



University of Concepcion
Masters Program in Economics of Natural Resources and the Environment
Department of Economics

**A Micro-data Analysis of Fuels' Factor Demand
The Case of Chilean Manufacturing Sector**

**Análisis de Demanda de Factores de Combustibles con Micro-Datos
El Caso del Sector Manufacturero Chileno**



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Acknowledgements

In the search for precision of estimations, valid research, and possibility of contribution to the real world, one keeps discovering that congruency, efficient application of methodologies, experience and intuition are key ingredients. However, all of those can only be attained through persistency, stability and a mix of peace and craziness, not only in the mind but also in the heart.

I take this work as an initial step in the world of research and as a long way to keep learning and growing academically and professionally to contribute by applying economic analysis to policy evaluation. Results are timely only in matters of being useful for a decision-maker, building capacity in a student and instituting responsibility as a researcher. I am sure this work attains these objectives, although for the first one, additional research is pending. Further work in later studies will be attained for a deeper understanding of various topics and to discover plausible contributions of this research.

While presenting this end product as my thesis and as the culmination of my masters program, I would like to thank to my parents, uncle and siblings, in whose structure of values I have built my character and academic interest; to my thesis Advisor, Felipe Vasquez, my professors at the University and Concepcion, in special to Professor Jorge Dresdner and Professor Manuel Estay, and my Advisor from LACEEP, Dale Whittington, all of them with whom I have been able to grow academically in this stage and who have helped me to improve my work and research abilities; to my classmates for sharing with me these two last years of life, and to my partner, Matias, with whom I have been able to share my worries, analysis and satisfactions of my work and feel in such sharing his support and comradeship.

Abstract

This study presents an estimation of price elasticities of fuels demand with micro-data for Chilean manufacturing sector at the firm level. This becomes a timely analysis on energy consumption and fuel inter-substitution in a country that is currently embarking in ambitious programs and policies for its energy matrix diversification.

Conditional factor demands are estimated employing multi-equation static panel techniques with seemingly unrelated regression and maximum likelihood estimation. Two functional forms (translog and linear logit) have been compared, with robust results. The analysis focuses on short run responses to price changes in firms that have different fuel-portfolios. This approach helps to treat the zero consumption problem present in micro-data analysis, and also it helps capturing differences in elasticities of firms that count with distinct types of technologies.

Given that some firms change their fuel-combination throughout the time-points of observations, the estimation corrects for the probability of portfolio selection with a Heckman bias selection correction -two step procedure- based on the Dubin-McFadden approach to multi-alternative selection model for probability estimation.

Key findings show that:

- Most of the fuels in Chilean manufacturing firms are complements and not substitutes. In terms of own price elasticities, electricity is the most inelastic, while gas and gasoline are the most elastic.
- Cross price elasticities generally decreases as the fuel portfolio is diversified, while own price elasticities increases in more diversified portfolios.
- Contrarily to the hypothesis that once the estimation was controlled by fixed effects price elasticities would be lower than those predicted in previous aggregate studies, results show that micro-data estimations differ by fuel portfolio. Some results are lower than aggregate estimations while others are higher. This could be related to the firm access to technology.
- There are also some nuances of price responses related to firm size and industry type.

Key words: Interfuel substitution, linear logit, translog, micro-data analysis, conditional factor demand.

Resumen

Este estudio presenta una estimación de elasticidades de precios de demanda de combustibles con micro datos para el sector manufacturero Chileno al nivel de firma/establecimiento. Siendo este un análisis pertinente sobre consume de energía e intersustitución entre combustibles en un país el cual está iniciando un ambicioso programa de políticas para la diversificación de su matriz energética.

Las demandas condicionales de factores son estimadas empleando un sistema multi-ecuacional estático con técnicas de panel, con regresión aparentemente no relacionada y con estimación de máxima verosimilitud. Dos formas funcionales (translog y linear logit) han sido comparadas con resultados robustos. El análisis se enfoca en respuestas de corto plazo a cambios de precios de establecimientos industriales los cuales tienen diferentes portafolios de combustibles. Este enfoque ayuda a tratar el problema de consume cero, el cual está presente en los análisis con micro-datos, y a la vez ayuda a capturar diferencias en elasticidades de empresas que cuentan con distintos tipos de tecnologías.

Algunos establecimientos industriales cambian la combinación de combustibles a lo largo de las observaciones, en diferentes períodos de tiempo. Por ello, la estimación corrige por la probabilidad de selección del portafolio, con un procedimiento de dos etapas basado en un enfoque planteado por Dubin y McFadden para modelar la elección de multi-alternativas con la estimación de sus probabilidades y así corregir por sesgo de selección.

Los resultados principales son:

- La mayoría de combustibles en las empresas/establecimientos manufactureros con complementos y no sustitutos. En términos de las elasticidades propias de precio, la electricidad es la más inelástica, mientras que el gas y la gasolina son los más elásticos.
- Las elasticidades cruzadas disminuyen a medida que el portafolio es diversificado, mientras que las elasticidades propias de precio incrementan cuando se diversifica el portafolio.
- Contrario a la hipótesis que la una vez que se haya controlado por efectos fijos, las elasticidades de precio serían más bajas que aquellas predichas por modelos agregados, los resultados muestran que las estimaciones con micro-datos difieren por portafolio de combustibles. Algunas elasticidades son mayores a las estimaciones agregadas, mientras que otros son menores. Esto pudiese estar relacionado al acceso de tecnología de la empresa/establecimiento.
- También hay ciertos matices en elasticidades de precio relacionadas con el tamaño de empresa y el tipo de industria.

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INTRODUCTION

This study analyzes fuel inter-substitution and estimates short-run price elasticities for four main fuel types used in Chilean manufacturing firms: electricity, oil, gas and gasoline. The objectives of the study include evaluate price elasticities by scrutinizing data at the firm/establishment level, comparing these results with previous aggregate estimations, and highlight differences in elasticities depending on fuel-portfolio and firm size.

To this date, few studies have been performed at the firm/establishment level.¹ Some of these studies address industrial energy demand as a whole, while others analyze interfuel substitution. On the other hand dozens other studies are aggregate, either by sector or national level, generally for country and sectorial comparisons.

This study uses micro-data with a panel data structure with fixed effects estimator to evaluate the decision-making at the firm/establishment level. Steinbuks (2011) mentions, "because most empirical studies on inter-fuel substitution in industrial energy demand rely on aggregate macroeconomic data across industries and types of energy use, the estimated elasticities are likely to be biased." A study that uses micro-data for Danish industrial companies (Bjorner et al., 2001) and another study that compares aggregate analysis and then separates it by energy use for the twelve most energy intensive UK industrial sectors (Steinbuks, 2011) confirms differences between aggregate and disaggregate estimations.

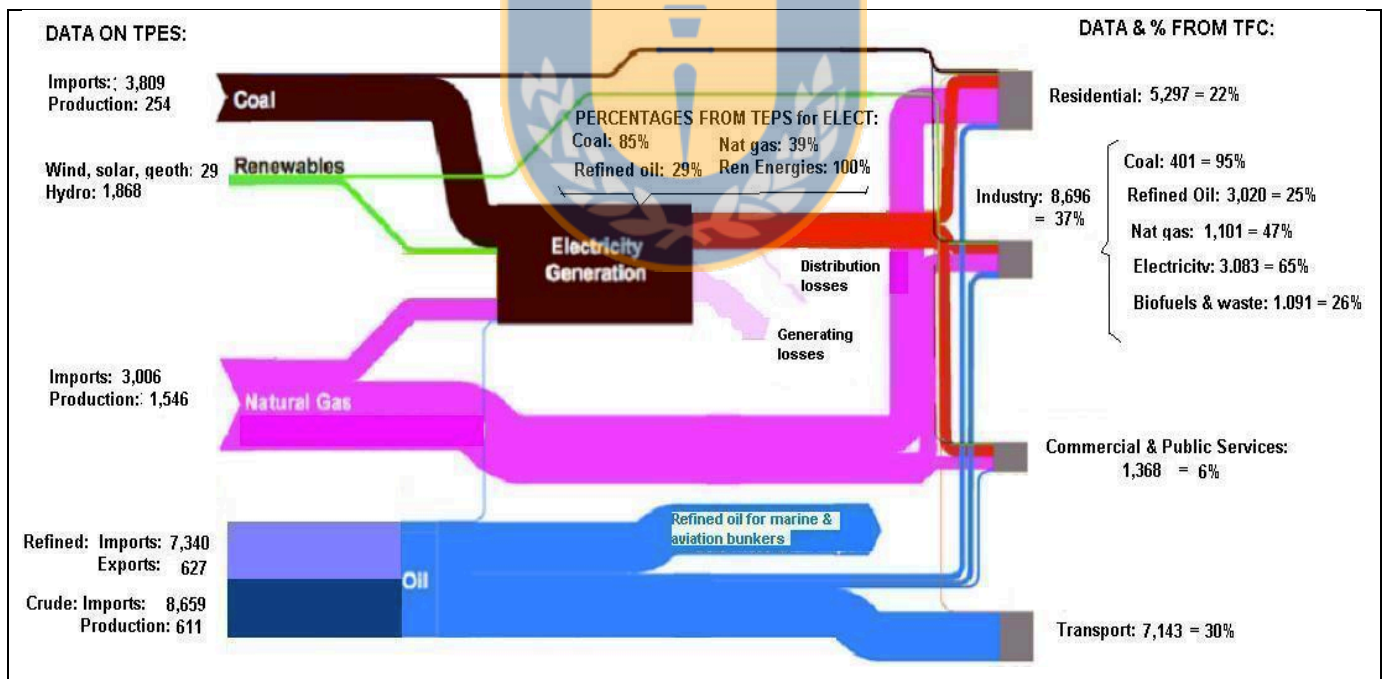
Main problems of the aggregate approach are that it uses average prices, while the appropriate price to be used in a cost-minimization model is the marginal price. Also, the aggregate estimation is more prone to have endogeneity in prices. Other advantages of using micro-data involve the possibility of analyzing firm characteristics in the model and evaluation of subsamples by industry, sizes, location, among others.

Chile is not a self-sufficient energy producer; it is a net importer of its primary energy supply sources. (Refer to Graph No. 1). Its dependence on energy imports makes it vulnerable to international energy prices and impacts on its competitiveness. According to the OECD report on *'Inventory of Estimated Budgetary Support and Tax Expenditures for Fossil Fuels,'* Chile imports about 75% of its total primary energy supply -TPES- in the form of oil, natural gas and coal). Also, since 2010 Chile became a member of the OECD and energy diversification, in particular integration of renewable energies, is part of the OECD agenda.

¹ These studies include: Bousquet and Ivaldi, 1998; Woodland, 1993; Chakir et al., 2004; Bjorner et al., 2001; Kleijweg et al., 1990; Martinez-Budria et al., 2003; Doms and Dunne, 1993.

Also, the industrial/manufacturing share of energy consumption is significant in Latin American countries, and in particular in Chile. As shown in Graph No. 1 below, the Chilean industrial sector, the shares of the industrial sector to national consumption correspond to: 65% for electricity; 95% for coal; 47% for natural gas and 25% for oil. (IEA-2010) Chile is one of the most highly industrialized countries in Latin America. Since the 1940s, manufacturing has contributed a larger share of GDP than agriculture. After the mid-1970s, Chilean industry moved away from concentration on import substitution to become more export-oriented. According to the Chilean National Institute of Statistics, the main manufacturing sectors include: food processing and beverage production, tobacco products, refining, alloying, and fabrication of metals², textiles and apparel and wood products and paper. These sectors are clearly represented in the National Industrial Survey data –ENIA-, which is used in this study.

Graph No. 1
Macro-level Flow Chart of Energy Sources in the Chilean economy
-Year 2010-



Unit: Thousand tonnes of oil equivalent (ktoe) on net calorific value basis. TPES: Total Primary Energy Supply, TFC: Total Final Consumption.
 Source: Diagram elaborated with data from the International Energy Agency (IEA). 2010 Data

² Since the 1960s, the metallurgic and especially copper has been importantly produced in Chile. While copper extraction is not considered part of the manufacturing sector, the transformation activities of refining, alloying, and fabrication of metals are included as industrial activities.

This study pretends to tackle some challenges of micro-data analysis and it is of particular interest the evaluation of decision-making at the firm/establishment level. In particular, differentiation by firm characteristics and by sub-samples could help to evaluate whether it would be necessary to create any differentiation (by technology and/or firm-size) when designing the energy matrix-diversification and/or environmental programs.

This study is timely in Chile as it is currently embarking in an ambitious program for changing its energy matrix. The Chilean government is prioritizing energy diversification due to issues of energy security and international commitments. Results on own-price elasticities, as well as elasticities of substitution, could become inputs for policy makers to evaluate and design policies and programs on energy policy; for example, when deciding in the national targets and strategies for energy matrix diversification and environmental standards, and to evaluate whether it would be necessary to create any differentiation (by technology and/or firm-size) when designing these programs.

The next sections include: **(i)** objectives of the study, **(ii)** economic model specification, **(iii)** data and variables, **(iv)** econometric model and methodological aspects, **(v)** estimation results and key findings, and **(vi)** conclusions and further research.



I. OBJECTIVE

This study uses micro-data to analyze price elasticities of the manufacturing sector in Chile at the firm level. It analyzes how these results differ among firms that use different patterns of fuels portfolio, how they compare to aggregate results from previous studies, and if they differ by company size and industry type.

In contrast to aggregate studies which evaluate elasticities at the sectorial and/or country levels, this study pretends to scrutinize the firm decision level, and while doing so evaluates methodological aspects, challenges and advantages immersed in the use of micro-data.



II. ECONOMIC MODEL SPECIFICATION

This section describes the economic model that was specified for analyzing inter-fuel substitution in the context of production theory. While doing so, it reviews and explains the functional forms that have been selected for this analysis, their ability to be coherent with the economic theory (in particular on issues of conditional factor separability and cost minimization), their advantages in their use in an empirical study and their limitations.

2.1 General Economic Model Specification

In production theory, conditional factor demand functions are derived from cost or production functions. In this study, we use a cost function that is specified in terms of input prices and output:

$$C(p_1, \dots, p_N, Y) \quad (1)$$

Where, (N) is the number of inputs, and in this study it corresponds to four fuels included in the analysis: oil, gas, gasoline and electricity; p_i correspond to prices of inputs, and x_i to the quantities of inputs. C is the minimum cost value, calculated as: $\sum_{j=1}^N p_j x_j$, for all feasible levels of inputs that produce an output greater than or equal to Y (level of output).

According to Considine and Mount (1984), the sufficient conditions for the existence of a cost function (once the underlying production technology is well behaved -regular and which exhibits monotonicity and convexity-) includes that this cost function is: non-decreasing, homogeneous of degree one in factor prices, and concave and continuous function of input prices.

Then, by the Shephard's lemma, conditional factor demand functions can be derived from the cost function:

$$\left(x_i = \frac{\partial C}{\partial p_i} \right) \quad (2)$$

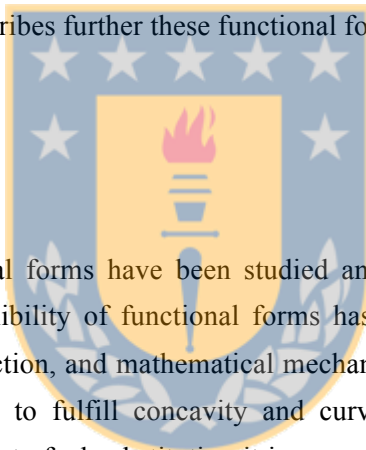
The conditional factor demand function is obtained by equation (2) and is defined as:

$$x_i(p_1, p_2, p_3, p_4, Y) \quad (3)$$

These factor demand functions need to comply with conditions to meet a micro-economic structure. These are called by Considine and Mount (1984) as 'sufficient conditions' for the existence of well behaved demand functions for inputs, and they include: **(i)** levels of inputs

must be non-negative, then, for any set of positive prices, the corresponding input levels are all positive, **(ii)** each function must be zero-degree homogeneous in prices, and **(iii)** own price effects are negative and cross-price effects are symmetric $\frac{\partial x_i}{\partial p_j} = \frac{\partial x_j}{\partial p_i}$. This last condition implies that the $N \times N$ matrix of elements, $\frac{\partial x_i}{\partial p_i}$ is symmetric and negative semi-definite. Condition **(iii)** is generally imposed before estimation with parameter restrictions to obtain symmetry of the coefficients matrix.

Also, as it is evident in equation (2), the specification of the factor demand equations, and consequently its elasticities, will depend on the functional form assumed for the cost function. Industrial interfuel substitution has been modeled with multiple equations and most commonly with a cost function with translog or linear logit functional forms³. The importance of the selected functional form in these estimations rely on the fact that they allow to set up a modeling structure to incorporate core concepts of micro-economics, which guarantees that the estimation that is being performed portrays the economic relation of variables that is being tested. The next subsection describes further these functional forms.



2.2 Functional forms

In production theory, functional forms have been studied and developed to incorporate key micro-economic concepts. Flexibility of functional forms has been developed to incorporate separability of factors of production, and mathematical mechanisms (such as restrictions on the parameters) have been created to fulfill concavity and curvature conditions to model cost minimization. In this study on interfuel substitution it is convenient to incorporate these micro-economic structure, as firms aim to minimize production costs and they combine energy inputs with other factors of production, some of them as substitutes.

In this study, the selected functional forms correspond to two functions that have been largely used in production studies: linear logit and translog. Some authors have used a translog cost function to analyze energy consumption, among them: Brendt and Wood (1975), Uri (1979), Siddayao (1987), Griffin (1993), and Adeyemi and Hunt (2007), Pindyck (1979), Jones (1995), Urga and Walters (2003). Other authors have used the linear logit form, among them: Cosidine (1984, 1989, 1990), (2009), Pindyck (1979), Jones (1995), Urga and Walters (2003).

³On the other hand, studies that have not been focused on inter-fuel substitution, but on a single fuel (or energy in general) have been modeled with single equation models. These have generally been aggregate models and many of them have used time series or panel data techniques, because they have mostly been used for comparisons among industries and/or countries. As explained by Bhattacharya and Timilsina, "in the 1990s, following the co- integration revolution, the trend (of studies on energy demand) changed to rely on single equations; studies often adopted an aggregated analysis but used more advanced time-series data analysis techniques." Some of these studies include: Erdogdu, Erkan (2007), Hunt and Lynk (1992), Dimtriopoulos, Hunt and Judge (2005) Kulshreshta and Parikh (2000), Adeyemi and Hunt (2007) Adeyemi et al (2010).

In a production or cost function, weakly separability is present if the marginal rate of technical substitution (MRTS) between two inputs within the same group is independent of inputs used in other groups. In this particular case, the MRTS among fuel inputs could not be independent from other inputs of production, such as capital and labor and even other raw materials. Substitutability and complementarity between energy, labor and capital has been studied. The assumption of separability among these production factors would imply that all the inputs of production change (increase or decrease) in the same proportion, and that all the additional input groups, have a marginal rate of technical substitution of zero. Studies that have found substitutability between energy and labor, include: Hudson and Jorgenson (1974), Fuss (1977) and Magnus (1979). Pindyck (1979), Adeyemo, Mabugu, and Hassan (2007), Hengyun et al. (2009). Studies that have found substitutability between energy and capital include: Pindyck (1979), Bataille (1998), Adeyemo, Mabugu, and Hassan (2007), Hengyun et al. (2009).

To test substitutability of energy inputs with these other factor of production, data on prices of labor and capital would be required, which goes beyond the scope of this study. Due to the different studies that have found substitutability of energy inputs with other factors of production, it is most convenient to not make the assumption of zero MRTS for fuel inputs with other factors of production.

The standard CES function meets most of the theoretical structure of homogeneity of degree one in factor prices, monotonicity in factor prices and product, and concavity in factor prices. However, it does so when analyzing two factors, but it has limitations when modeling multiple factors. This limitation is related to the fact that it imposes a common elasticity of substitution among factors (the "impossibility theorem"). Although homotheticity is an important feature that provides structure to the production and cost minimization modeling (as it allows for curvature and concavity of these functions), it does not allow for nuances and exceptions of (weakly and strong) additive separability of inputs. On the other hand, flexible forms allow for such nuances to be incorporated. To allow for different degrees of substitutability between inputs, several "flexible" production/cost functions (derived from the CES) have been proposed, two of these are the translog and the normalized quadratic functional forms. (The translog has been most commonly used for energy demand modeling). Another functional form that allows for such flexibility is the linear logit model.

The translog and linear logit forms allow including flexibility for non-homotheticity, non-zero MRTS and non-separability. The flexibility in the translog function is related to the fact that these functions include enough parameters to approximate an arbitrary function up to the second order and no restrictions are imposed on the sign or values of the first and second derivatives. (Martínez-Budría et al., 2003; Reynes, 2011)The flexibility in the linear logit is related to the

fact that the cost shares are expressed in terms of exponential functions; this also allows approximating an arbitrary function. In both cases, when allowing flexibility of the function, it loses its homothetic capacity (monotonic transformation of an homogeneous function, meaning its strictness as increasing function) and therefore its ability to meet concavity conditions. Table No. 1 below provides an summary of the conceptual structure of the CES in comparison to flexible forms and how the relaxation of non-homotheticity of the flexible forms allows for the inclusion of non-zero MRTS and non-separability.

Table No. 1
Micro-Economic Concepts in CES Cost Function & in Flexible Forms

	Standard CES	NQ	Translog	Linear-Logit
Linearly homogeneous in factor prices	✓	✓ (when normalized)	✓ (when normalized)	✓ (when normalized)
Monotonicity in factor prices	✓	Must be verified	Must be verified	Must be verified
Homotheticity	✓	Non-Homothetic	Non-Homothetic	Non-Homothetic
Allows Non-Zero degree MRTS	✗	✓	✓	✓
Elasticity of Substitution	$0 < \sigma < \infty$	$0 < \sigma < \infty$	$0 < \sigma < \infty$	$0 < \sigma < \infty$
Allows Non-Separability	✗	✓	✓	✓
Guarantees Curvature Conditions	✓	✗ (can be imposed globally)	✗ can be imposed locally	✗ (can be imposed locally)

It is important to highlight that the approximation to the general non-homothetic cost function, is necessary in this type of studies as the marginal cost is not independent of the firms output levels.

In the flexible forms, linear homogeneity is then imposed by normalizing each equation in terms of a factor price (obtaining N-1 equations). On the other hand, as mentioned earlier, these flexible forms lose their capacity of guaranteeing concavity conditions. Thus, parameter restrictions are generally imposed before estimation to anticipate curvature conditions.

In the literature it is found that the translog and linear logit models generally yield parameters that violate the concavity conditions over some/most of the sample. Some authors, (including Jones, 1995 and Urga and Walters, 2003) have used a deterministic time trends to reduce the number of concavity violations, especially in aggregate studies. Positive results have been found for the linear logit model, but not for the translog model, which continues to violate the concavity conditions over a large part of the sample.

Although, this is a common critic to the type of studies that use these flexible functional forms, especially the translog model⁴, these forms are still preferred to the CES for conditional factor analysis. For the empirical work, there are particular concavity tests to be programmed to test the concavity conditions over the whole sample⁵. The programming of these tests was beyond the scope of this study. The implications that these forms might meet local but not global curvature conditions, is that the local approximation of the demand that may not be plausible globally.

Nevertheless, these functional forms count with other advantages in the empirical work. The translog model: has minimum restrictions on the parameters, fits a theoretical derivation and avoids pre-specification of particular relationships. While the linear logit is specified mostly because of a mathematical convenience, it ensures that the outcomes are non-negative and add to one, and it provides a close approximation to the cumulative normal distribution. (Urga and Walters, 2003, and Chavas and Segerson, 1986).

Thus, the linear logit and the translog functions were the selected functional forms for the empirical work in this study, in order to incorporate non-homotheticity, non-zero MRTS and non-separability. Nevertheless, the results must be considered with the caution on possibility of not-compliance with global curvature conditions. In this study, it was key to include year dummies to control for macro-economic effects; hence, it was not necessary to include a time trend variable. In the following paragraphs, the model development and their derivation of elasticities for each of these functional forms will be briefly described.

2.3 Model Specification with the Linear Logit(LLM) Functional form

The linear logit model of inputs (fuels) demand is derived by representing a set of N cost shares by a logistics function:

⁴ Another critic to the translog function, is in regards to its poor performance for a dynamic estimation. This does not apply to this study as it is an static estimation. Several authors that mention this limitations include: Considine and Mount (1984); Jones (1995), Asche and Salvanes (1996), and Urga and Walters (2003).

⁵ Procedures on evaluating the curvature for the Translog and Linear Logit Functions are explained in detail in Baum and Linz (2009), and Considine (1989).

$$w_i = \frac{e^{f_i}}{\sum_{j=1}^N e^{f_j}}, \text{ for } i=1,2,\dots, N \quad (4)$$

In addition of the nomenclature already described above, $w_i = \left(\frac{p_i x_i}{C}\right)$ is the share of total cost allocated to the i^{th} input (fuel), f_i is a function of the N input prices, and i, j, k represent input prices ($i \neq k$).

The log-linear specification of f_i represents consumers' preference choices for the input i :

$$f_{it} = \alpha + \sum_{j=1}^N \beta_{ij} \cdot \ln P_{jt} + \beta_y Y_t + \varepsilon \quad (5)$$

Where, t is the time-points in the panel data. Equation (5) of fuel demand has been specified in this section in its most simple form in order to describe the economic model. Other studies incorporate other explicative variables of fuel demand, such as time trends, lagged quantities of fuels and others. The model description in this section includes the core variables from the micro-economic conceptual base, and the next section describes other explanatory variables that have been evaluated in the empirical study.

Given that this functional form originally specifies the model based on cost shares (equation (4)), accordingly, the shares' elasticities, for any specified set of cost shares, can be written as follows:

$$H_{ik} = \frac{\partial \ln w_i}{\partial \ln P_k} = \beta_{ik} - \sum_{j=1}^N w_j \beta_{jk}, \text{ where } i \neq k \quad (6)$$

By using the Shephard's Lemma (equation (2)) and equation (5), price elasticities can be derived in the following formulas:

$$E_{ii} = \frac{\partial x_i P_i}{\partial P_i x_i} = H_{ii} + w_i - 1 \quad (7)$$

$$= \beta_{ii}^* \cdot \bar{w}_i + \bar{w}_i - 1$$

$$E_{ik} = \frac{\partial x_i P_k}{\partial P_k x_i} = H_{ik} + w_k \quad (8)$$

$$= \beta_{ik}^* \cdot \bar{w}_k + \bar{w}_k$$

The development of this model has been described in detail by Cosidine and Mount (1984), and Jones (1995). These authors have explained the derivation of own-price and cross-price elasticities, as well as the procedure to define a system of N-1 equations after imposing normalizing constraints to identify the system and after imposing homogeneity and symmetry constraints of the coefficient matrix.

What appears intriguing in the Linear Logit model and which is not explained in general by papers on energy demand estimations that use this model, is how the evolution of the logit form to a linear form is implemented. Berry (1994) explains this transition from discrete choice model where the unobserved product characteristics are set in a non-linear specification (in the market shares). Interestingly, the logistic specification of the estimation in the linear logit becomes linear when input shares become the dependent variable. This estimation is implemented by inverting the market share equation to find the implied mean levels of utility for each good.

2.4 Model Specification with the Translog Functional form

The nomenclature of the previous model, LLM, will be maintained for the specification of the translog model. This includes: C : cost; p_i : prices of energy inputs; Y : output level; β : estimated parameters; t : year, and i, j, k : input prices ($i \neq k$).

Also, as it was mentioned in the previous model, this section describes the model in its most simple form; other explanatory variables are described in the next section. The translog cost function is given by:

$$\ln C(p_1, p_2, p_3, p_4, Y) = \beta_0 + \beta_y \ln Y + \sum_{i=1}^N \beta_i \cdot \ln P_i + \frac{1}{2} \sum_{i=1}^N \sum_{k=1}^N \beta_{ik} \cdot \ln P_{ik} \quad (9)$$

$$+ \sum_{i=1}^N \beta_{iy} \cdot \ln P_i \ln Y + \frac{1}{2} \beta_{yy} \ln Y^2$$

As in the case of the Linear Logit, in this model symmetry constraints are also imposed ($\beta_{ik}^* = \beta_{ki}^*$), as well as the constraints for homogeneity of degree one in prices in the cost function (degree zero in the demand function).

By the Sheppard's Lemma, equation (2), it is possible to obtain the share equations (which represent the cost share of each input as proportion of all costs). These equations are used for estimation:

$$w_i = \beta_i + \sum_{k=1}^N \beta_{ik} \cdot \ln P_k + \beta_{iy} \cdot \ln Y \quad (10)$$

Equation (10), which is used for estimation in this model is an equation of the shares (while the equation that is used for estimation in the LLM is an equation of ratio of costs shares⁶).

⁶ For a description of the system of equations used for estimation in the linear logit model, refer to Cosidine and Mount (1984).

Once the model is estimated, the following the equation is used to obtain own and cross-elasticities:

$$E_{ik} = \frac{\beta_{ik}^* + w_i \cdot w_k - \delta_{ik} \cdot w_i}{w_i} \quad (11)$$

Where δ_{ik} is a function that takes the value of 1 if $i = k$ or 0 otherwise. The development of this model has been described in detail by Urga and Walters (2003), Kleijweg et al. (1990), and Jones (1995).



III. DATA & VARIABLES

3.1 Sample Characterization

The data for this study was obtained from the Chilean Annual National Industrial Survey (ENIA, for its acronym in Spanish). This industrial survey counts with plant-based information that has been tracked for several years to the same firms. The sample for this study corresponds to industries that are registered in the ENIA database. ENIA registers information from firms which have a workforce of 5 or more people and which have operated more than 6 months. The survey gathers data on fuels consumption and fuels prices (among many other variables). The data was obtained for the period 1998-2007⁷. This study counts with a privileged data set of approximately 39,000 observations, belonging to 8,450 firms throughout 10 years (un-balanced panel) and pertaining to various manufacturing sectors -22 industrial sectors if counted by 2 digits in the CIU classification-. [Refer to Table 2 for a list of the industrial sectors included in ENIA, classified by 2 digits of the CIU code].

Definition of Fuel-Portfolio Patterns:

This study has evaluated conditional factor demand by fuel-portfolio pattern, which is the combination of fuels that a firm uses as factor inputs. This strategy, its purposes and implications will be described in detail in Section IV on methodologies. However, it is necessary to define in this section the patterns of fuels-portfolio that have been evaluated in order to present percentages and descriptive statistics by patterns. Chilean manufacturing firms consume various fuels, mainly: electricity, petroleum-oil, gas (which includes natural and liquefied gas), gasoline, wood, paraffin, biomass and others. In terms of dollar value of consumption, the main consumed fuels are electricity, oil, gas and gasoline. Thus, the five most frequent fuel portfolios have been selected for study, these portfolios are: (i) E: Electricity, (ii) EO: Electricity-Oil, (iii) EG: Electricity-Gas, (iv) EOG: Electricity-Oil-Gas, and (v) EOGGA: Electricity-Oil-Gas-Gasoline. The next table shows, the frequency and percentage of firms with the sample of firms that use the 5 most common patterns of fuel-combination.

Table No. 2
Evaluated Patterns of Fuels-Portfolio
Frequency and Percentage of Observations in
Sample ENIA, 1998- 2007

Pattern of Fuel Portfolio	Freq.	Percent
Elect	12.013	30,3
Elect-Oil	7.945	19,9
Elect-Gas	7.582	18,7
Elect-Oil-Gas	6.979	17,2
Elect-Oil-Gasol-Gas	4.824	11,5
Total	39.343	100

⁷Data for 2008 and 2009 was also obtained from INE. However, the codification for firms had changed. For this reason, this two years were finally not included in the study.

In order to have a better overall description of the sample, the following Table No. 3 shows the percentages of observations from the sample. It includes percentages of the overall sample, as well as percentages of every fuel portfolio by year, region, industry and firm size.

Table No. 3
Sample Percentages – Overall and By Fuel Portfolio –

		Tota Sample	Sample by Fuel Portfolio*				
		Colum %	Row %				
YEAR			E	EO	EG	EOG	EOGGA
	1998	10.0	36.0	18.5	20.2	12.7	12.6
	1999	10.3	35.0	18.4	21.6	14.6	10.5
	2000	10.0	35.5	17.6	21.2	14.4	11.4
	2001	10.0	34.3	19.7	19.8	14.4	11.9
	2002	10.0	34.5	16.9	21.2	15.8	11.6
	2003	9.3	30.3	20.1	20.2	17.3	12.1
	2004	9.8	24.2	23.5	17.8	21.5	13.1
	2005	10.8	26.3	22.2	17.5	20.6	13.3
	2006	10.0	26.2	22.1	16.7	22.0	13.0
	2007	9.9	23.2	22.8	16.7	24.1	13.1
	Total	100.0	30.5	20.2	19.3	17.7	12.3
REGION			E	EO	EG	EOG	EOGGA
	1	2.7	43.2	24.4	9.2	9.7	13.5
	2	2.4	32.3	26.6	9.0	12.4	19.7
	3	1.4	31.7	30.6	7.7	10.9	19.0
	4	2.1	27.6	25.9	8.0	17.0	21.6
	5	7.6	39.3	12.0	21.4	17.2	10.1
	6	3.3	29.6	26.5	13.7	16.1	14.1
	7	4.7	34.1	32.8	9.1	15.1	8.9
	8	11.4	32.0	26.7	11.8	15.5	14.0
	9	3.2	28.5	39.7	9.2	12.6	10.0
	10	4.7	29.3	26.8	12.4	16.1	15.5
	11	0.6	26.3	26.3	14.3	15.2	18.0
	12	1.0	16.4	9.7	23.6	23.3	27.0
	13	54.6	28.4	15.9	24.7	19.9	11.1
	14	0.2	54.7	27.9	5.8	8.1	3.5
	15	0.2	67.5	14.5	7.2	4.8	6.0
	Total	100.0	30.5	20.2	19.3	17.7	12.3
INDUSTRY			E	EO	EG	EOG	EOGGA
	15_food&beverages	31.7	20.9	28.1	18.1	20.3	12.7
	16_tobacco	0.02	42.9	0.0	14.3	0.0	42.9
	17_textiles	5.2	38.1	8.8	27.6	19.4	6.1
	18_apparel	5.6	52.2	5.6	28.1	9.2	4.9
	19_leather	2.8	47.3	10.1	21.0	13.3	8.3
	20_wood	6.2	34.1	38.6	6.9	8.4	12.0
	21_paper	3.0	23.6	16.2	29.4	21.5	9.4
	22_print&media	4.3	53.5	12.0	17.4	13.3	3.9
	23_refinedpetroleum	0.1	4.5	27.3	27.3	40.9	0.0
	24_chemicals	5.7	22.7	15.8	24.1	24.0	13.4
	25_rubber&plast	6.2	32.9	17.1	20.4	17.8	11.8
	26_minerals	5.2	21.8	21.8	11.9	21.7	22.9
	27_basic-metals	2.4	19.9	15.1	13.9	28.3	22.8
	28_fabricated_metals	7.2	31.3	17.5	19.9	17.2	14.1
	29_machinery&equipment	5.2	34.6	15.8	17.1	15.6	17.0
	30_office-machinery	0.0	0.0	0.0	0.0	100.0	0.0
	31_electrical-machinery	1.5	25.9	10.0	30.7	19.4	14.1
	32_communication-equipment	0.2	53.2	9.7	24.2	12.9	0.0
	33_medical-instruments	0.4	35.2	9.1	38.1	9.1	8.5
	34_motor-vehicles	1.4	33.5	14.3	25.2	13.9	13.0
	35_transport-equipment	1.0	30.5	12.7	14.3	17.2	25.2
	36_furnitures	4.7	45.6	15.9	16.4	13.1	9.1
	37_recycling	0.01	0.0	0.0	0.0	0.0	100.0
	Total	100.0	30.5	20.2	19.3	17.7	12.3
SIZE			E	EO	EG	EOG	EOGGA
	Size 1: 1 - 19 workers	37.2	46.8	21.0	18.8	9.1	4.4
	Size 2: 20 - 100 workers	44.1	24.7	21.9	19.7	19.5	14.3
	Size 3: > 100 workers	18.7	12.1	14.8	19.3	30.7	23.2
	Total	100.0	30.5	20.2	19.3	17.7	12.3

* Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

From Table No. 3, main conclusions include:

- Percentages of establishments by sector are about the same throughout the period of analysis (1998 – 2007). Percentages of establishments by size are also similar throughout the years. The fuel portfolio of electricity is the pattern that has most percentage of observations; however, this has decreased throughout the period of analysis. The portfolio of electricity-gas has also decreased in this period, this is reasonable, because of the natural gas shortages in some of the last years of the period of analysis. On the other hand, the portfolios of electricity-oil and electricity-oil-gas have increased throughout the years. The portfolio of electricity-oil-gas-gasoline has maintained its share throughout the period of analysis.
- The regions with most observations of establishments are: the metropolitan region, with 55% of the observations of the sample, followed by the 8th and 5th regions with 11,5% and 7,6% of observations respectively. In terms of fuel-portfolio, the most frequent pattern in most of the regions is of electricity only, although in the metropolitan and in the 5th regions the patterns of EG and EOG have also large shares (in terms of observations), and for the region 8th the pattern EO also has an important participation. However, it is important to reiterate that percentages from Table No. 3 show shares in terms of sample observations. This perspective changes when we analyze percentage of fuels' aggregate consumption per region. In this case, the level of importance of the second region increases significantly, because this region consumes more electricity and oil than even the metropolitan region. Also, the importance of the regions 1st, 3rd, 5th, 7th and 10th is more evident in terms of fuel consumption than in terms of number of establishments. [Refer to Annex A.2, for graphs on Aggregate Fuel Consumption per Region]
- The most important industry sectors in terms of number of establishments/plants (not in terms of economic production or capital) are: food & beverages, fabricated metals and mineral products⁸, textiles, apparel and leather, wood products, plastic and rubber, machinery and equipment, refined petroleum products. These industries also correspond to the ones that have the highest fuels' consumption, with some variations per fuel type. [Refer to Annex A.3, for graphs on Aggregate Fuel Consumption by Industrial Sector].
- In terms of size, the majority of establishments (44%) are of medium size (which corresponds to 20-100 workers), although an important percentage is also of small size firms (less than 20 workers). In terms of fuel portfolio, small firms are more

⁸It is important to explain that for the mining sector, the ENIA database only includes the productive activities related to manufacturing classification (only fabrication and manipulation of metals), but it does not include mining extraction activities.

concentrated in the portfolio of only electricity, medium size firms are somehow evenly distributed among patterns (with a lesser share in the EOGGA portfolio), and larger firms have their biggest share in the portfolio of electricity-oil-gas.

3.2 Variables Description

The variables included in the model correspond to the theoretical specification of conditional factor demand functions: input consumption as dependent variable and input price, prices of inputs' substitutes, and output level as explanatory variables. In addition, other variables for number of workers and natural gas availability were evaluated as explanatory variables, to capture firm size and national access to imports of natural gas, respectively, and time dummies to capture macro-economic effects affecting energy consumption.

Fuels' Consumption

Fuels that were considered in the study are those of highest consumption (in value –Chilean Pesos-) in the industrial firms from the ENIA sample: electricity, oil, gas and gasoline. ENIA included information on liquefied gas, natural gas and pipe gas; all of them were unified in one only variable of natural gas. Like other studies that have used ENIA database, we also found some inconsistencies in the units of fuels consumption. Thus, the original data on consumption was tracked and evaluated. Evidently, some data on consumption had been registered with different units in different years; then, changes were made to have uniform units of consumption and consistent data on prices throughout the years. These changes were later confirmed in an in-person interview with representatives of the Chilean National Institute of Statistics, Office of Industrial data.

From all fuel-types, only electricity could be self-generated. ENIA database identifies self-generated electricity and distinguishes it from purchased electricity. The amount of electricity that is self-generated has not been included in the demand estimation for this fuel. The reason is that the cost of electricity generation is not reported in ENIA data, but firm only report the price of electricity purchased from the market. However, the percentage of firms that report self-generation is small, about 3%, and this correspond to about 2 % of electricity consumption throughout the sample.

Variable for Output Level

In ENIA database there are several variables that could be used to proxy for output level, among them: value added revenues, revenues from sales and gross value of net production. In this study, the selected variable was the 'gross value of net production' as it accounts for: revenues

of all products and services that were sold plus the value of products that were produced during the period (and have not yet been sold), minus the value of products that were ready at the initial stage of the accounted period.

Prices of Fuels

ENIA counts with value (in Chilean pesos) spent in each fuel throughout the year and consumed quantity of every fuel per year. With this information, fuels' prices per unit of fuel were calculated. These prices were calculated in the units of every fuel as well as in BTU (British Thermal Units). Even after correction from units of fuels' consumed quantities, the prices from this data corresponded to a wide range. From a discussion with representatives of the Chilean National Institute of Statistics, Office of Industrial data, such wide range of price variation in self-reported prices could be explained by differences at distributor prices not only among regions, but also for micro-location and distance of fuel delivery, agreements with particular customers (firms), and also by errors in self-reporting data to the national industrial survey. Thus, for every fuel price variable, observations corresponding to the 1st and 99th percentiles of the distribution of each fuel price were eliminated from the sample. Also, the estimation included dummies for remaining outliers to take into account possible data-entry and/or self-reported errors.

All prices were adjusted for inflation, using a production price index, the industrial component for wholesale prices from the Chilean National Statistics Institute. For verification, the ENIA data price unit was compared to a reference price for every fuel. Data from the National Association of Fuels Distributor (ADICO) was gathered to obtain mean prices of distributors of liquid fuels (petroleum and gasoline) by region and year. These mean prices were compared with the empirical mean prices (also by region and year) of the sample data. The empirical statistics on mean prices was within a range of (-20%) – (+20%) confidence interval in relation to data reported by ADICO. For gas and electricity, it was not possible to obtain distributor data prices, however empirical statistics were compared to national average prices, which are reported by the National Energy Commission, and most of these data were comparable.

Number of Employees & Firm size

One of the firm characteristics evaluated in the study was firm size. In the literature, there are several ways in which to capture firm size, including value of fixed assets and number of employees. ENIA counts with number of employees. This variable was analyzed in the study as regressor, and it was also used to divide the sample in three categories of firm size: small firm (1-19 workers), medium size (20-100 workers) and large size (>100 workers).

Natural gas availability

This variable has been included in the model to account for the periods of natural gas rationing in Chile, which have an impact not only on natural gas consumption but on the consumption of all the other fuels used by Chilean industries. In the period of analysis, 1998-2007, there were several energy rationings in Chile, especially during the years 2004, 2005 and 2006. These were principally due to the shortages of Argentinean gas supply to Chile. The data for the percentages of gas availability for each geographical region were obtained from calculations of Benavente et al. (2010). It is convenient to mention that apparently the increases in electricity prices due to changes in gas price were evident in the wholesale market, but not so evident in the retail market. The average market price calculated by the National Energy Council, which guides the price of the retail market, has been analyzed for the different electric systems in Chile (SIC and SING). Annex A.1 shows the electricity average market price (for the retail market) from 1998 to 2008.

Individual Unit of analysis: the establishment (plant)

The information from ENIA is based on manufacturing establishments, meaning plants and not firms. ENIA registers their information in this way to deal with differences between firms that operate with multi-units (several plants) and multi-activities (several manufacturing products). Thus, the estimation on electricity demand will be based on the establishment (plant) and not the firm (juridical name of a company). ENIA identifies the establishments with an identification number that is kept over the years that the establishment exists.

Descriptive Statistics

In order to give a general view of the variables included in the empirical model, the following Tables No. 4 and 5 show a summary of the descriptive statistics of the main dependent and explanatory variables in the overall samples, as well as for each of the fuel portfolios. Moreover, Table No. 6 presents the cost shares of each fuel in the overall sample and by fuel portfolio.

Table No. 4
Descriptive Statistics: Fuels Quantities & Prices

Variable	Unit	Total Obs	All Sample		PATTERN OF FUEL PORTFOLIO*									
			Mean	St. Dev	E		EO		EG		EOG		EOGGA	
					Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Electricity Demand	MWh	39.343	2.540,0	27.570,3	769,3	8.014,3	2.204,4	34.858,4	1.317,8	9.472,5	4.113,2	26.836,1	7.147,4	53.112,2
Oil Demand	m3	19.748	335,6	2.639,8	-	-	277,5	3.115,0	-	-	296,8	1.870,3	487,4	2.730,8
Gas Demand	m3	19.385	221,7	2.450,0	-	-	-	-	244,3	3.500,3	198,1	953,3	220,3	1.884,3
Gasoline Demand	m3	4.824	35,2	452,5	-	-	-	-	-	-	-	-	35,2	452,5
Electricity Price (+)	ChileanPesos /MWh	39.343	31,1	12,0	32,7	12,3	31,2	12,1	31,2	11,5	29,2	11,5	29,4	11,9
Oil Price (+)	ChileanPesos /m3	19.748	136,5	51,4	-	-	137,1	51,7	-	-	138,0	51,9	133,3	50,1
Gas Price (+)	ChileanPesos /m3	19.385	159,4	101,9	-	-	-	-	152,87	105,4	165,8	102,9	160,3	93,8
Gasoline Price (+)	ChileanPesos /m3	4.824	197,5	59,5	-	-	-	-	-	-	-	-	197,5	59,5
# of Observations			39.343		12.013		7.945		7.582		6.979		4.824	

* Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

(+) All Chilean Pesos values have been deflated with a National Industry Price Index (base date June 1992)

Table No. 5
Descriptive Statistics: Additional Explanatory Variables

Variable	Unit	Total Obs	All Sample		PATTERN OF FUEL PORTFOLIO*											
			Mean	St. Dev	E		EO		EG		EOG		EOGGA			
					Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Output(+)	Thousand Chilean Pesos	39.343	3.788.263	3.61e+07	1.294.721	1.80e+07	3.135.326	4.97e+07	3.796.206	4.03e+07	5.706.556	2.12e+07	8.285.464	5.02e+07		
Direct Employment	# Employees	39.343	73	156	33	70	58	124	66	119	120	206	139	259		
Capital Stock (+)	Thousand Chilean Pesos	25.876**	1.455.349	1.31e+07	401.306	4,86E+06	1.362.289	1.89e+07	1.059.773	8,60E+06	2.018.437	8,94E+06	3.412.895	2.07e+07		
Gas Availability	Percentage	39.343	0,71	0,30	0,74	0,28	0,69	0,31	0,75	0,28	0,68	0,32	0,69	0,31		
Electric System	Categorical	39.343	1,97	0,26	1,96	0,28	1,95	0,28	1,99	0,20	1,99	0,23	1,96	0,32		
# of Observations			39.343		12.013		7.945		7.582		6.979		4.824			

* Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

** Data on capital stock is not available for years 1998 - 2000

(+) All Chilean Pesos values have been deflated with a National Industry Price Index (base date June 1992)

Table No. 6
Cost Shares By Fuel and Fuel Portfolio

Variable	Total Obs	All Sample		PATTERN OF FUEL PORTFOLIO*											
		Mean	St. Dev	E		EO		EG		EOG		EOGGA			
				Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Electricity Cost Share	39.343	0,68	0,31	1,00	0,00	0,47	0,28	0,67	0,26	0,50	0,25	0,46	0,25		
Oil Cost Share	19.748	0.39	0,28	-	-	0,53	0,28	-	-	0,31	0,25	0,27	0,23		
Gas Cost Share	19.385	0,23	0,23	-	-	-	-	0,33	0,26	0,19	0,20	0,14	0,16		
Gasoline Cost Share	4.824	0,14	0,15	-	-	-	-	-	-	-	-	0,14	0,15		
# of Observations		42.519		12.013		7.945		7.582		6.979		4.824			

* Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

In Table No. 4 it is possible to observe that mean and standard deviation are very similar among fuel-portfolios. From Table 5 it is worth to highlight that as the fuel-portfolio is further diversified, the mean of some explanatory variables increases, including mean output level, mean number of employees, and mean capital stock, which gives an intuition that in general larger firms use a wider variety of fuels in their production.

Table No. 6 shows that in the overall sample, electricity is the fuel that has the highest mean cost share, followed by oil, gas and gasoline (in that order). In general, the prevalence of fuels keeps the same order by fuel portfolios, with the exception of pattern of electricity-oil, where oil has a higher mean cost share.



IV. ECONOMETRIC MODEL AND METHODOLOGICAL ASPECTS

This sub-section describes the methodology used for estimation. First it describes the econometric model, which corresponds to a panel data (fixed effects) with seemingly unrelated estimation regression and maximum likelihood estimation. Then, it explains various difficulties and concerns present in the estimation strategy, related to zero consumption, possible endogeneity of prices and attrition, and how they were analyzed and solved as well as their implications.

4.1 Panel Data Structure and Within Estimator

To exploit the advantage of counting with micro-data, this study tries to capture the firm-level decision. The panel structure that has been chosen addresses this objective. Annex A.4 shows a comparison of the estimation with pooled data, fixed effects and between effects (the results of Annex A.4 corresponds to pattern 5 and for the linear logit functional form). The coefficients from the pooled and within estimation are higher and this is consistent with the fact that the between variation of explanatory variables is higher than the within variation because of the large number of firms vs. a 10 years time period –annual periodicity-. Accordingly, the levels of elasticities are higher in the pooled and between estimation than the within estimation.

However, in the pooled estimation and between-effects estimation, the capacity of capturing firm-individual heterogeneity is diminished, as it is not possible to control for firm characteristics that could only be observable throughout time. On the other hand, a fixed effects panel structure allows capturing such heterogeneity. Test for fixed effects or random effects, show that these explanatory variables are highly correlated with the constant term, meaning that although it is possible to include some firm characteristics, their correlation with the unobserved heterogeneity could lead us to erroneous results. [**statistic results that support fixed effects: (i)** Hausmann test: rejects the null hypothesis that the individual effects are uncorrelated with the other regressors in the model; **(ii)** high fraction of variance due to individual effects: ~0.75; **(iii)** relatively high correlation of individual effects with the explanatory variables: 0.40 – 0.60 ; and **(iv)** F test shows that individual effects are significant at 1%].

Also, in Annex A.4 it is shown that variables of capital stock and direct employment become non significant in the within estimator model, meaning that they are not influencing factors in the individual firm decisions on fuels' consumption. However, these results pertain to an estimation where labor and capital are not included in terms of prices, but in terms of number of workers and total value of capital stock. This means that in this case labor and capital are exogenous variables. This result is intuitive, because the characteristic of firm size (represented

as number of workers and capital stock⁹) in a within estimator seem to be somewhat constant in short periods of time (changes in deviations from the individual mean throughout time are fairly small)¹⁰.

The selected panel structure (fixed effects –within estimator-) acknowledges the relation of the explanatory variables with the constant term (unobserved heterogeneity). In this way, it allows for a differentiated constant per firm. However, this does not allow seeing the impact of variables that are invariant in time. This means that we do not see time invariant firm heterogeneity and the error μ_{it} will be an idiosyncratic error and time varying error. Because of this limitation to capture the impact of some variables of interest, such as localization, industrial sector and firm-size, these firm characteristics, in particular size categories and industry type have been analyzed separately.

4.2 Endogeneity of prices

At the individual firm level, it is generally assumed that input prices on the right hand side are exogenous. This is related to two factors: 1) individual firm prices are closer to the marginal price, and 2) individual firms most probably cannot influence by themselves fuels prices. Furthermore, in various countries, fuels' markets are strongly regulated by the central government (because of issues of national security and basic service for the population). Thus, how much individuals and/or firms can influence energy markets is related to the level of regulation of the market, and tariff structures. In Chile, energy retail markets are regulated by a central institution, the National Energy Commission -CNE-; thus firms in the retail market do not directly influence market prices. However, tariff structures for each fuel, in particular for electricity, could become a potential source of influence on prices from consumers¹¹.

Furthermore, the prices that are used in this study are not precisely marginal prices, because we count with annual data, which are still average prices (although not sectorial average prices). Therefore, we tested for endogeneity of the variables of factor prices [Durbin-Wu-Hausman (DWH) test and the difference of two Sargan-Hansen statistics]. Both tests accept the null hypothesis for exogeneity of prices. Results on these tests were robust; however, there is still a concern the instrument used for these tests. The instrument was the variable for region (geographical localization), which has been used in other studies (Bjorner et al, 2001).

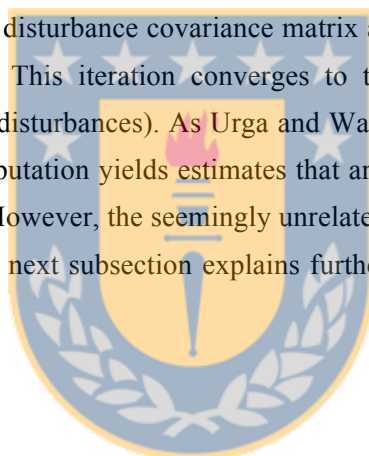
⁹Capital stock could also represent the level of economic health of a company.

¹⁰To see the joint impact of capital and/or employment on energy demand it would be necessary to include these variables in terms of prices and to implement a conditional factor analysis of substitution or complementarity between production factors, which goes beyond the scope of this research. If a model with labor and capital as factor inputs is estimated, another functional form, probably a nested model -which distinguishes the differences in substitutability between fuels and non-fuels factor inputs- would be a better fit.

¹¹ In the Chilean electricity market, there is no block pricing in the tariff alternatives available for firms. Nevertheless, there is a system of peak hours, in which there are two alternatives of tariff types that include differentials in peak hours. Each firm decides which alternative tariff would like to pay for, causing in this case an indirect influence in how tariff alternative are determined, although distributor companies follow regulations from the CNE.

Also, in various previous studies for other countries, especially aggregate studies for industrial sector or country-comparison, the possibility of endogeneity in prices has been addressed by using iterative three-stage least squares (3SLS). Nevertheless, as Serletis et al. (2009) mention, that results generally have been about the same as those with iterative Zellner estimation (Barnett, 1991), and in such cases the results would depend on the exogeneity level of the set of instrumental variables. (Diewert and Fox (2008))

Therefore, in this study, the estimation technique selected is the Zellner estimation for seemingly unrelated regression and has not used any instrumental variable to correct for possible endogeneity of prices. The SUREG estimator allows for an improvement in efficiency of the estimator. This improvement in efficiency is obtained due to the potential nonzero covariance across equations. The seemingly unrelated regression obtains estimates of the parameters for every equation, then obtains consistent estimates of the covariance matrix and minimizes a generalized least squares objective function. In addition, the program can be set to iterate over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge. This iteration converges to the maximum likelihood results (assuming multivariate normal disturbances). As Urga and Walters (2003) explain, “in the case of demand systems, this recomputation yields estimates that are invariant to whichever input is dropped or used as the base.” However, the seemingly unrelated regression does not allow for a correction of any bias, thus the next subsection explains further the problem and correction of selection bias.



4.3 Zero Consumption: Analysis by patterns & Selection Bias Correction

One of the main challenges of estimating a set of conditional factor inputs with micro-data is that not all firms consume all the alternative factor inputs (in this case, fuel options). Hence, when implementing regression analysis this would cause biased results, because of the truncated nature of the sample. This truncation is present because it is not possible to see negative consumption of the factor inputs, neither the observations of the explanatory variables that would produce such consumption below zero (including prices). This is called zero consumption problem.

Some of the alternatives to deal with this challenge include: aggregation and average prices, selection bias correction, virtual prices, multi-alternative Discrete Continuous Extreme Value model, as well as an analysis by consumption patterns. To take advantage that micro-econometric analysis allows distinguishing among firm (individual) decision making, the strategy of most of these options is to decompose in a qualitative and quantitative decisions.

Hence, there is a combined effect between portfolio of fuel consumption (pattern) and quantity levels of fuel. As Bousquet and Ivaldi (1998) mention “*substitution effect (price elasticities) between energies can be separated in a ‘direct’ effect on quantities (the distribution of regimes being unchanged), and in an ‘indirect’ effect through probabilities of observing a particular energy mix.*”

The strategy of analyzing by consumption patterns is an attractive alternative to capture differences in technologies, as it separates the sample to analyze price elasticities of firms that have different portfolios of fuel consumption. In this study, separated estimations were implemented for every observed pattern of fuel portfolio. Fuel portfolios patterns considered in this study were described in section 3.2 (Table No.2).

However, even though this strategy reduces the problem of zero consumption, it does not eliminate it completely. This is because not all firms stay in the same pattern of fuel portfolio during the considered period (1998-2007). (Annex A.5 shows the percentages and frequency of firms that keep the same pattern in various numbers of years). To consider this persistent problem that could cause biased estimations, and to correct the estimation for such selection bias, a Heckman two-step procedure for selection bias correction has been considered.

Heckman (1976) used a two-step procedure to model the selection process first, and then used the estimated conditional probability to control for bias induced by selection in the outcome analysis. From this first step, called the ‘selection equation’ the necessary probabilities for the selection case/s are calculated to obtain a correction factor (inverse mills ratio), which is then included in the main estimation (outcome equation). Dubin and McFadden (1984) extended the bivariate Heckman selection bias correction to various alternatives in the first stage of the choice selection model. Dubin and McFadden (1984) constructed the inverse mill ratio from a multinomial logit in the first stage (selection equation)¹².

In this study, the selection equation was estimated with a mixed logit, because this model does not assume independence of irrelevant alternatives (IIA). IIA was tested with the Hausman-McFadden test for IIA [Results of this test show that the alternatives are not independent: $\chi^2=39.79$, $\text{Prob}>\chi^2=0.000$]. Another important reason to select a mixed logit estimation was that programmatically it is easier to set up the panel structure of the data in a mixed logit estimation than in a ASC conditional model. The mixed logit estimation recognizes and identifies that different firms are observed throughout various time periods¹³.

¹²Dubin and McFadden (1984) presented a formula for a case in which the outcome equation is a single equation estimation. In this case, the selection bias is calculated for a system of equations.

¹³ The choice model was also estimated with a hybrid conditional logit (alternative specific constant) that allows including characteristics of the individual and characteristics of the alternatives. The results on probabilities were similar to those calculated by the mixed logit, which guarantees robust results. However, the results from the mixed logit were preferably used in the final estimation, as the ASC logit estimation did not consider the panel structure of the data.

With the mixed logit model, probabilities of selection of each alternative (pattern of fuel portfolio) were estimated per observation, and this new variables were used to construct the correction term (inverse mills ratio). The inverse mills ratio provides a potential correction and an informative estimation of the selection bias and its construction is based on the way we construct the likelihood function of any tobit model of limited dependent variable (based on the density function for non-limited observations that represents the probability of obtaining such value, together with the cumulative density distribution for limited observations).

In this case, equations (5) in the linear logit model or equation (10) in the translog model depend of a new term ($\hat{\beta}_H IMR$). The following formula shows the example for the Linear Logit model (the same would be applicable for equation 10):

$$f_{it} = \alpha + \sum_{j=1}^N \beta_{ij} \cdot \ln P_{jt} + \beta_y Y_t + \hat{\beta}_H IMR + \epsilon_p + \nu \quad (12)$$

Where, IMR stands for inverse mills ratio and $\hat{\beta}_H$ for the parameter of the Heckman bias correction. $\hat{\beta}_H$ is obtained by first-step mix logit regression for the probabilities of each firm to choose a given portfolio. If ϵ_p are the unobserved attributes of the portfolio p (and they are assumed to have independent extreme value distributions, then, the distribution of error term of the outcome equation (ν) is conditional to such ϵ_p from the alternatives portfolios (Dubin and McFadden, 1984). Then, for a maximum of t alternative portfolios and if alternative p is chosen¹⁴:

$$E(\eta|p) = \sum_{j \neq p}^t \left[\frac{\sigma \sqrt{6R_j}}{\pi} \right] \left[\frac{P_j \ln P_j}{1 - P_j} + \ln P_p \right] \quad (13)$$

If the outcome equation corresponds to demand for a good and such consumption considers all the alternatives simultaneously, then the inverse mills ratio will include the $E(\eta|p)$ for all the alternatives ($\epsilon_1, \epsilon_2, \dots, \epsilon_t$). However, in this case, where the demand for fuels is being estimated separately for every alternative portfolio, in the fuels estimation of each portfolio it is only necessary to include the $E(\eta|p)$ that corresponds to the p alternative portfolio. Tables No. 8 and 9 on results show four coefficients estimates for each term from equation (13).

It is pertinent to explain further two topics, which differ in this estimation from the bivariate case developed by Heckman. The first is related to the error distributions of the two stages and the second is related to exclusion terms. In the case of the Heckman two-stage procedure with

¹⁴ For further detail on the development of this equation, refer to Dubin and McFadden (1984).

the bivariate case, the distribution of error terms for the first and second equations are recommended to be normally distributed. Cameron and Trivedi (2005) mention “the Heckman two-step method can be applied with distributions for the error term of the selection equation other than normal.” And in the case of multivariate alternatives applied by Dubin and McFadden, they have a Weibull distribution in the error terms of the first stage, as they use a multinomial logit. In this study, the first stage of multi-alternatives also has a Weibull distribution for the error term of the selection equation and the distribution of the error term for the second stage is normal.

The second topic is related to identification considerations. Cameron and Trivedi (2005) explain that the “bivariate sample selection model with normal errors is theoretically identified without any restriction on the regressors.” The risk is that the inverse mill ratio term would be approximately linear over a wide range of the argument in the outcome equation. This could lead to evident problems of multicollinearity. Therefore correlation of the inverse mills ratio with the regressors of the outcome equation was calculated. These results showed low correlation for the estimations of different patterns [correlation levels: 0.0008 - 0.3338]. Another way in which econometricians guarantee identification is by finding exclusion term/s, which are explanatory variables that explain the decision to select, but that are unrelated to the outcome of interest. In this case, there are two variables that were not finally included in the fixed effect model for fuels demand: capital stock and number of employees. On the other hand, these variables were useful when explaining the selection model for fuel portfolio. Then, these two variables became exclusion terms. Furthermore, another important differentiation between regressors from the first and second stages is related to the variables on prices. In the fuels’ demand equations, a different price variable per fuel was included, while in the selection equation a different variable of average price per energy unit (BTU) was constructed. Such variable on energy price per BTU for each of the patterns was necessary, because price of fuels is a characteristic of the alternative and this variable must differ among alternatives.

The next table summarizes the results of the mixed logit estimation for the selection equation.

Table No. 7
Results Mixed Logit Estimation on
Probabilities of Fuel-Portfolio Selection

VARIABLES	Mean	SD
FuelAvgPrice	337.5*** (16.27)	
direct_employm	-177,402*** -9,49	
gasAvailability	33.96* (19.14)	
Output	85,712* -51,866	7.050e+06*** -629,537
Observations	192,965	192,965

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table No. 7 shows 192,965 observations, because the data structure for estimating a mixed logit requires expanding the database to set up as an observation for every alternative. Thus, this number of observations corresponds to the database expanded by 5 (number of alternatives) and minus a few observations that were lost when calculating average prices. Also, Table No. 7 shows the results of the mixed logit without the explanatory variable of capital stock, as this variable is not available in ENIA for some years of the period in analysis.

It is also worth to notice that various of the terms of the inverse mills ratio included in the estimations are significant at 10%, 5% and 1%. [Refer to estimation results Tables No. 8 and 9), which corroborates the effect of the correction of selection bias.

4.4 Attrition

When modeling the change of enterprises overtime, we find attrition (unbalanced panel) in the number of years that such firms were observed in the data, as well as in the number of years that the firms have kept the same pattern(portfolio of fuel consumption). It is important to highlight that the percentage of firms that is lost in the subsamples of firms that keep the same pattern, is similar in terms of firm size, region and industry. This only assures that the sub-sample keeps its level of randomness, in particular in relation to industrial sector, size and geographical region.

A sensitivity analysis was implemented to analyze how the elasticities change when including only firms that would keep the same fuels portfolio for several years (3, 5 and 7 years). [Annex A.6 shows a Linear Logit Fuels Demand Estimation with a Sample of Firms that keeps the same pattern for more than 7 years] The sample size was then reduced in these cases. The results show that the elasticities are maintained at similar levels and with the same tendencies. Interestingly, the coefficients of the mills ratio (of the selection bias correction) become

increasingly more significant as the sample includes more firms that change the pattern throughout the years (higher attrition). This is intuitive as the probabilities for changing the pattern have more variability in the cases where the sample is specified with firms that keep the same pattern for fewer years.



V. ESTIMATION RESULTS & KEY FINDINGS

5.1 Estimation Results

Results for the estimations of both functional forms are presented in the next Tables No. 8 and 9.

Table No. 8
Linear Logit Fuels' Demand Estimation By Fuel-Portfolio Chilean
Manufacturing Firms – ENIA- 1998-2007

VARIABLES	PATTERN EOGGA			PATTERN EOG		PATTERN EG	PATTERN EO
	ln(O/E)	ln(G/E)	ln(GA/E)	ln(O/E)	ln(G/E)	ln(G/E)	ln(O/E)
w1lnp1p4		0.0612 (0.0935)	-0.147 (0.119)		0.381*** (0.0706)		
w1lnp2p4		-0.776*** (0.0761)			-0.281*** (0.0631)		
w1lnp3p4			-0.709*** (0.0977)				
w1w4lnp1p4	0.547*** (0.0377)			0.0995*** (0.0277)			0.0771*** (0.0254)
w2lnp1p4	-0.776*** (0.0761)			-0.281*** (0.0631)			
w2lnp2p4	-0.676*** (0.0893)		-0.511*** (0.131)	0.321*** (0.0672)			
w2lnp3p4			-0.755*** (0.124)				
w2w4lnp2p4		0.450*** (0.0352)			0.0397* (0.0231)	-0.0174 (0.0201)	
w3lnp1p4	-0.709*** (0.0977)						
w3lnp2p4		-0.461*** (0.151)					
w3lnp3p4	-0.763*** (0.109)	-0.901*** (0.151)					
w3w4lnp3p4			0.519*** (0.0399)				
lnoutput	0.146*** (0.0434)	0.112** (0.0436)	-0.0537 (0.0465)	-0.0155 (0.0361)	0.0992*** (0.0321)	0.0207 (0.0285)	0.101*** (0.0256)
lngasavail	-0.0116 (0.0145)	0.0225 (0.0145)	0.0703*** (0.0154)	-0.0348*** (0.0129)	0.0335*** (0.0114)	0.00750 (0.0117)	0.0119 (0.0102)
D1999	0.141** (0.0580)	0.190*** (0.0588)	0.0958 (0.0621)	0.122** (0.0544)	0.195*** (0.0488)	0.0751* (0.0385)	0.0795** (0.0395)
D2000	0.268*** (0.0572)	0.375*** (0.0581)	0.241*** (0.0616)	0.163*** (0.0546)	0.308*** (0.0490)	0.154*** (0.0380)	0.176*** (0.0400)
D2001	0.148*** (0.0570)	0.270*** (0.0573)	0.118* (0.0610)	0.0336 (0.0543)	0.276*** (0.0485)	0.161*** (0.0387)	0.0829** (0.0398)
D2002	0.0462 (0.0575)	0.222*** (0.0579)	0.00635 (0.0616)	-0.111** (0.0533)	0.244*** (0.0476)	0.129*** (0.0391)	0.0561 (0.0410)
D2003	0.205*** (0.0592)	0.278*** (0.0593)	0.0576 (0.0635)	-0.0603 (0.0542)	0.293*** (0.0483)	0.120*** (0.0406)	0.0654 (0.0417)
D2004	0.237*** (0.0589)	0.353*** (0.0589)	0.113* (0.0633)	-0.00152 (0.0531)	0.251*** (0.0471)	0.127*** (0.0421)	0.127*** (0.0415)
D2005	0.289*** (0.0563)	0.341*** (0.0563)	0.0553 (0.0603)	0.236*** (0.0513)	0.233*** (0.0455)	0.138*** (0.0403)	0.146*** (0.0394)
D2006	0.284*** (0.0586)	0.286*** (0.0587)	-0.0418 (0.0628)	0.274*** (0.0528)	0.201*** (0.0468)	0.1000** (0.0422)	0.131*** (0.0406)
D2007	0.00197 (0.0889)	0.175* (0.0895)	0.0539 (0.0952)	-0.0510 (0.0797)	0.184*** (0.0713)	0.0498 (0.0693)	0.00280 (0.0604)
Inv_Mills_Ratio_Term1	0.556*** (0.154)	0.231 (0.154)	0.0182 (0.165)	0.147 (0.149)	0.271** (0.132)	-0.0268 (0.113)	0.0962 (0.115)
Inv_Mills_Ratio_Term2	-0.422* (0.249)	-0.683*** (0.250)	-0.575** (0.267)	-0.978*** (0.272)	-0.408* (0.242)	1.098*** (0.284)	0.208 (0.249)
Inv_Mills_Ratio_Term3	0.794*** (0.246)	0.544** (0.246)	1.166*** (0.263)	0.0794 (0.237)	-0.0899 (0.211)	-0.264 (0.563)	-1.455** (0.570)
Inv_Mills_Ratio_Term4	-0.924*** (0.301)	0.114 (0.302)	-0.598* (0.321)	0.930*** (0.319)	0.216 (0.283)	-0.958* (0.490)	1.327** (0.535)
Constant	-0.178*** (0.0419)	-0.263*** (0.0421)	-0.0756* (0.0449)	-0.0645 (0.0410)	-0.232*** (0.0365)	-0.111*** (0.0283)	-0.0897*** (0.0293)
Observations	4,231	4,231	4,231	5,911	5,911	6,497	6,853
R-squared	-0.098	-0.138	-0.170	0.039	0.027	0.012	0.016
AIC		25,620.61			26,373.48	13,174.73	14,059.26
BIC		26,065.13			26,654.23	13,303.53	14,189.08
RMSE	0.7728	0.7775	0.8261	0.7810	0.6968	0.6649	0.6725
AR(1)	54.09***	44.93***	21.10***	98.95***	46.72***	34.68***	92.48***

Nomenclature: PRICES: p1: oil, p2: gas, p3: gasoline, p4: electricity; COST SHARES: w1: oil, w2: gas, w3: gasoline, w4: electricity

Standard errors in parentheses/ RSME: (root mean square error)

AR(n) refers to the n(th) Wooldridge test for autocorrelation in panel data under the null of serial independence.

*** p<0.01, ** p<0.05, * p<0.1

Table No. 9
Translog Fuels' Demand Estimation By Fuel Portfolio Chilean
Manufacturing Firms – ENIA- 1998-2007

VARIABLES	PATTERN EOGGA			PATTERN EOG		PATTERN EG	PATTERN EO
	ln(O/E)	ln(G/E)	ln(GA/E)	ln(O/E)	ln(G/E)	ln(G/E)	ln(O/E)
lnp1p4	0.0186*** (0.00660)	0.00486 (0.00390)	-0.0172*** (0.00434)	-0.00847** (0.00366)	0.0153*** (0.00384)		0.0129*** (0.00428)
lnp2p4	0.00486 (0.00390)	-0.00104 (0.00383)	0.000586 (0.00283)	0.0153*** (0.00384)	-0.00889 (0.00566)	-0.00171 (0.00303)	
lnp3p4	-0.0172*** (0.00434)	0.000586 (0.00283)	0.0147*** (0.00480)				
lnoutput	0.0288*** (0.00511)	0.00311 (0.00397)	-0.0105*** (0.00322)	0.0123*** (0.00376)	-0.00494 (0.00477)	0.00147 (0.00429)	0.0192*** (0.00433)
lngasavail	-0.00426** (0.00171)	0.00163 (0.00132)	0.00607*** (0.00108)	0.00617*** (0.00134)	-0.00700*** (0.00170)	-0.000145 (0.00174)	0.00191 (0.00171)
D1999	0.0187*** (0.00687)	0.00723 (0.00537)	0.00122 (0.00438)	0.0273*** (0.00571)	0.00887 (0.00722)	0.0138** (0.00578)	0.0138** (0.00578)
D2000	0.0295*** (0.00683)	0.0211*** (0.00535)	-0.00112 (0.00435)	0.0387*** (0.00576)	0.0147** (0.00727)	0.0254*** (0.00570)	0.0254*** (0.00570)
D2001	0.00717 (0.00675)	0.0196*** (0.00525)	0.000342 (0.00426)	0.0386*** (0.00570)	0.00185 (0.00722)	0.0284*** (0.00580)	0.0284*** (0.00580)
D2002	0.00288 (0.00682)	0.0215*** (0.00531)	-0.00528 (0.00431)	0.0417*** (0.00560)	-0.0153** (0.00708)	0.0212*** (0.00587)	0.0212*** (0.00587)
D2003	0.0166** (0.00698)	0.0222*** (0.00541)	-0.00738* (0.00443)	0.0412*** (0.00565)	-0.00386 (0.00719)	0.0206*** (0.00608)	0.0206*** (0.00608)
D2004	0.0234*** (0.00699)	0.0216*** (0.00540)	-0.00950** (0.00445)	0.0338*** (0.00556)	-0.00204 (0.00713)	0.0175*** (0.00632)	0.0175*** (0.00632)
D2005	0.0325*** (0.00667)	0.0170*** (0.00515)	-0.0102** (0.00420)	0.0230*** (0.00535)	0.0218*** (0.00685)	0.0215*** (0.00604)	0.0215*** (0.00604)
D2006	0.0274*** (0.00695)	0.0167*** (0.00537)	-0.0146*** (0.00439)	0.0178*** (0.00551)	0.0309*** (0.00706)	0.0200*** (0.00634)	0.0200*** (0.00634)
D2007	0.0156 (0.0105)	0.00541 (0.00817)	0.00675 (0.00663)	0.0318*** (0.00834)	-0.00717 (0.0105)	0.0101 (0.0103)	0.0101 (0.0103)
Inv_Mills_Ratio_Term1	0.0669*** (0.0181)	-0.00465 (0.0141)	-0.0247** (0.0115)	0.0303* (0.0155)	-0.00455 (0.0198)	-0.00375 (0.0169)	0.0176 (0.0193)
Inv_Mills_Ratio_Term2	0.00316 (0.0294)	-0.0424* (0.0228)	-0.0354* (0.0185)	-0.0206 (0.0283)	-0.0589 (0.0360)	0.147*** (0.0427)	0.0584 (0.0421)
Inv_Mills_Ratio_Term3	0.0227 (0.0289)	0.0248 (0.0225)	0.0437** (0.0183)	0.00529 (0.0247)	0.0244 (0.0314)	-0.0469 (0.0847)	-0.191** (0.0962)
Inv_Mills_Ratio_Term4	-0.104*** (0.0354)	0.0422 (0.0275)	0.00533 (0.0223)	-0.00894 (0.0332)	0.0661 (0.0421)	-0.102 (0.0736)	0.130 (0.0903)
Constant	-0.0176*** (0.00497)	-0.0160*** (0.00386)	0.00420 (0.00314)	-0.0307*** (0.00429)	-0.00486 (0.00545)	-0.0187*** (0.00424)	-0.0180*** (0.00495)
Observations	4,231	4,231	4,231	5,92	5,92	6,517	6,864
R-squared	0.045	0.022	0.046	0.036	0.030	0.008	0.017
AIC		-31547.61		-24408.33		-11.488,68	-10346.01
BIC		31147.55		-24134.2		-11.359,82	-10216.17
RMSE	0.0911	0.0709	0.0575	0.0815	0.1034	0.0999	0.1134
AR(1)	47.55***	27.31***	38.48***	99.21***	60.55***	36.05***	10.44***

Nomenclature: PRICES: p1: oil, p2: gas, p3: gasoline, p4: electricity; COST SHARES: w1: oil, w2: gas, w3: gasoline, w4: electricity

Standard errors in parentheses/ RSME: (root mean square error)

AR(n) refers to the n(th) Wooldridge test for autocorrelation in panel data under the null of serial independence.

*** p<0.01, ** p<0.05, * p<0.1

From these results, it is interesting to highlight conclusions about the coefficients of the estimations for the different patterns and functional forms.

When estimating the linear logit model, the dependent variable is a logarithmic cost share ratio whereas the dependent variable for the translog model is simply the logarithmic cost share. Due to these differences in the way the dependent variables are constructed in both models, the goodness of fit statistics are not comparable between the two models. This fact has been reported by Jones (1995). However, there is an evident trend when comparing the results of both functional forms across the patterns of fuel portfolio: for both functional forms, the goodness of fit (measured by the Akaike and the Bayesian Information Criterion¹⁵) improves (lower AIC/BIC) as the pattern of fuel portfolio includes more types of fuels –even though the patterns with more fuel-types have more observations-.

The coefficients of the estimated parameters cannot be directly contrasted between functional forms either (for the same reason of the differences in the dependent variables). These coefficients do not represent elasticities, but they are used, as shown in equation (7), (8) and (9), to calculate own and cross price elasticities. Nevertheless, it is possible to evaluate the signs of the estimated coefficients and their significance levels:

- Most of the constructed variables of prices are significant in both models.
- The variable of output is significant and with the right sign in most of the cases, especially in linear logit model.
- The variable of gas availability is significant in some estimations and patterns; however, its sign is the expected sign and in other cases it is not. As described in section 3.2, this variable was constructed to show as a percentage that represented gas availability for specific regions and years. This variable had been used in aggregate studies for Chilean energy demand (Benavente et al, 2010). However, this variable has not been able to capture the same effect at the firm-level.
- Thus, to correct for changes of gas availability and other macro-economic changes that Chile has gone through in the period of study, it was crucial to control for temporal effects. In both estimations, most of the year dummies are significant at 1% level.
- Various terms from inverse mills ratio are significant. This is true for both models. This guarantees the ability of the instrument to correct for selection bias. It is worth to mention, that in some cases of endogeneity, such as this case of selection bias (omitted variable endogeneity) could be partially solved by the availability of panel data. However, in this particular case, when the estimations are performed by patterns, the ability to track when firms leave or enter in a pattern is lost. This is the reason why to correct for selection of patterns is relevant.

¹⁵ The AIC and BIC estimates show an expected distance between the fitted model and the unknown true mechanism that generated the observed data. Aike (1973) In this way, these criterions inform about how much respond to information (data-set) rather to randomness.

- Also, in the estimations, some dummies were included for outliers of prices, in order to control for some self-reported or entering data errors. (These coefficients have not been included in Tables 9 and 10 because of matters of space).
- Overall, fuel demand estimations for most of the patterns seem to have a good level of explanatory capacity, given the significance of the regressors, with the exception of the pattern Oil-Gas. For this pattern estimation, most of the explanatory variables are not significant, and this happens with both models. This could be related to the difficulty to capture at the micro-level the challenges of accessibility to gas that Chile experienced in the years 2003 – 2006. Such differences in gas shortages for several years will be captured mostly by the year dummies, but this might not be enough because at the firm level, there will be much more differentiation of gas availability depending on other factors, such as localization, negotiation capacity with distributors, among others.

The next Table No. 10 shows the estimated elasticities obtained for the linear logit and translog models, and compares the results between these two models, but also with the results from a previous aggregate study on price elasticities.

Table No. 10
Results from Elasticities Calculated for LLM & Translog &
Comparison with Aggregate Estimation

	LINEAR LOGIT					TRANSLOG					COMPARATIVE (++) AGGREGATE STUDY
	E	EO	EG	EOG	EOGGA	E	EO	EG	EOG	EOGGA	
Oil Consumption											
Own Price	-	-0.44	-	-0.70	-0.68	-	-0.45	-	-0.72	-0.66	-0.88
Gas	-	-	-	0.39	0.47	-	-	-	0.39	0.31	0.25
Gasoline	-	-	-	-	0.45	-	-	-	-	0.14	0.14
Electricity	-	0.50	-	0.28	0.12	-	0.51	-	0.29	0.25	0.13
Gas Consumption											
Own Price	-	-	-0.68	-0.87	-0.92	-	-	-0.67	-0.85	-0.87	-0.87
Oil	-	-	-	0.25	0.24	-	-	-	0.25	0.16	0.18
Gasoline	-	-	-	-	0.20	-	-	-	-	0.14	0.11
Electricity	-	-	0.34	0.19	0.08	-	-	0.33	0.18	0.13	0.13
Gasoline Consumption											
Own Price	-	-	-	-	-0.88	-	-	-	-	-0.76	-0.93
Oil	-	-	-	-	0.23	-	-	-	-	0.07	0.04
Gas	-	-	-	-	0.19	-	-	-	-	0.14	0.04
Electricity	-	-	-	-	0.06	-	-	-	-	0.13	0.06
Electricity Consumption											
Own Price	-0.36 (+)	-0.50	-0.34	-0.47	-0.26	-0.36 (+)	-0.51	-0.34	-0.48	-0.52	-0.4
Oil	-	0.43	-	0.45	0.21	-	0.44	-	0.48	0.44	0.66
Gas	-	-	0.67	0.48	0.25	-	-	0.68	0.46	0.43	0.58
Gasoline	-	-	-	-	0.22	-	-	-	-	0.48	0.68

* Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

(+) IN this case where there was only one factor input, this elasticity corresponds to a log-linear model for only firms that consume electricity.

(++) The elasticities from this column correspond to an aggregate study of fuels's price elasticities for Chile (Benavente et al, 2010)

- These results show that not all the aggregate price elasticities are greater than micro-data estimates, as Steinbuks (2010) reports as a usual result from studies that compare aggregate and disaggregates energy price elasticities.
- Moreover, results for elasticities with both functional forms are very robust for all patterns (in both, own and cross price elasticities), with the exception of pattern

EOGGA, where there are significant differences (5% -25%) in the levels (although not in trends) of elasticities.

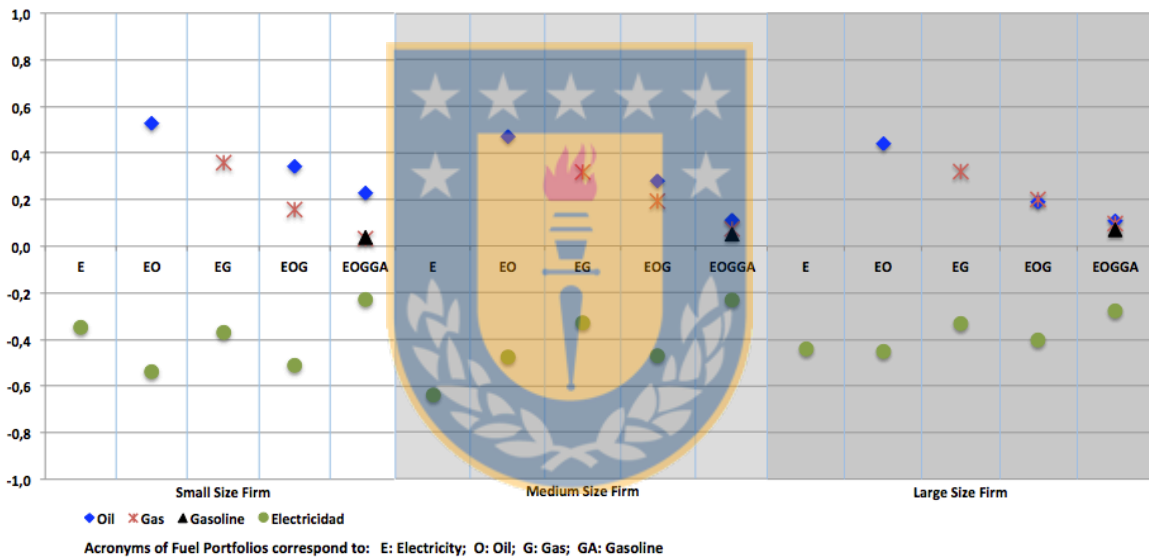
- For the pattern EOGGA, the Linear Logit indicates lower price responses of the different fuels to electricity price (including electricity own price elasticity), and larger cross and own price elasticities for prices of oil, gas and gasoline.
- Among fuels, electricity consumption is the most inelastic to price changes of other fuels. Although its cross price elasticity increases as the portfolio/pattern includes less fuels. The same happens with other fuels, their cross price elasticity increases as the fuel portfolio becomes more restrained.
- Electricity own price elasticity is within -0,30 and -0,50. Oil own price elasticity is around -0.70, with the exception of firms that count with the type of fuel combination of oil and electricity; in this case, oil own price elasticity drops to -0,45. Gas own price elasticity is within -0.70 and -0.95. Gasoline own price elasticity is within -0,74 and -0,85.
- Elasticity among fuels is also found to be low, in general, there are no cases of fuels' substitution. Throughout patterns, gas is the one that reaches the highest level of price response to other fuels' prices. The highest cross price elasticity is found for gas consumption as reaction to electricity price, which could reach 0.68 in the case of only two fuels portfolio.
- Gas responses to oil price are between 0.30 – 0.45. Oil responses to other fuels' prices are also low, about 0.20, and about 0.40 for electricity in the cases of fewer fuels combination.
- Electricity consumption is the most inelastic with responses as low as about 0.10 to gasoline price and about 0.20 – 0.30 for oil and gas prices.
- The response of gasoline to other fuels' prices is not clear. In particular for this fuel there are incongruences between the two functional forms. However, this is between 14% - 45% for oil, 14% - 20% for gas and between 22% - 48% for electricity price.

As explained in section 4.1, given that in the fixed effects estimation we do not see the impact of variables that are invariant in time, an additional analysis has been made for firm-size categories and particular industries. This analysis is presented in the following subsections.

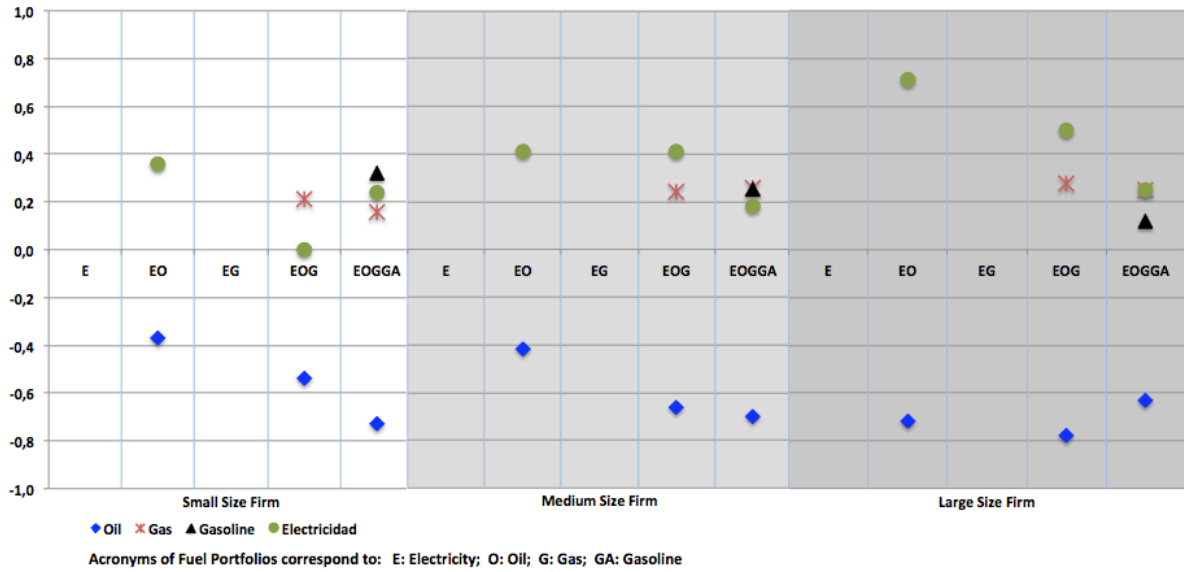
5.2 Analysis by Firm Size

The following Graphs No. 1, 2, 3 and 4 show the elasticities estimated by pattern for three firm-size categories (small, medium and large firm). The elasticities shown in these graphs correspond to Linear Logit estimations. The decision was to include in this graphical analysis only the Linear Logit estimations, because, as shown in Table No. 10, the elasticities for almost all patterns are very similar between the two functional forms –with the exception of the EOAGGA pattern- [this can also be seen in Annex A.7], and because in the literature it is generally the Linear Logit the functional form that violates fewer times concavity conditions [Considine and Mount (1984); Jones (1995), Asche and Salvanes (1996), and Urga and Walters (2003)].

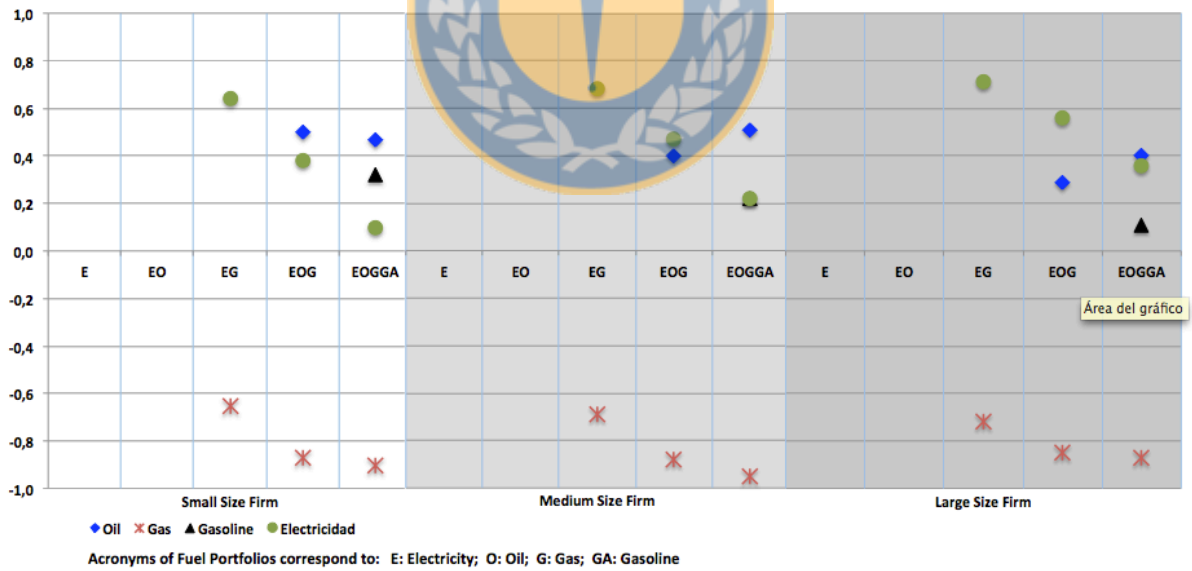
Graph No. 1
Electricity Own & Cross Price Elasticities
 -By Fuel Portfolio and Firm Size-



Graph No. 2
Oil Own & Cross Price Elasticities
 -By Fuel Portfolio and Firm Size-



Graph No. 3
Gas Own & Cross Price Elasticities
 -By Fuel Portfolio and Firm Size-



Graph No. 4
Gasoline Own& Cross Price Elasticities
 -By Fuel Portfolio and Firm Size-



From these graphs, the following conclusions are worth to highlight:

- The differences in elasticities differ mostly by pattern more than by firm size.
- For all firm sizes, electricity cross price elasticity with the other three fuels (oil, gas and gasoline) decreases when the fuel portfolio includes more fuel options.
- Firm responses to fuel consumption do seem to matter when measuring elasticities. As firm size increases:
 - The elasticity of demand for oil with respect to electricity price and oil own price increases.
 - The elasticity of demand for gas cross with respect to electricity price increases.
 - The elasticities of demand for oil and gas cross price elasticity with respect to gasoline price decreases.
 - The elasticity of demand for gasoline with respect to electricity and gas prices increases.
 - The elasticity of demand for gasoline with respect to oil price and its own price decreases.
 - The elasticity of demand for electricity remains almost unchanged in different firm sizes. Electricity own price elasticity varies in changes as firm size increases, depending on the fuel portfolio.

This means that as a firm is larger its response in oil consumption with respect to oil and electricity prices is greater. The same happens with gas and gasoline consumption as a response to electricity price. On the other hand, as a firm is larger their oil and gas consumption as a

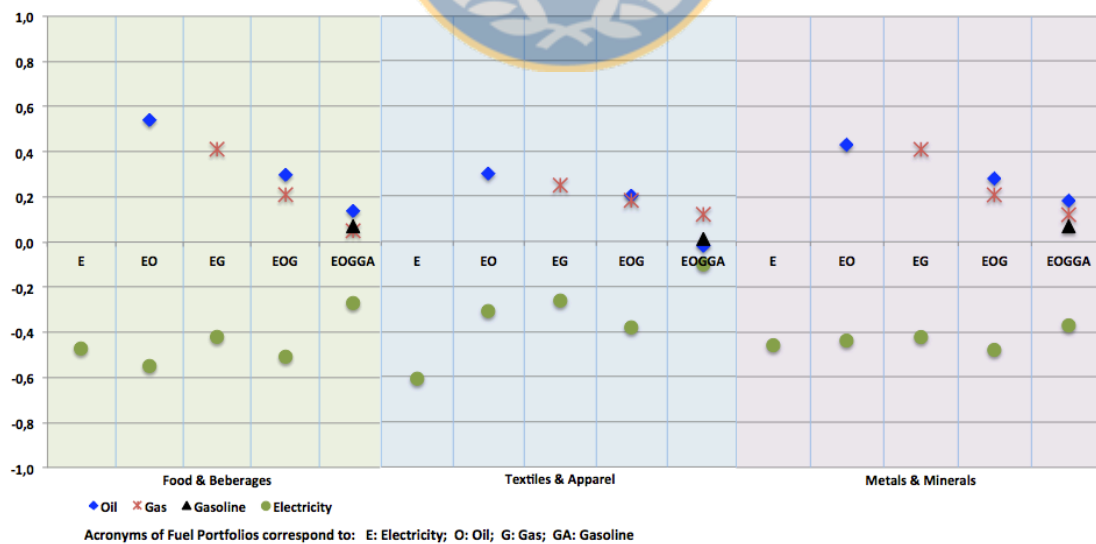
response to positive changes in gasoline price decreases, and their gasoline consumption as a response to oil and its own price decreases.

5.3 Analysis by Industry

The following Graphs No. 4, 5 and 6 show the elasticities estimated for three particular industry sectors: food & beverages, textiles and apparel and metals and minerals. The first manufacturing sector, food & beverages represents 31,7% of the sample size; the manufacturing sectors of minerals, basic metals and fabricated metals represent together 14,8% of the sample size, and the manufacturing sectors of textiles, apparel and leather represent together 13,6% of the sample size. [Refer to Table 2]

As in the analysis by size, the following graphs correspond to Linear Logit estimations. Nevertheless, Annex A.7 shows a comparison of the estimation of both functional forms for these three manufacturing sectors. Most of the results from the translog and linear logit forms are similar, especially in trends and with some mild differences in levels; however, major differences are found for the elasticities of demand of gasoline.

Graph No. 5
Electricity Own & Cross Price Elasticities
 -By Fuel Portfolio and Manufacturing Sector-

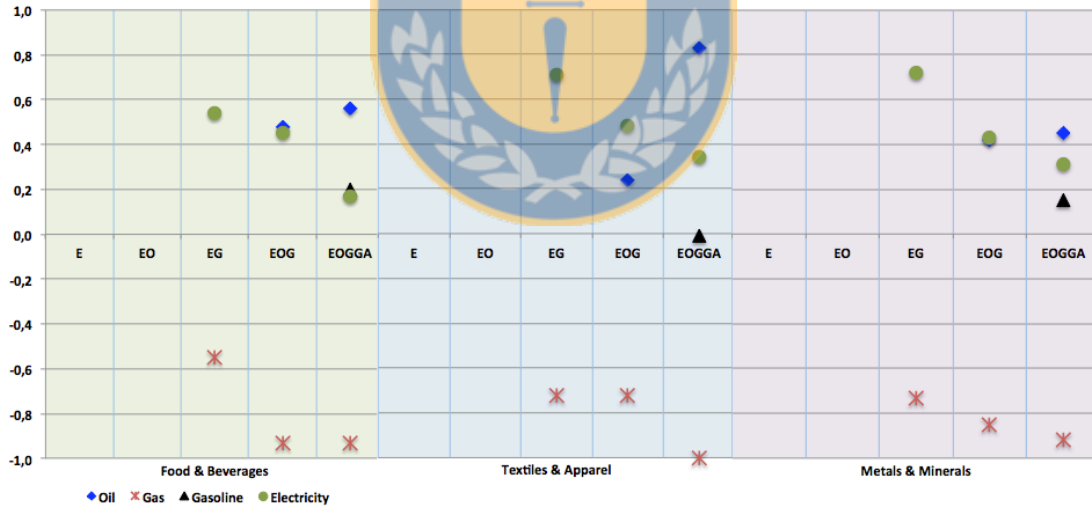


Graph No. 6
Oil Own & Cross Price Elasticities
 -By Fuel Portfolio and Manufacturing Sector-



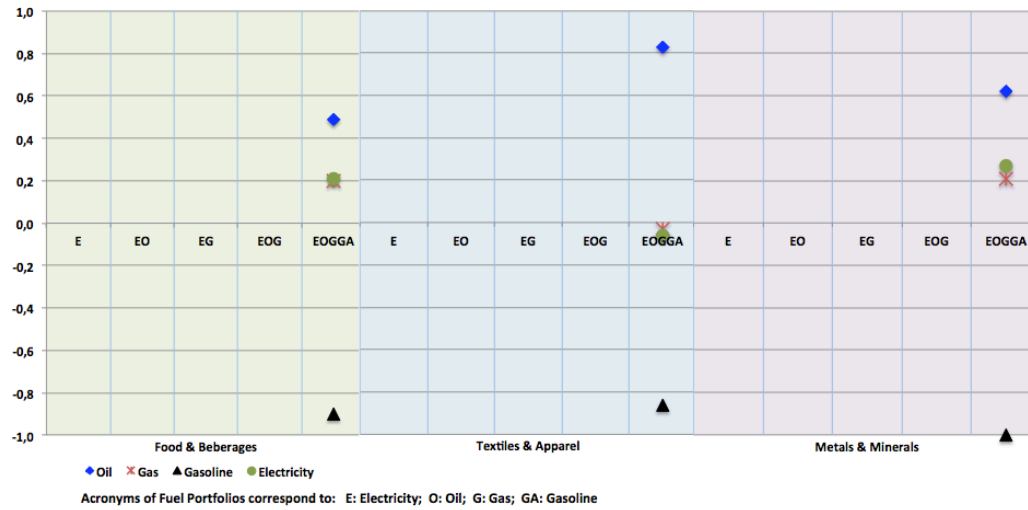
Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

Graph No. 7
Gas Own & Cross Price Elasticities
 -By Fuel Portfolio and Manufacturing Sector-



Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline

Graph No. 8
Gasoline Own & Cross Price Elasticities
 -By Fuel Portfolio and Manufacturing Sector-



From these graphs, it is possible to highlight that as these three industries vary:

- Cross price elasticities are still decreasing as the pattern of fuel portfolio diversifies. Electricity is still the most inelastic fuel in these industries, while gas and gasoline the most elastic.
- The sector of minerals and metals, electricity own price elasticity maintains a similar level among patterns, while in the sectors of textiles and food & beverages electricity own price elasticity varies considerably among patterns. The sector of textiles and apparel show the lowest elasticity of demand for electricity with respect to oil price.
- The fuel that has the highest (~0,5%) cross price elasticity for electricity consumption is oil, and this is found in the sector of food and beverages and in the fuel portfolio of electricity and oil. In the sector of metals and minerals, the highest cross price elasticity for electricity consumption is in oil and gas prices and is about 0,4%.
- In the case of oil consumption, it is still observed a low level or capacity of fuel substitution across industries. However, oil own price elasticity is higher across industries, especially for the patterns of three and four fuels.
- Elasticity of demand for gas with respect to electricity price is higher in the fuel combination of oil and gas and for the sectors of metals and minerals and textiles. Elasticity of demand for gas with respect to oil price is particularly high in the EOGGA pattern and for the textiles and apparel sector.
- Gas own price elasticity is also very high, especially for the industries in analysis and for the patterns of three and four fuels combination.
- Elasticities of gas, oil and electricity are robust for both functional forms; nevertheless, results of gasoline elasticities differ between the two functional forms, and this was evident

especially in the analysis by industry type. Then conclusions on elasticities of demand for gasoline are not robust. [Refer to Annex A.7]



VI. CONCLUSIONS

6.1 Methodological:

- Micro-data analysis entails difficulties in terms of data management and zero consumption problem; however, it provides opportunities to capture responses at the firm-level and to subdivide the sample for more detailed analysis, for example by fuel-portfolio, firm-size or by industrial sector.
- Selecting a suitable panel data structure allows meeting the objective of capturing firm-level responses. Using a fixed-effects –within estimator- can help to meet this purpose, especially if explanatory variables are related to the error term. Nevertheless, once selecting a within estimator, the ability to capture the influence of time-invariant variables is lost. If the sample is large enough such variables could be further analyzed by subdividing the sample.
- When taking the strategy to subdivide the sample by factor input portfolios as an approach to the zero-consumption problem, it is recommendable to evaluate, and correct if possible, for selection bias. This procedure allows including an error correction term in the estimation, which is constructed with the probabilities for selecting such portfolio. If the correction terms are significant in the final demand estimation, it is an assertion that such correction was necessary for obtaining unbiased results.
- The selection of a functional form for conditional factor demand analysis is not trivial. Embedded in this decision is the ability to incorporate micro-economic concepts of non-separability among factors of production and cost minimization. CES flexible forms, such as the translog function, and other functional forms like the Linear Logit, are effective for incorporating non-separability; however, these forms violate curvature conditions over some part of the sample. According to the literature, the Linear Logit model violates this condition less frequently than the translog function. Both functional forms were programmed and estimated for this study. Results are robust for all estimations, with the exception of some differences in level (but not in trends) for the portfolio with four fuels: EOGGA and in estimated gasoline elasticities.

6.2 Policy Related:

➤ **Substitutability of fuels in Chilean manufacturing firms:**

The fuels analyzed in this study: electricity, oil, gas and gasoline, which are the fuels most widely used in Chilean manufacturing firms, are complements and not substitutes. In general, cross price elasticities are low among all fuels. The highest cross price elasticity is found for gas consumption with respect to electricity price (0.68), in the case of two fuels portfolio –EG-. In terms of own price elasticities, electricity is the most inelastic fuel, while gas and gasoline are the most elastic. Furthermore, cross price elasticities generally decrease as the fuel portfolio is diversified, while own price elasticities generally increase in more diversified portfolios. This pattern is maintained in the different firm sizes and in the different fuels of oil, gas and gasoline. Interestingly, for electricity this pattern is maintained for cross price elasticities, but it is not for electricity's own price elasticity.

➤ **Comparison of Micro-data Estimates**

Even though the hypothesis was that once the estimation was controlled by fixed effects, price elasticities would be lower than those predicted in previous aggregate studies, results show that micro-data estimations differ by fuel portfolio, some results are lower than aggregate estimations while others are higher. Thus, these results show that not all the aggregate price elasticities are greater than micro-data estimates, as Steinbuks (2011) reports as a usual result from studies that compare aggregate and disaggregate energy price elasticities. The differences in elasticities are marked mostly by pattern of fuel portfolio; even more influenced by pattern than by firm size or type of industry. This could be related to the firm access to technology that allows them to respond more rapidly to prices and adapt new types and/or quantity of fuels (access to flexible technology or fixed technology which influences their ability to accommodate or use one fuel or more than one fuel).

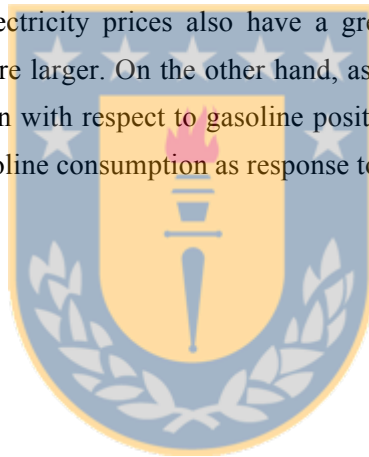
➤ **Explanatory Variables & Variable for Technology Change**

The model set-up in this study incorporates the main explanatory variables from the micro-economic conceptual foundation. However, more firm-characteristics variables could have been included if data would be available. The variables on number of workers and capital stock (when these variables are not incorporated in price units) proved to be not significant in the estimation. However, if available, it would have been convenient to include in the estimation other variables, especially variable that would

capture technology change. Actually, one of the challenges in energy modeling has been precisely to capture technology change. In the literature, it is commonly found that researchers use a time trend (especially in aggregate studies); however, the applicability of using such variable as proxy for technology transformation has generally been debated and it has been seen as not very appropriate. The Office of Industrial data at the Chilean National Institute of Statistics could analyze the possibility of including questions to evaluate the level of technology and innovation of firms when they evaluate and redefine the ENIA survey design.

➤ **Nuances in Price Elasticities by Firm-Size**

While, Chile diversifies its energy matrix, it needs to take into account some of the nuances of responses of interfuel substitution for their manufacturing firms. Policies that are directed to changes in oil consumption will need to take into account that as a firm is larger, its response in oil consumption to oil and electricity price is greater. Positive changes in electricity prices also have a greater effect in gas and gasoline consumption as firms are larger. On the other hand, as a firm is smaller its response in oil and gas consumption with respect to gasoline positive price changes is greater. The same happens with gasoline consumption as response to oil price and its own price.



6.3 Further research

➤ **Dynamic Model**

The model presented in this study is a static model. The main reasons for estimating a static model were related to programmatic limitations as well as number of observations that would be lost in a dynamic estimation when counting with an unbalanced panel. The programmatic limitation was related to the ability to estimate a fixed effects model for a seemingly unrelated regression. A common solution to estimate a fixed effects model for a dynamic panel is with the Arellano and Bond estimator; however the programming for this estimator has been developed for one-equation cases. Implementing an Arellano and Bond estimator with SUREG for a multi-equation case would require developing programmatically such econometric development itself. In regards to the second topic on attrition, by using lagged variables, the sample size would have been significantly reduced. For these reasons, it was the best option for this thesis to estimate a static model. Nevertheless, it is acknowledged the advantages (especially for policy recommendation) and accuracy of a dynamic model. As it can be observed in Tables No. 8 and 9, despite the inclusion of the time dummies, evidence of serial correlation is present in the equation residuals. This is mostly related to the fact that these are static estimates. Generally dynamic estimations perform better in terms of correcting for serial correlation and in the overall fit than static versions.

➤ **Discrete-Continuous choice model**

In this study, the selected strategy to deal with the zero consumption problem was to implement the estimations by patterns of fuel-portfolios and to correct for selection bias. While this strategy is convenient in the sense of analyzing and contrasting elasticities of firms with different technologies, this strategy can be time demanding because of the number of estimations to be programmed and performed for every input-portfolio. Moreover, and as it was explained in section 3, this strategy does not solve entirely the problem of zero consumption as firms can change their fuel-portfolio throughout the observed points in time and a new strategy, such as the selection bias correction will be necessary. Therefore, it might be convenient to analyze another model that could incorporate quantity and quality decision-making modeling at once. Such a model could be a Discrete-Continuous model, such as the Multiple Continuous-Discrete Extreme Value Model –MCDEV- developed by Bhat (2007). This model has been implemented for demand analysis from the consumer perspective. An extrapolation of such case for demand analysis from the producer perspective would be a very interesting area to test and develop.

➤ **Global Curvature Conditions, Functional Form and FIML**

As explained in section 2.2, other studies have reported that the functional forms of Linear Logit and Translog still violate curvature conditions. Another CES flexible functional form is the Normalized Quadratic form, and for this form further parameter restrictions have been analyzed to impose global curvature conditions. Studies that model with this functional form use the Full Information Maximum Likelihood estimator and the TPS program is commonly used.

➤ **Energy Substitution with Capital and Labor Analysis**

Substitution elasticities with other production factors, such as labor and capital is an area that would also be very interesting to analyze for the Chilean manufacturing case. For this analysis prices of labor and capital would be required and possibly a nested model -to distinguishes the differences in substitutability between fuels and non-fuels factor inputs- would be a better fit.



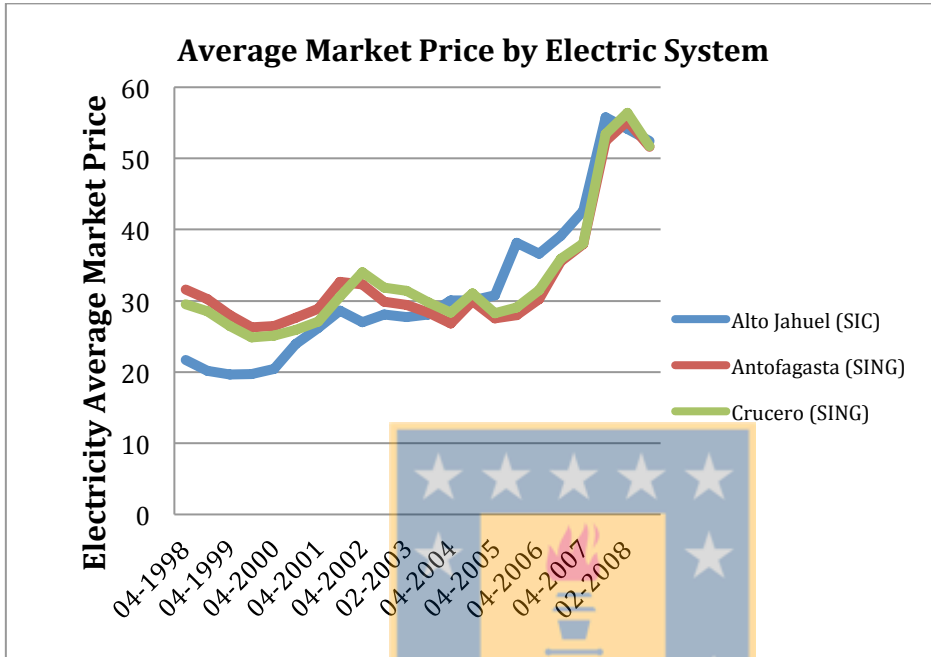
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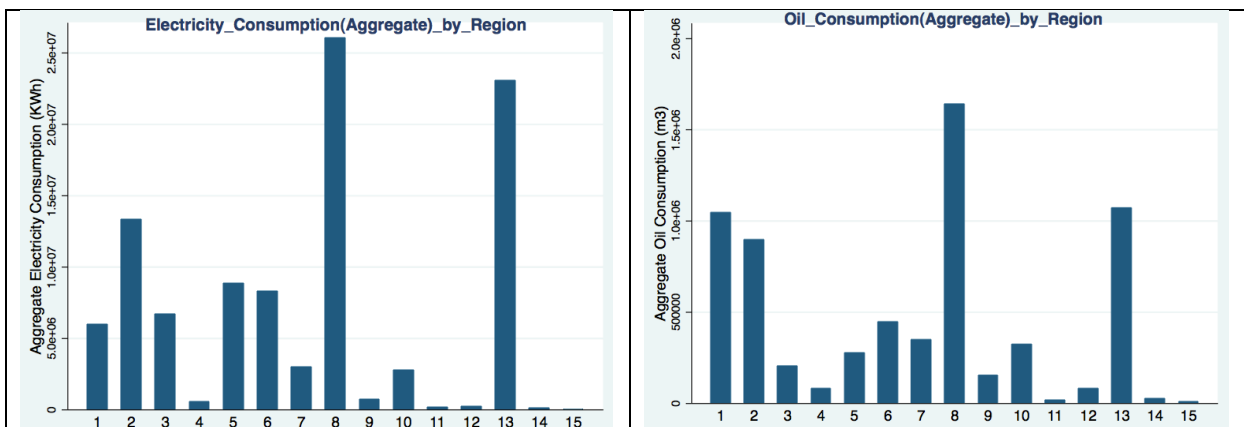
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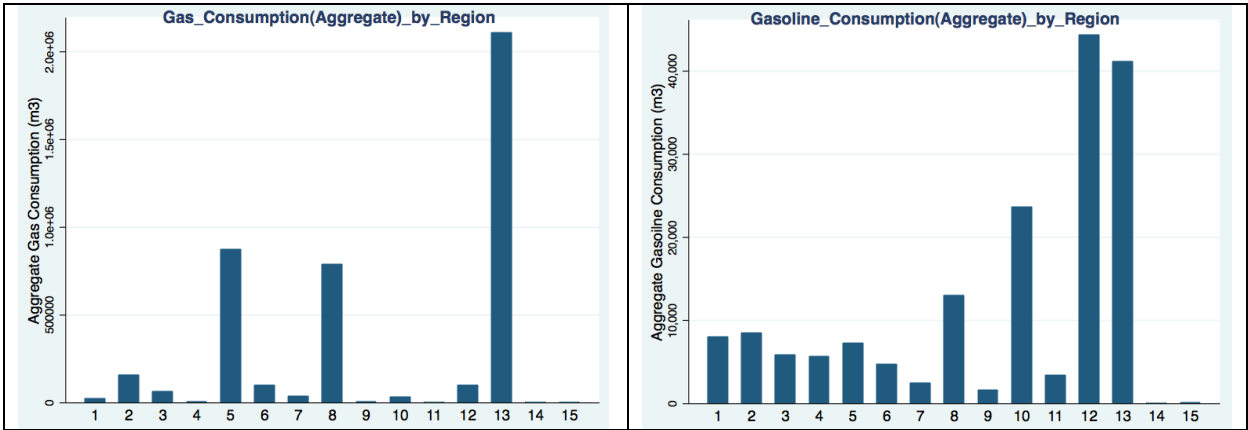
ANNEXES

A.1 Electricity Average Market Price in Retail Market for Different Electric Systems

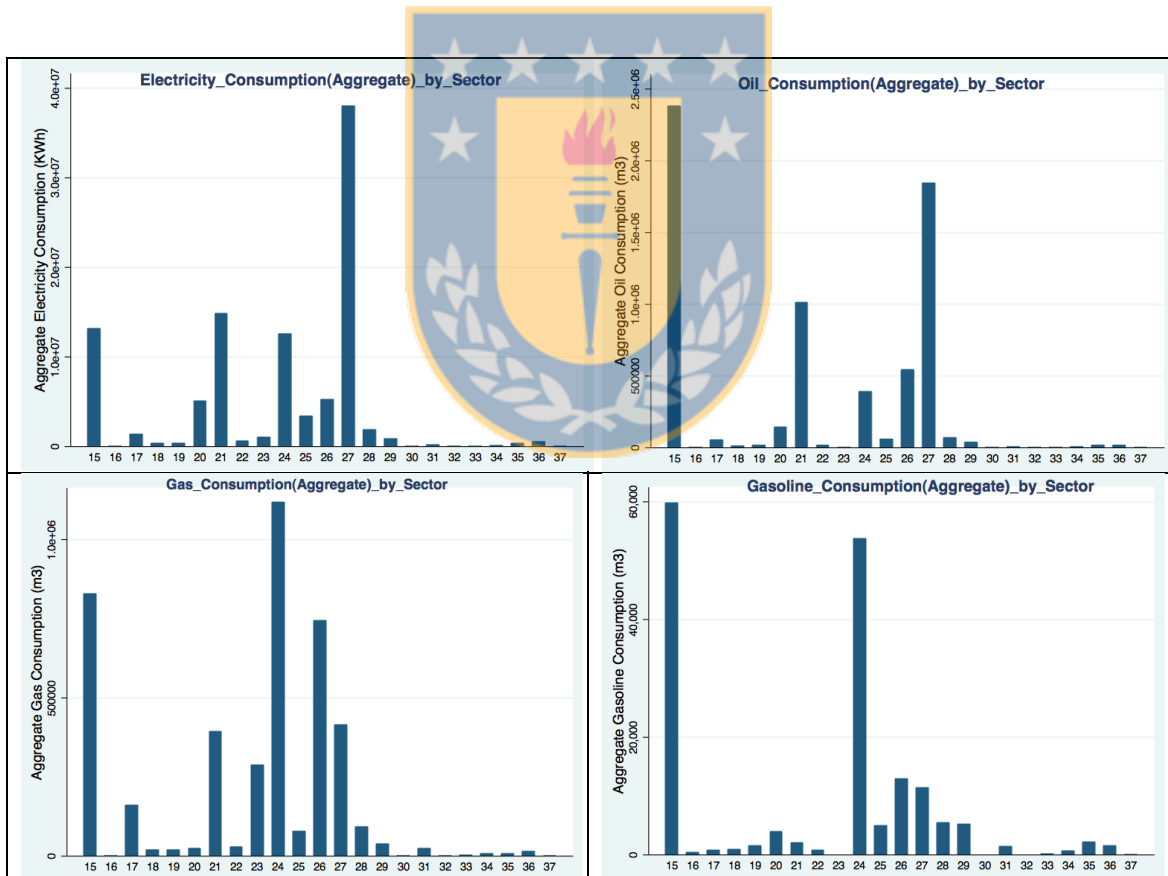


A.2 Aggregate Fuel Consumption by Region





A.3 Aggregate Fuel Consumption per Industrial Sector



A.4 Comparison of Panel Structures Estimations (Pattern EOGGA with Linear Logit)

VARIABLES	Pooled ($\alpha_i = \alpha$)			Fixed Effect (α_i)			Between Effect		
	PATTERN EOGGA			PATTERN EOGGA			PATTERN EOGGA		
	ln(O/E)	ln(G/E)	ln(GA/E)	ln(O/E)	ln(G/E)	ln(GA/E)	ln(O/E)	ln(G/E)	ln(GA/E)
ln_output	-0.0721* (0.0385)	-0.0993** (0.0415)	-0.308*** (0.0463)	0.00494 (0.0538)	-0.0391 (0.0541)	-0.180*** (0.0586)	-0.0201 (0.0587)	-0.0967 (0.0653)	-0.303*** (0.0727)
ln_gasavail	-0.311 (0.197)	0.0507 (0.212)	-0.456* (0.237)	0.0735 (0.0528)	0.143*** (0.0531)	0.0578 (0.0577)	0.00290 (0.0381)	0.0309 (0.0421)	0.0239 (0.0472)
ln_diremploy	-0.0669 (0.0733)	0.102 (0.0790)	0.208** (0.0883)	0.108* (0.0570)	0.0419 (0.0573)	0.123** (0.0622)	-0.309*** (0.116)	-0.0839 (0.129)	-0.0394 (0.144)
ln_capitalStck	-0.288*** (0.0276)	-0.331*** (0.0298)	-0.347*** (0.0333)	0.0313 (0.0337)	-0.0503 (0.0339)	0.0614* (0.0368)	-0.321*** (0.0430)	-0.362*** (0.0480)	-0.387*** (0.0533)
w2lnp1p4	-1.280*** (0.123)			-0.748*** (0.0887)			-4.088*** (0.373)		
w3lnp1p4	-1.415*** (0.192)			-0.666*** (0.135)			0.0996 (0.666)		
w1w4lnp1p4	0.423*** (0.0719)			0.503*** (0.0467)			0.557*** (0.126)		
w2lnp2p4	-1.243*** (0.143)		-0.624** (0.262)	-0.843*** (0.105)		-0.528*** (0.168)	1.260*** (0.353)		0.970** (0.461)
w3lnp3p4	-0.732*** (0.186)	-1.477*** (0.275)		-0.757*** (0.141)	-0.818*** (0.207)		-1.852*** (0.578)	-1.600*** (0.551)	
w1lnp2p4		-1.280*** (0.123)			-0.748*** (0.0887)			-0.518 (0.322)	
w3lnp2p4		-0.594** (0.291)			-0.497** (0.209)			-0.312 (0.600)	
w2w4lnp2p4		0.456*** (0.0705)			0.408*** (0.0428)			0.768*** (0.123)	
w1lnp1p4		-0.669*** (0.162)	-0.366 (0.250)		-0.0229 (0.109)	0.000226 (0.161)		-1.524*** (0.385)	0.274 (0.567)
w1lnp3p4			-1.415*** (0.192)			-0.666*** (0.135)			-2.145*** (0.457)
w2lnp3p4			-1.907*** (0.229)			-0.638*** (0.157)			-3.537*** (0.414)
w3w4lnp3p4			0.534*** (0.0770)			0.587*** (0.0492)			0.595*** (0.137)
d2001	1.670 -1.453	-0.637 -1.567	3.219* -1.751	-0.0562 (0.0540)	0.0266 (0.0542)	-0.135** (0.0588)			
d2002	1.742 -1.411	-0.571 -1.522	3.245* -1.701	0.188*** (0.0603)	0.159*** (0.0604)	-0.130** (0.0661)			
d2003	1.996 -1.389	-0.379 -1.498	3.403** -1.674	0.314*** (0.0669)	0.334*** (0.0664)	-0.0848 (0.0731)			
d2004	2.155 -1.352	-0.188 -1.459	3.503** -1.629	0.412*** (0.0698)	0.365*** (0.0699)	-0.171** (0.0755)			
d2005	2.140* -1.266	-0.0947 -1.366	3.222** -1.526	0.431*** (0.0774)	0.359*** (0.0775)	-0.272*** (0.0839)			
d2006	2.408** -1.218	0.0767 -1.314	3.337** -1.468	0.671* (0.357)	1.001*** (0.359)	-0.249 (0.390)			
Constant	6.127** -2.435	7.642*** -2.625	5.544* -2.934	-0.187 (0.252)	0.280 (0.253)	-0.0355 (0.274)	9.039*** -1.636	8.551*** -1.824	12.57*** -2.028
Observations	3,385	3,385	3,385	3,043	3,043	3,043	1,254	1,254	1,254
R-squared	-0.155	-0.432	-0.303	-0.074	-0.145	-0.137	-0.191	-0.491	-0.331

Nomenclature: PRICES: p1: oil, p2: gas, p3: gasoline, p4: electricity; COST SHARES: w1: oil, w2: gas, w3: gasoline, w4: electricity

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

A.5 Percentages & Number of Observations of Firms that Keep the Same Pattern

frequency
row percentage

pattern	Number_Years_Firm_Keeps_Pattern										Total
	1	2	3	4	5	6	7	8	9	10	
E	1,661 13.83	1,664 13.85	1,917 15.96	1,256 10.46	1,340 11.15	1,206 10.04	903 7.52	800 6.66	486 4.05	780 6.49	12,013 100.00
EO	1,029 12.95	1,188 14.95	981 12.35	1,192 15.00	840 10.57	708 8.91	574 7.22	568 7.15	405 5.10	460 5.79	7,945 100.00
EG	901 11.88	928 12.24	1,062 14.01	972 12.82	825 10.88	798 10.52	574 7.57	472 6.23	540 7.12	510 6.73	7,582 100.00
EOG	948 13.58	984 14.10	987 14.14	1,084 15.53	725 10.39	564 8.08	497 7.12	440 6.30	450 6.45	300 4.30	6,979 100.00
EOGGA	593 12.29	636 13.18	735 15.24	732 15.17	480 9.95	360 7.46	420 8.71	304 6.30	324 6.72	240 4.98	4,824 100.00
Total	5,132 13.04	5,400 13.73	5,682 14.44	5,236 13.31	4,210 10.70	3,636 9.24	2,968 7.54	2,584 6.57	2,205 5.60	2,290 5.82	39,343 100.00



A.6 Linear Logit Fuels Demand Estimation Sample of Firms that keep Pattern More than 7 years

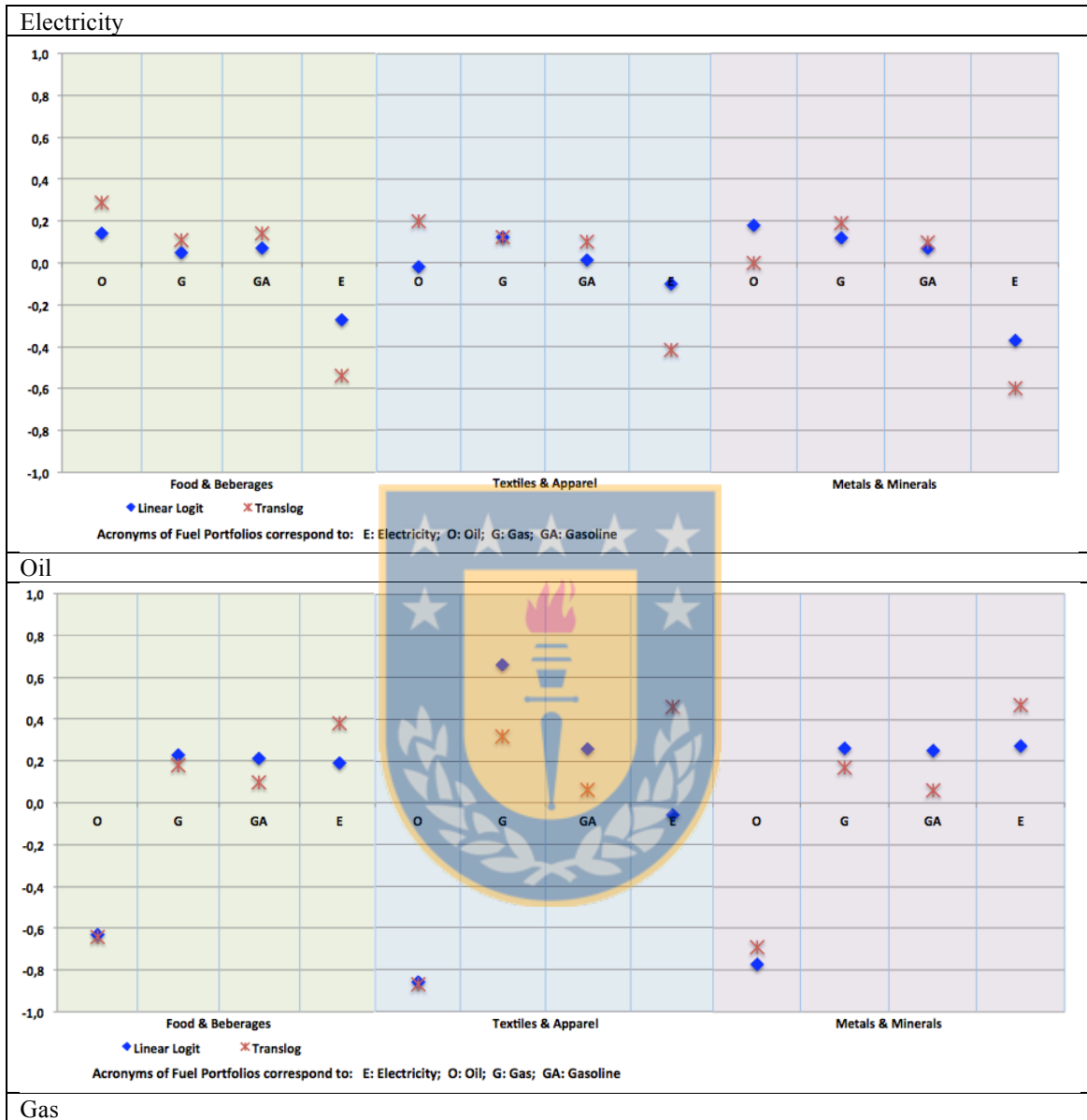
VARIABLES	PATTERN EOGGA			PATTERN EOG		PATTERN EG	PATTERN EO
	ln(O/E)	ln(G/E)	ln(GA/E)	ln(O/E)	ln(G/E)	ln(G/E)	ln(O/E)
lnoutput	0.0744 (0.0851)	0.104 (0.0858)	-0.00992 (0.0881)	-0.330*** (0.0760)	0.182*** (0.0631)	0.0424 (0.0533)	0.0594 (0.0481)
lngasavail	-0.0545 (0.0425)	-0.0246 (0.0427)	0.0166 (0.0440)	0.0309 (0.0754)	0.0744 (0.0626)	0.0674 (0.0904)	0.00180 (0.0341)
w1lnp1p4		-0.320** (0.162)	-0.504** (0.205)		0.577*** (0.138)		
w1lnp2p4		-0.758*** (0.129)			-0.554*** (0.122)		
w1lnp3p4			-0.424** (0.167)				
w1w4lnp1p4	0.377*** (0.0694)			0.0233 (0.0545)			0.0687 (0.0456)
w2lnp1p4	-0.758*** (0.129)			-0.554*** (0.122)			
w2lnp2p4	-0.772*** (0.152)		-0.466** (0.208)	0.514*** (0.129)			
w2lnp3p4			-0.819*** (0.194)				
w2w4lnp2p4		0.298*** (0.0618)			-0.0396 (0.0420)	0.0357 (0.0374)	
w3lnp1p4	-0.424** (0.167)						
w3lnp2p4		-0.400* (0.224)					
w3lnp3p4	-1.159*** (0.196)	-1.292*** (0.246)					
w3w4lnp3p4			0.433*** (0.0682)				
MD1999	0.290** (0.120)	0.128 (0.123)	0.152 (0.125)	0.185 (0.121)	0.222** (0.100)	0.109 (0.0781)	0.136 (0.0884)
MD2000	0.412*** (0.136)	0.364*** (0.139)	0.326** (0.143)	0.598*** (0.158)	0.447*** (0.131)	0.268*** (0.0922)	0.389*** (0.108)
MD2001	0.0459 (0.169)	0.161 (0.171)	0.0720 (0.176)	0.712*** (0.225)	0.567*** (0.186)	0.216 (0.133)	0.486*** (0.161)
MD2002	-0.108 (0.202)	0.0524 (0.203)	-0.180 (0.210)	0.656** (0.279)	0.714*** (0.230)	0.174 (0.164)	0.520*** (0.201)
MD2003	0.0963 (0.222)	0.222 (0.223)	-0.124 (0.233)	0.897*** (0.323)	0.835*** (0.267)	0.151 (0.197)	0.628*** (0.240)
MD2004	0.122 (0.245)	0.304 (0.246)	-0.0983 (0.258)	1.278*** (0.366)	0.817*** (0.303)	0.139 (0.222)	0.719*** (0.274)
MD2005	0.255 (0.263)	0.346 (0.264)	-0.0589 (0.274)	1.820*** (0.402)	0.813** (0.333)	0.161 (0.244)	0.784*** (0.303)
MD2006	0.186 (0.300)	0.123 (0.301)	-0.453 (0.313)	2.051*** (0.456)	0.770** (0.377)	0.152 (0.276)	0.861** (0.343)
MD2007	-0.390 (0.435)	-0.404 (0.436)	-0.765* (0.451)	2.393*** (0.694)	0.871 (0.574)	0.477 (0.683)	0.680 (0.456)
Inv_Mills_Ratio_Term1	4.326*** (0.804)	2.359*** (0.813)	3.446*** (0.838)	4.062*** (0.838)	1.262 (0.838)	0.478 (0.838)	0.455 (0.838)
Inv_Mills_Ratio_Term2	-3.734*** (0.973)	-4.284*** (0.980)	-5.453*** (1.010)	0.718 (1.020)	-1.189 (0.845)	-0.278 (0.807)	-0.576 (0.963)
Inv_Mills_Ratio_Term3	-0.610 (1.045)	1.629 (1.049)	0.522 (1.084)	-4.564*** (1.209)	1.199 (1.001)	-0.0819 (2.023)	4.754* (2.520)
Inv_Mills_Ratio_Term4	-1.463 (1.452)	-0.707 (1.462)	0.454 (1.511)	-3.207** (1.487)	-2.660** (1.231)	-0.168 (2.019)	-4.552** (2.251)
Constant	-0.0125 (0.0240)	-0.0176 (0.0242)	-0.0137 (0.0248)	0.00287 (0.0226)	-0.0100 (0.0187)	0.00312 (0.0156)	0.00375 (0.0157)
Observations	1,288	1,288	1,288	1,616	1,616	1,968	1,982
R-squared	-0.017	-0.112	-0.099	0.090	0.051	0.015	0.036

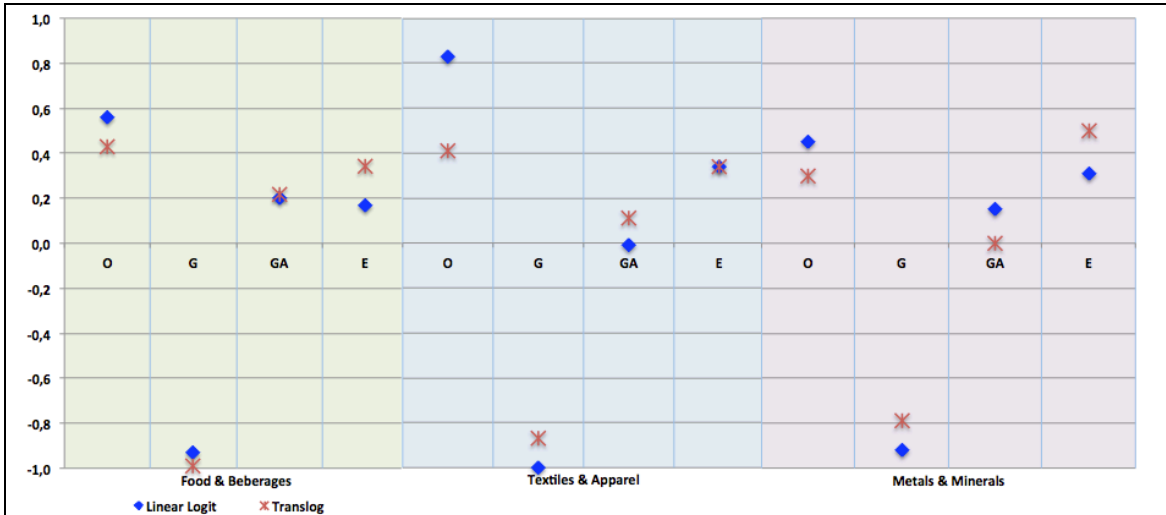
Nomenclature: PRICES: p1: oil, p2: gas, p3: gasoline, p4: electricity; COST SHARES: w1: oil, w2: gas, w3: gasoline, w4: electricity

Standard errors in parentheses

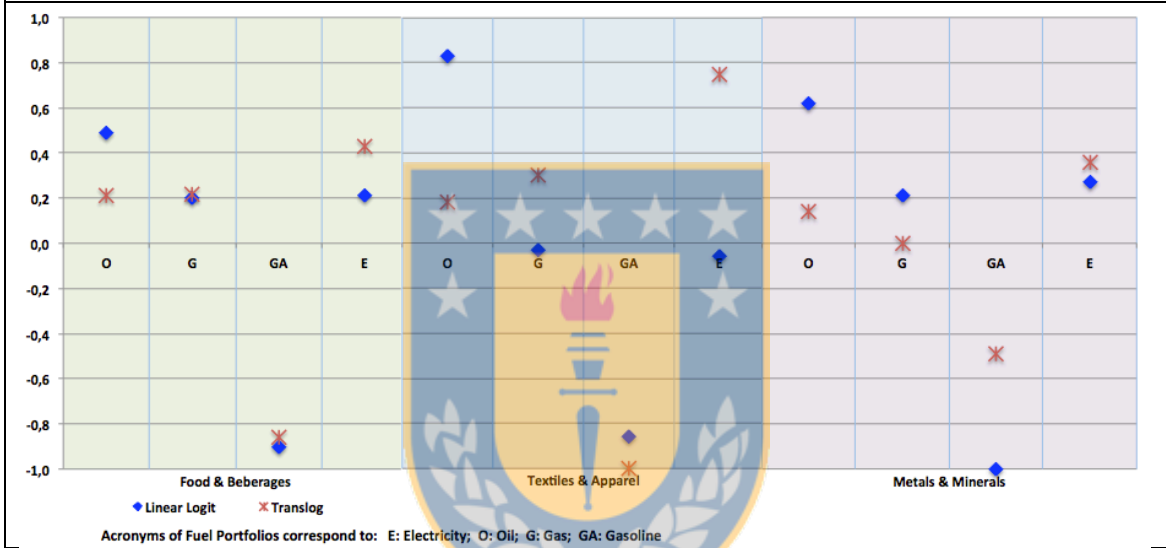
*** p<0.01, ** p<0.05, * p<0.1

A.7 Comparison between Linear Logit and Translog Estimations for Estimations by Industry Sectors





Gasoline



Acronyms of Fuel Portfolios correspond to: E: Electricity; O: Oil; G: Gas; GA: Gasoline