0.0331)	(0.0148)	(0.0560)	(0.126)	(0.0797)	(0.0730)	(0.0591)	(0.000504)	(0.0547)
logNZX	0.0716**	0.0237**	-0.313***	0.0722	0.171***	0.280***	0.0172	0.00366***	-0.134***
	(0.0301)	(0.0110)	(0.0584)	(0.0590)	(0.0629)	(0.0595)	(0.0324)	(0.00118)	(0.0299)
Constant	2.231***	7.331***	12.24***	8.320***	1.124**	5.042***	2.936***	0.560***	7.600***
	(0.523)	(0.781)	(2.012)	(1.690)	(0.503)	(0.797)	(0.878)	(0.170)	(1.500)
Observations	2,732	2,818	2,810	2,649	2,428	2,811	2,815	2,816	2,818
Standard errors in parentheses									
*** $p<0.01$, ** $p<0.05$, * $p<0.1$									

Table 12: Daily data by firm, with NZX 50, quarter and year controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.756***	0.622***	0.483***	0.539***	0.831***	0.622***	0.836***	0.885***	0.685***
	(0.0294)	(0.0284)	(0.0600)	(0.0814)	(0.0235)	(0.0395)	(0.0290)	(0.0353)	(0.0671)
logp	0.0760**	-0.00277	0.206***	0.400***	0.0817	0.175*	0.131**	-0.00133**	0.0730
	(0.0302)	(0.0175)	(0.0749)	(0.147)	(0.0840)	(0.0894)	(0.0575)	(0.000621)	(0.0595)
L.logp	-0.0692*	-0.00897	-0.132**	-0.257**	-0.115	-0.00858	-0.113**	0.000354	-0.0470
	(0.0361)	(0.0151)	(0.0511)	(0.124)	(0.0746)	(0.0768)	(0.0573)	(0.000485)	(0.0508)
logNZX	-0.531	-0.136	0.200	0.180	0.786	-1.298	-0.380	-0.00531	-1.042*
	(0.425)	(0.150)	(0.228)	(0.443)	(0.664)	(0.823)	(0.696)	(0.00376)	(0.576)
Constant	9.269***	10.61***	11.36***	9.245***	-2.804	17.15***	6.061	3.355***	15.32***
	(3.526)	(1.310)	(2.245)	(3.311)	(5.590)	(5.996)	(5.077)	(1.025)	(4.006)
Observations	2,732	2,818	2,810	2,649	2,428	2,811	2,815	2,816	2,818
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 13: Daily data by firm, with NZX 50, month and year controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.674***	0.430***	0.397***	0.489***	0.725***	0.557***	0.784***	0.698***	0.659***
	(0.0301)	(0.0312)	(0.0595)	(0.0812)	(0.0267)	(0.0357)	(0.0345)	(0.0776)	(0.0662)
logp	0.0908***	0.00132	0.204***	0.423***	0.0889	0.252***	0.124*	-0.00107*	0.102*
	(0.0288)	(0.0193)	(0.0722)	(0.139)	(0.0872)	(0.0942)	(0.0648)	(0.000601)	(0.0572)
L.logp	-0.0622*	-0.0121	-0.0990*	-0.193	-0.103	0.103	-0.0964*	0.000651	-0.0117
	(0.0367)	(0.0150)	(0.0517)	(0.134)	(0.0677)	(0.0816)	(0.0515)	(0.000456)	(0.0523)
logNZX	-0.160	-0.231	1.135*	1.331	1.447	-1.811	0.142	-0.0124*	-2.070**
	(0.733)	(0.225)	(0.580)	(0.934)	(1.480)	(1.235)	(1.263)	(0.00682)	(0.981)
Constant	7.714	16.12***	6.589	0.498	-6.103	21.96**	2.735	8.825***	23.26***
	(6.126)	(1.872)	(4.173)	(7.047)	(12.30)	(9.168)	(9.129)	(2.256)	(7.064)
Observations	2,732	2,818	2,810	2,649	2,428	2,811	2,815	2,816	2,818
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 14: Daily data, by firm, no time controls. Non-linear price behavior specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.679***	0.700***	0.655***	0.659***	0.519***	0.589***	0.861***	0.976***	0.724***
	(0.0337)	(0.0308)	(0.0481)	(0.0791)	(0.0513)	(0.0397)	(0.0318)	(0.00697)	(0.0590)
c.I_low#c.logp	0.0811**	0.0180	0.198***	0.144***	0.173***	0.181*	0.160**	2.93e-05	0.139*
	(0.0341)	(0.0187)	(0.0554)	(0.0415)	(0.0628)	(0.0992)	(0.0796)	(0.000393)	(0.0731)
c.I_high#c.logp	0.0344	-0.103	0.218**	0.355***	0.0395	0.418*	0.130	-0.0157**	-0.188
	(0.101)	(0.0696)	(0.0934)	(0.128)	(0.101)	(0.218)	(0.210)	(0.00678)	(0.130)
c.I_low#cL.logp	-0.0671*	-0.0161	-0.165***	-0.152***	-0.148**	-0.0560	-0.153**	-7.80e-05	-0.0860
	(0.0382)	(0.0165)	(0.0424)	(0.0432)	(0.0605)	(0.0754)	(0.0711)	(0.000428)	(0.0619)
c.I_high#cL.logp	-0.0187	0.102	-0.191**	-0.358***	-0.00325	-0.303	-0.134	0.0149**	0.214
	(0.0988)	(0.0698)	(0.0916)	(0.131)	(0.100)	(0.207)	(0.218)	(0.00681)	(0.132)
logNZX	0.111***	0.0234**	-0.273***	0.0902***	0.262***	0.329***	0.0161	0.00424***	-0.152***
	(0.0287)	(0.0113)	(0.0447)	(0.0283)	(0.0381)	(0.0657)	(0.0332)	(0.00131)	(0.0313)
Constant	5.486***	7.332***	10.49***	7.747***	8.081***	6.262***	3.088***	0.658***	7.730***
	(0.717)	(0.787)	(1.489)	(1.885)	(1.075)	(0.818)	(0.927)	(0.193)	(1.522)
Observations	2,637	2,793	2,784	2,607	2,257	2,767	2,785	2,777	2,800
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 15: Daily data, by firm, quarter and year controls. Non-linear price behavior specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.572***	0.619***	0.520***	0.416***	0.403***	0.537***	0.825***	0.871***	0.681***
	(0.0348)	(0.0289)	(0.0604)	(0.0774)	(0.0453)	(0.0429)	(0.0310)	(0.0376)	(0.0677)
c.I_low#c.logp	0.0792**	0.0240	0.190***	0.139***	0.158**	0.216**	0.172**	-0.000218	0.134*
	(0.0336)	(0.0199)	(0.0554)	(0.0397)	(0.0640)	(0.106)	(0.0732)	(0.000390)	(0.0721)
c.I_high#c.logp	0.0311	-0.0860	0.247***	0.324***	-0.0718	0.302	0.131	-0.0122*	-0.224*
	(0.105)	(0.0684)	(0.0925)	(0.114)	(0.109)	(0.213)	(0.204)	(0.00661)	(0.135)
c.I_low#cL.logp	-0.0572	-0.0220	-0.126***	-0.103**	-0.126**	-0.0211	-0.138**	-9.67e-05	-0.0694
	(0.0408)	(0.0168)	(0.0405)	(0.0406)	(0.0537)	(0.0817)	(0.0696)	(0.000419)	(0.0572)
c.I_high#cL.logp	-0.0150	0.0763	-0.190**	-0.300***	0.124	-0.118	-0.120	0.0108	0.264*
	(0.102)	(0.0685)	(0.0890)	(0.113)	(0.112)	(0.199)	(0.211)	(0.00664)	(0.136)
logNZX	-0.376	-0.133	0.150	0.453	-0.662	-0.768	-0.228	-0.00647	-1.067*
	(0.429)	(0.150)	(0.216)	(0.295)	(0.680)	(0.826)	(0.640)	(0.00413)	(0.575)
Constant	11.67***	10.60***	10.83***	10.38***	18.19***	15.36**	5.122	3.787***	15.46***
	(3.529)	(1.311)	(2.450)	(2.794)	(5.712)	(6.133)	(4.722)	(1.090)	(3.994)
Observations	2,637	2,793	2,784	2,607	2,257	2,767	2,785	2,777	2,800
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 16: Daily data, by firm, month and year controls. Non-linear price behavior specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.511***	0.427***	0.419***	0.354***	0.321***	0.476***	0.769***	0.674***	0.656***
	(0.0356)	(0.0315)	(0.0629)	(0.0755)	(0.0474)	(0.0390)	(0.0375)	(0.0799)	(0.0669)
c.I_low#c.logp	0.0922***	0.0248	0.166***	0.146***	0.173**	0.258**	0.164**	-0.000172	0.162**
	(0.0325)	(0.0214)	(0.0488)	(0.0410)	(0.0688)	(0.106)	(0.0812)	(0.000385)	(0.0688)
c.I_high#c.logp	0.0561	-0.0636	0.191**	0.280**	-0.0592	0.259	0.155	-0.0119*	-0.125
	(0.116)	(0.0716)	(0.0861)	(0.127)	(0.126)	(0.224)	(0.222)	(0.00686)	(0.141)
c.I_low#cL.logp	-0.0513	-0.0276*	-0.0968**	-0.0747*	-0.0878	0.0745	-0.127**	0.000152	-0.0349
	(0.0409)	(0.0162)	(0.0413)	(0.0399)	(0.0535)	(0.0881)	(0.0596)	(0.000394)	(0.0586)
c.I_high#cL.logp	-0.0263	0.0463	-0.113	-0.206	0.168	0.0939	-0.156	0.0112	0.211
	(0.118)	(0.0728)	(0.0869)	(0.133)	(0.131)	(0.214)	(0.232)	(0.00700)	(0.139)
logNZX	0.164	-0.246	0.929*	0.540	1.735*	-1.082	0.555	-0.0160**	-2.070**
	(0.644)	(0.224)	(0.497)	(0.486)	(0.887)	(1.190)	(1.187)	(0.00763)	(0.981)
Constant	8.351	16.28***	7.689*	10.89***	-0.200	18.55**	-0.0703	9.534***	23.20***
	(5.308)	(1.872)	(4.062)	(4.160)	(7.723)	(8.918)	(8.611)	(2.321)	(7.054)
Observations	2,637	2,793	2,784	2,607	2,257	2,767	2,785	2,777	2,800
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 17: Monthly data, full sample

	(1)	(2)
VARIABLES	logq	logq
L.logq	0.525***	–
	(0.0483)	–
logp	-0.0700	-0.0335
	(0.0693)	(0.0712)
L.logp	–	-0.0460
	–	(0.0926)
lognz50	0.0534	0.118**
	(0.0368)	(0.0483)
logworldp	0.275**	-0.937
	(0.132)	(0.909)
logforestp	-0.0473	0.432**
	(0.192)	(0.184)
logaluminiump	-0.127	0.217
	(0.137)	(0.175)
Constant	9.503***	-0.477***
	(2.930)	(0.0903)
Observations	1,160	1,148
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Notes: (1) OLS specification with newey-west standard errors; (2) 2SLS specification with lake levels as instruments, with newey-west standard errors

Table 18: Monthly data, full sample. Non-linear price specifcation

	(1)
VARIABLES	logq
L.logq	0.641***
	(0.0394)
c.I_low#c.logp	0.0219
	(0.0162)
c.I_high#c.logp	-0.0718*
	(0.0427)
c.I_low#cL.logp	-0.00779
	(0.0159)
c.I_high#cL.logp	0.0813*
	(0.0440)
lognz50	0.0342
	(0.0272)
logbc	-0.0202
	(0.389)
logworldp	0.103
	(0.0944)
logforestp	0.119
	(0.0867)
logaluminiump	-0.183***
	(0.0521)
Constant	8.043***
	(2.034)
Observations	1,148
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Table 19: Monthly data, by firm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
L.logq	0.501***	0.408***	0.538***	0.503***	0.470***	0.400***	0.366***	0.328***	0.485***
	(0.0208)	(0.121)	(0.0908)	(0.113)	(0.120)	(0.0883)	(0.104)	(0.0800)	(0.0736)
logp	0.0457*	0.00440	-0.0558	0.00237	-0.741	0.0420	0.0175	-0.0240***	-0.0797***
	(0.0248)	(0.0303)	(0.0379)	(0.0415)	(0.672)	(0.0413)	(0.0346)	(0.00611)	(0.0286)
lognz50	0.0638	0.116*	-0.253***	0.149*	0.365	0.502***	-0.186**	0.139***	-0.0981*
	(0.0769)	(0.0692)	(0.0895)	(0.0814)	(0.299)	(0.0961)	(0.0774)	(0.0253)	(0.0561)
logworldp	0.456**	-0.137	-0.0115	0.00180	1.835	0.194	0.315	0.0911	0.590***
	(0.229)	(0.305)	(0.299)	(0.251)	(1.269)	(0.330)	(0.274)	(0.0602)	(0.205)
logforestp	0.0920	0.104	-0.291	0.348	-1.518	0.823***	0.173	0.0432	0.215
	(0.278)	(0.302)	(0.259)	(0.249)	(1.399)	(0.268)	(0.247)	(0.0569)	(0.184)
logaluminiump	-0.221*	-0.168	-0.265	-0.204	0.724	-0.570**	-0.331**	-0.110***	-0.458***
	(0.118)	(0.113)	(0.181)	(0.137)	(0.889)	(0.237)	(0.134)	(0.0351)	(0.121)
Constant	2.509	22.15***	27.36***	9.968	-9.150	14.12*	10.22*	18.24***	13.92***
	(5.901)	(7.565)	(6.843)	(6.330)	(28.61)	(7.331)	(5.286)	(2.412)	(4.382)
Observations	131	131	131	126	117	131	131	131	131
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 20: Monthly data, by firm, 2SLS specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	gxp 1	gxp 2	gxp 3	gxp 4	gxp 5	gxp 6	gxp 7	gxp 8	gxp 9
VARIABLES	logq	logq	logq	logq	logq	logq	logq	logq	logq
logp	-0.184***	-0.246	0.384	0.312	-0.210	0.119	-0.121	-0.0435**	0.0373
	(0.0708)	(0.175)	(0.393)	(0.617)	(0.274)	(0.307)	(0.163)	(0.0192)	(0.108)
L.logp	0.319***	0.100	-0.461	-0.604	0.0519	0.120	-0.172	-0.0202	-0.261*
	(0.106)	(0.302)	(0.373)	(0.616)	(0.298)	(0.391)	(0.311)	(0.0255)	(0.145)
lognz50	0.211**	0.190**	-0.509***	0.322**	0.417**	0.831***	-0.213**	0.213***	-0.215***
	(0.100)	(0.0816)	(0.127)	(0.141)	(0.175)	(0.105)	(0.101)	(0.0238)	(0.0761)
logbc	3.353*	-3.092	-4.554*	-1.557	0.621	-0.342	-1.260	0.428	-0.997
	(1.859)	(2.675)	(2.368)	(3.175)	(3.690)	(2.628)	(2.631)	(0.381)	(1.260)
logworldp	0.805**	0.0240	-0.529	0.824	0.814	0.139	0.748	0.170**	1.301***
	(0.341)	(0.478)	(0.585)	(0.840)	(0.511)	(0.386)	(0.528)	(0.0779)	(0.311)
logforestp	0.567*	-0.0926	-0.379	0.174	0.0127	1.591***	0.0536	0.0320	0.147
	(0.326)	(0.449)	(0.515)	(0.635)	(0.539)	(0.445)	(0.414)	(0.0742)	(0.319)
logaluminiump	-0.579***	-0.248*	-0.426	-0.420	-0.222	-0.970***	-0.520**	-0.160***	-0.874***
	(0.158)	(0.134)	(0.316)	(0.327)	(0.249)	(0.214)	(0.221)	(0.0414)	(0.150)
Constant	2.046	43.34***	59.84***	31.13**	16.25	16.68	34.05***	28.85***	32.18***
	(8.827)	(12.55)	(11.45)	(15.56)	(19.06)	(12.85)	(12.37)	(1.829)	(6.215)
Observations	125	131	131	126	111	131	131	131	131
R-squared	0.209	-0.050	0.480	-0.539	0.109	0.553	0.087	0.604	0.496
Robust standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

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