Energy prices, firms' productivity and market power by industry. Evidence from a developing country

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Abstract

I study how electricity price and energy-price induced variations in costs affect firms' productivity and industry markups. The first part presents a structural estimation method to compute markups and productivity. The estimator overcomes potential circularity issues in the proxy-variable technique. The second part studies the relationship between energy prices, markups, and productivity using an instrumental variables research design. I first explore a natural experiment, the 2004 Argentine crisis, as a potential source of exogenous variations for electricity prices. I complement the research design by instrumenting for average variable cost constructing instruments from variations in energy prices. While results support flexible markups in Chile, productivity does not seem to be affected for energy costs. Estimates suggest that energy cost-shock that increase in 10 percent average variable costs lead to about 3 percent decrease in markups.

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1 Introduction

Supply-side shocks play an important role in explaining economic performance. Fossil fuels and electricity are critical inputs in the production of manufactured goods, and consequently, have a significant impact on shaping variable costs. Thus, sudden variations in energy prices can alter optimal firms' decisions, as firms attempt to respond to the shock. Variations in quantities, changes in the price of final goods, adjustments via flexible markups, substitution between inputs or sectors to operate (which may also affect productivity), are potential mechanisms that firms could put in place to respond to energy cost shocks.

Understanding these responses is interesting from a policymaking perspective. To illustrate, if electricity price shocks affect firms' productivity, basically because electricity is directly involved in the production process, studying changes in productivity can contribute to policy discussions related to the importance of investment in electricity generation and distribution infrastructure.[1] Moreover, whether firms respond or not by passing cost shocks to final prices (pass-through), perhaps by exploiting flexible markups, is relevant for discussions in public economics and industrial organization. In this case, pass-through is central to the theory of tax incidence in public economics, and price-markup plays a central role in understanding market power. [2]

In this paper, I attempt to contribute to the empirical literature on energy cost shocks and manufacturing firms by studying the following research question: How do firms' productivity and markups respond to energy price shocks? To address this question, I use a panel of Chilean manufacturing firms over 1995-2007 and an identification strategy that relies first on structural estimation methods, to recover markups and productivity, and then on instrumental variables. I explore the 2004 Argentine energy crisis as a natural experiment for exogenous variation in electricity prices, and also complement the research design with shift-share type instruments for variable costs.

This paper proceeds in two steps. The first part presents the structural estimation method to compute markups using firm-level data without having specific information about marginal costs.

I begin by reviewing the widely used technique proposed by De Loecker (2011), De Loecker and Warzynski (2012) and De Loecker et al. (2016), in which one can com-

[1] Some examples are Allcott et al. (2016) and Abeberese (2017).
[2] See, for instance, Ganapati et al. (2020) or De Loecker et al. (2016).

pute a multiplicative price over marginal cost markup from the ratio of the output elasticity of flexible inputs to the share of input expenditures in sales. Here I state that, at least in the context of my paper, estimating the output elasticity by recovering production functions using the *proxy-variable* approach in Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015), arises two important methodological concerns.

The first methodological concern is that, under imperfect competition, estimating production functions using the *proxy-variable* technique requires to know markups in advance, which would introduce a circularity problem (Doraszelski and Jaumandreu, 2019; Jaumandreu, 2018; Jaumandreu and Yin, 2018; Jaumandreu and Lin, 2018). A second concern relates to a potential violation of the scalar unobservable assumption in the first stage of the *proxy-variable* method. Firms operating under monopolistic competition and facing unobserved idiosyncratic demand shocks will have optimal intermediate input demand functions that depend on those demand shocks, which basically means a violation of the scalar unobservable assumption in Olley and Pakes (1996). To illustrate, in the Chilean data used in this paper there is only information on industry-level price deflators rather than firm-level prices,[3] which is a common characteristic of the few public available firm-level datasets. This makes necessary to set additional assumptions about the demand curve (see, for instance, De Loecker, 2011). In this case, a demand curve subject to unobservable variables makes explicit that the intermediate input demand function for materials will depend on unobserved productivity components and also on additional unobserved components from the demand curve.[4] Hence, it is less clear that a monotonic relationship between intermediate inputs and productivity still holds.

These aforementioned issues motivate the use of an alternative estimation procedure that does not rely on inverting a demand function, and perhaps that makes a better fit with the available data. Gandhi, Navarro, and Rivers (2020) propose a different estimation technique to the first stage in the *proxy-variable* method. The idea is to exploit the information stemming from a firm's profit optimization problem, and also some properties from the Fundamental Theorem of Calculus, to nonparametrically estimate a firm's production function. I thus describe in detail this method in the first part of the paper, listing the necessary assumptions for the case of a revenue pro-

[3]This has additional implications for productivity measurements. The production function would be a revenue production function, and therefore the measure of productivity is revenue-based (RTFP) rather than physical volume (QTFP). See Foster et al. (2008) and Garcia-Marin and Voigtländer (2019) for a discussion. Results in this paper are interpreted accordingly.

[4]De Loecker (2011) uses information on the demand to control for those shocks. The Chilean data does not contain such similar information.

duction functions, and state some potential limitations. To the best of my knowledge, my paper would be the first empirical implementation of Gandhi et al. (2020) to study revenue production functions, markups, and productivity.

The second part of the paper studies the empirical relationship between the outcomes of interest, markups and productivity, and energy prices. The research design takes advantage of some characteristics that made the Chilean economy an interesting case study. First, Argentina cut off natural gas exports to Chile in 2004, creating an unexpected situation that affected electricity generation in Chile. This crisis marked a critical moment in the recent history of the electricity supply in Chile because about 35 percent of the electricity generation was based on natural gas, which was exclusively imported from Argentina. I thus explore this natural experiment as a potential source of exogenous variation in electricity prices to study how firms respond to energy shocks. Moreover, because this identification strategy may lack enough cross-sectional variation from the shock, I also complement the research design with additional instruments that take advantage of another unique characteristic of the Chilean economy. Chile is a small and open economy with a low production of fossil fuels, which makes the economy highly dependent upon imported energy. This environment facilitates the construction of additional instruments that can be computed from the interaction between energy prices and the share of expenditures in fuels in each industry (shift-share or Bartik type instruments). The intuition here is that higher energy prices affect more the costs of those industries that rely more on energy to manufacture goods.

The paper presents two central findings. First, productivity does not seem to be affected by short-run energy cost-shocks. This result is consistent with previous empirical findings that, using alternative estimation techniques and datasets, also state that potential adverse effects on productivity may come through alternative channels, such as industry switching (e.g., Abeberese, 2017). Second, negative energy cost-shows reduce markups for Chilean manufacturing sectors. The results from the instrumental variables research design suggest that a 1 percent increase in energy costs leads to a decrease of about 0.3 percent in markups.

In additional empirical findings, the paper shows that Chilean firms exhibit constant returns to scales, with average input elasticities of 0.5 for flexible inputs and 0.2 for capital. Moreover, results from the structural estimation also suggest that Chilean manufacturing firms have an average value of markups of 1.05, which is close to the expected value in a competitive market (a value of one). Lower values of markups are in the Food and Beverages industry, which is the largest sector in Chile.

The outline of the paper is as follows: The remainder of this introduction briefly reviews some related works in a large body of research on energy shocks, manufacturing firms, productivity, and production functions. In this part, I highlight some of the contributions to the existing literature. Section 2 lays out the link between a firm's profit maximization problem and the two outcomes of interest: markups and productivity. It then describes the empirical strategy. Thus, this section presents further details about the Chile-Argentina natural gas crisis, the electricity sector in Chile, the construction of the additional shift-share type instruments, and finally states the econometric specification. Section 3 describes the panel data of Chilean manufacturing firms. Finally, section 4 presents the results, and section 5 concludes.

Related literature This paper builds on several pieces of literature. One of the strands of research is the empirical literature in Development Economics analyzing the importance of electricity generation and transmission for manufacturing firms. For instance, Allcott et al. (2016) study how electricity supply impact manufacturers in India. The authors use an empirical strategy that combines structural estimation for the production function, following the *proxy-variable* method, with instruments from hydroelectric power availability. They find that shortages affect firms' input choices and revenues. In a similar fashion, Abeberese (2017) and Elliott et al. (2019) present suggesting evidence for India and China, respectively, that electricity prices affect firms' decisions about which sectors to operate in. These results are relevant for productivity because switching production to less electricity-intensive production processes, as a response to an exogenous increase in electricity price, could drive firms away from productivity-enhancing opportunities available in more electricity-intensive sectors. Conversely, this literature does find a direct impact of electricity prices on productivity. I contribute to this literature by providing external validity to this result. I study variations in productivity due to energy prices in Chile, a different country, and also a different research design.[5]

A second related body of literature is the empirical literature studying changes in the final price of goods that result from cost shocks, which is best known as cost pass-through (De Loecker et al., 2016; Ganapati et al., 2020; Goldberg and Hellerstein, 2008; Gopinath et al., 2010; Nakamura and Zerom, 2010). In this literature, whether the price-markup is flexible or not plays a relevant role through which firms can adjust variations in costs. Ganapati et al. (2020) explore the potential consequences of carbon taxes on fossil fuels by researching on how increases in energy cost are split

[5] Another related paper using a similar Chilean dataset is Álvarez et al. (2015). They use System-GMM to study the effect of electricity prices on labor productivity (output per worker).

between consumers and producers. They show that energy-price induced variations in marginal cost are indeed passed to the final price of manufactured goods in the U.S., and therefore some standard assumptions, such as complete pass-through and perfect competition in the incidence literature, may be too strong. Due to limitations in the data I cannot make conclusions about the connection between energy price shocks to the final price of goods. Despite the limitations, the context of the energy market in Chile is an interesting case of study, and results presented here add to the empirical evidence on variations in markups due to exogenous fluctuations in energy prices.

Likewise, competition is essential for a well-functioning economy. Recently De Loecker and Eeckhout (2019) have estimated an economy-wide markup of about 1.6, calling the attention to a rise in global markups. I also contribute to the study of firms' competition by looking at how markups react to changes in the economic environment. Although a firm may exhibit a markup greater than one, it can still be operating in a competitive framework. Whether we observe a sharp decrease in markups after a cost-shock may help to understand more about the industrial organization environment in which the firm operates.

Lastly, methodologically speaking, this project relates to the empirical literature on estimating production functions. Productivity, a key component in the production function, is not directly observed, and its approximation from a residual in, for instance, a log-linear Cobb-Douglas production function involves a simultaneity bias (Marschak and Andrews, 1944). My paper illustrates how to use a method that overcomes this endogeneity problem. Furthermore, as mentioned in the introduction, estimating production functions can eventually become a critical step in the estimation of markups (De Loecker et al., 2016; De Loecker and Warzynski, 2012; De Loecker, 2007). I contribute to the literature by reviewing some potential challenges that this approach may arise, and also by illustrating an alternative to the *proxy-variable* technique (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015).

2 Model and Empirical Strategy

This section is divided into two parts. The first part introduces a structural estimation technique to compute markups and productivity using production data and without having specific information about marginal costs. I first point out that the widely used approach in De Loecker and Warzynski (2012), in combination with the *proxy-variable* method (i.e., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015), involves two relevant difficulties in the context of this paper: circularity and a violation of the monotonicity assumption in Olley and Pakes (1996). After briefly going over the ideas in De Loecker's works (i.e., De Loecker, 2011; De Loecker and Warzynski, 2012; De Loecker et al., 2016), and the *proxy-variable* technique, I motivate the use of an alternative method proposed by Gandhi et al. (2020). To the best of my knowledge, my paper would be the first empirical implementation of this technique to study market power.

The second part describes the empirical strategy to study the relationship between the outcomes of interest, productivity and markups, and energy prices. In this part, I use instrumental variables in order to deal with potential endogeneity problems stemming from, for instance, measurement error and also to deliver a policy-relevant local average treatment effect. I first explore a natural experiment, the 2004 Argentine crisis, as a potential source of exogenous variations for electricity prices. I then complement the research design by studying how energy-price induced variations in average variable costs affect productivity and markups.

2.1 Markups and Revenue Productivity (TFPR)

2.1.1 Issues when using the proxy-variable technique.

A technique to compute markups, using only information from the supply side (i.e., firms-level data) and without having specific information about costs or how firms compete in the product market, is proposed in De Loecker and Warzynski (2012) and extended in De Loecker et al. (2016). Cost minimization with respect to a flexible input (i.e., materials) allows one to obtain a multiplicative price over marginal cost markup (μ) from the ratio of the output elasticity of the flexible input (f^m)[6] to the intermediate input share of output ($S^m = Expenditure\, on\, Materials / Revenues$). In other words, the markup for a firm i in period t is[7]

$$\mu_{it} \equiv f^m_{it} \left(S^m_{it}\right)^{-1} \tag{1}$$

The share S^m can directly be observed in the data and the only unknown variable in

[6]Let $F(K, L, M)$ be a production function, then the elasticity with respect to a flexible input (i.e., M), is given by $f^m = \partial \ln F(\cdot) / \partial \ln M$.

[7]There are some additional corrections to consider. For instance, one related to the residual term in the production function, ϵ, which would imply $\mu = f^m \left(S^m\right)^{-1} exp(-\epsilon)$. Appendix A describes how to obtain markups from the problem of a cost minimizing firm.

this equation would be the elasticity, f^m. Therefore, authors rely on the proxy-variable technique in Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) for estimating production functions, and therefore, to recover the elasticity f^m.

The proxy-variable technique is a two-step approach to estimate production functions. The first step is an attempt to replace the unobserved (to the econometrician) productivity component by a nonparametric function that depends upon a firm's capital, materials, and labor. In other words, productivity is 'proxied' by a nonparametric function on inputs. Generally speaking, the idea is that the optimal demand for the flexible input (materials) depends on capital, labor and, monotonically on only one unobserved variable, productivity. Thus, this monotonicity assumption allows one to invert the input demand, solving for productivity. The second step shares ideas with the literature in panel data (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995), and it is about the time in which firms optimally select inputs. This timing assumption does not vary much in recent literature on estimating production functions, and will be formally presented later.

Although this proxy-variable method deals with some of the most relevant issues when estimating production functions, such as the simultaneity bias in Marschak and Andrews (1944)[8] and the selection bias of Olley and Pakes (1996),[9] it arises two important concerns in the context of this paper.

First, if a firm has some market power, then the optimal demand for flexible inputs would be affected by the firm's markup, inducing a problem of circularity. In other words, markups affect the estimation of production functions and vice versa. This circularity problem has previously been pointed out by Doraszelski and Jaumandreu (2019), Jaumandreu (2018), Jaumandreu and Lin (2018), and Jaumandreu and Yin (2018). To illustrate, let's assume that the production function can be represented by a linear relationship between one output (y), a vector of inputs (x), one unobserved component named productivity (ω), and a measurement error component (ϵ)

$$y_{it} = \boldsymbol{x}_{it}'\boldsymbol{\beta} + \omega_{it} + \epsilon_{it} \tag{2}$$

According to the proxy-variable method, the demand for flexible inputs would be

[8]An OLS regression of outputs on inputs will lead to endogeneity problems because the residual, which includes the unobserved productivity component, will correlate with the optimal choice of inputs.

[9]It is the classical selection bias in econometrics, which may arise from the fact that firms with higher productivity have higher probability of survive over time, and therefore, are the observations that an econometrician can observe in the dataset.

a function h that depends on productivity and other predetermined inputs, namely, $\boldsymbol{x}^{flex} = h(\boldsymbol{x}^{nonflex}, \omega)$. Assuming that ω is the only unobserved component in this equation, and that there is a monotonic relationship between $\boldsymbol{x}^{flex}$ and ω, this equation can be inverted to solve for productivity, $\omega = h^{-1}(\boldsymbol{x}^{nonflex}, \boldsymbol{x}^{flex})$. Thus, this is used to replace productivity in the production function (equation 2). On the other hand, if the optimal demand for the intermediate inputs is also a function of market power, the inverse function should be like $h^{-1}(\boldsymbol{x}^{nonflex}, \boldsymbol{x}^{flex}, \mu)$. This basically means that it is necessary to know markups if we want to estimate production functions.

The second concern is somehow related but stems from the data and model specification. Specifically, the data used in this paper does not contain firm-level output prices. This is a common characteristic in those few panel datasets at the firm-level that are publicly available. Therefore, it is necessary to rely on additional assumptions on the demand side - for instance, as in Klette and Griliches (1996) and De Loecker (2011), I will assume a CES demand function. Then the optimal demand function for flexible inputs will also depend on unobserved (to the econometrician) demand shocks, which implies a violation of the monotonicity assumption in the *proxy-variable* method. As Olley and Pakes (1996) state, the inversion of the input demand function[10] "rests on there being only one unobserved firm specific state variable."(p. 1274). In other words, one crucial assumption for identification in the *proxy-variable* method is that there is a one-to-one relationship between a firm's decision for investment (or demand for materials in a more recent literature) and productivity, which allows to invert the investment (demand for materials) function. However, it is not longer clear that this one-to-one relationship holds once the investment function (or demand function) depends on additional unobservable variables.[11]

In brief, because the two issues are basically associated to the first stage in the *proxy-variable* method, the solution I propose is to compute markups and estimate the production function by avoiding the necessity of nonparametrically inverting an intermediate input demand function. Gandhi, Navarro, and Rivers (2020) is an alternative approach, which exploits information from a firm's optimization problem and some algebraic properties from the Fundamental Theorem of Calculus to nonparametrically identify production functions. In addition to overcome the aforementioned two concerns, this method does not rely on having access to exogenous price variations

[10] Olley and Pakes use investment rather than materials. See also Levinsohn and Petrin (2003) for more details.

[11] To illustrate, as I will show later using a CES demand curve, productivity becomes a linear combination of ω and let's say demand shocks, ξ, such as $\widetilde{\omega} = \kappa(\omega, \xi)$. Therefore, the optimal demand function will depend on two unobservable variables: $\boldsymbol{x}^{flex} = h(\boldsymbol{x}^{nonflex}, \widetilde{\omega}) \equiv h(\boldsymbol{x}^{nonflex}, \kappa(\omega, \xi))$.

or other exclusion restrictions. Furthermore, the method deals with an identification problem in the *proxy-variable* technique, which is related to a lack of additional source of variations to identify the production function.[12]

2.1.2 The Gandhi, Navarro, and Rivers (2020) Estimator.

I briefly being with a list some of the most relevant assumptions and then show a model for a firm that is setting inputs in order to maximize instant profits. The main goal of the model is to show how to set the identification moment conditions to recover productivity and markups without specific information about costs or product prices.

Definitions and Assumptions. Denote by $(Y_{it}, K_{it}, L_{it}, M_{it})$ a generic firm's output, capital, labor and intermediate inputs, respectively, and by lowercase letters $(y_{it}, k_{it}, l_{it}, m_{it})$ their log-values. Moreover, let $\mathcal{I}_{it}$ be the information set that contains all the information that firm i in segment j can use to solve its period t decision problem.

Assumption 1. Hicks-Neutral Production Function. The production function takes the form,

$$Y_{ijt} = F(K_{ijt}, L_{ijt}, M_{ijt})e^{a_{ijt}} \quad \Leftrightarrow \quad y_{ijt} = f(k_{ijt}, l_{ijt}, m_{ijt}) + a_{ijt} \tag{3}$$

moreover, $F(\cdot)$ is continuous and strictly concave in materials, and $a_{it} = \omega_{it} + \epsilon_{it}$.

This is a standard assumption in the literature on estimating production functions, and basically says that ω_{it} is a separable component representing productivity. The idea is that productivity is known to the firm, but not observed by the econometrician. On the other hand, ϵ_{it} is either measurement error or a shock that is unpredictable with time-t information, hence has zero conditional mean (given right-hand-side variables). The following assumption clearly states which information is available to the firm in period t.

Assumption 2. Timing - Information Assumption. $\{k_{it}, l_{it}, \omega_{it}\} \in \mathcal{I}_{it}$, while m_{it} is freely adjustable.
Assumption 2.A. Moreover, ω_{it} is a (controlled) Markovian, and ϵ_{it} is independent of the within period variation in information sets.

Assumption 2 states that ω_{it} is observed by the firm in period t, and also considers

[12] See Gandhi et al. (2020) for more details about this last issue.

possible dynamics in capital.[13] Moreover, in this assumption labor markets may not be so flexible or freely adjustable.[14] Hence, in this assumption m_{it} would be the only flexible factor that, in the short-term, if the price of energy varies, firms can easily adjust their consumption for intermediate inputs rather than capital or labor.

Assumption 2.A. is the same used in Olley and Pakes (1996) and provides more details about the information regarding the productivity process. Specifically, the distribution of ω is such that $\mathbb{P}_\omega(\omega_{it}|\mathcal{I}_{it}) = \mathbb{P}_\omega(\omega_{it}|\omega_{it-1})$, while for the residual ϵ is $\mathbb{P}_\epsilon(\epsilon_{it}|\mathcal{I}_{it}) = \mathbb{P}_\epsilon(\epsilon_{it})$. Moreover, without loss of generality, $\mathbb{E}(\epsilon_{it}|\mathcal{I}_{it}) = 0$. Part of the intuition in these assumptions is that productivity shocks in period $t+1$ are not correlated with any information available to the firm in period t, and therefore, it is possible to set moment conditions to identify the production function.

Finally, there are two additional assumptions related to prices. While Assumption 3 is about input prices, Assumption 4 helps to deal with missing output prices by introducing a demand system into the production framework.

Assumption 3. Firms are price taker in the intermediate input market. Firms take the price of materials (P^M_{ijt}) as given.

Assumption 4. Monopolistic competition with a constant elasticity of substitution (CES) demand system. Assume a standard horizontal product differentiation demand system that allows for different substitutions patterns by segment j:

$$P_{ijt} = \bar{P}_{jt} \left(\frac{Y_{ijt}}{\bar{Y}_{jt}} \right)^{1/\sigma_{jt}} exp(\xi_{ijt}) \tag{4}$$

where P_{ijt} is the output price, $\bar{P}_{jt}$ is the segment or industry price index, $\bar{Y}_{jt}$ is an aggregate demand shifter, ξ_{ijt} is a demand shocks. This last assumption is similar to the assumption in Klette and Griliches (1996) and De Loecker (2011), and allows to set information about output prices, which are not observed in the data. Moreover, from this assumption, segment-level time-variant markups are defined by $(1 + 1/\sigma_{jt})^{-1}$.

The Firm's Problem. Under Assumptions 1, 2, 3, and 4, the firm's profit maximization problem with respect to materials is

$$\max_{M_{ijt}} P_{ijt} \mathbb{E}_t \left\{ F(K_{ijt}, L_{ijt}, M_{ijt}) e^{\omega_{ijt} + \epsilon_{ijt}} - P^M_{ijt} M_{ijt} \right\} \tag{5}$$

[13] For instance, $K_t = I_{t-1} - (1-d)K_{t-1}$, where, I is investment and d is depreciation.

[14] This could be a more realistic assumption for developing economies.

because M does not have dynamic implications, the first-order condition of the problem is

$$(1+1/\sigma_{jt})\bar{P}_{jt}\left(\frac{Y_{ijt}}{\bar{Y}_{jt}}\right)^{1/\sigma_{jt}} e^{\xi_{ijt}}\left(\frac{\partial \mathcal{F}_{ijt}(\cdot)}{\partial M_{ijt}}\right) e^{\omega_{ijt}} e^{-(1/\sigma_{jt})\epsilon_{ijt}} \mathbb{E}_t\left\{e^{(1+1/\sigma_{jt})\epsilon_{ijt}}\right\} = P_t^M \tag{6}$$

writing this expression in terms of the (naural log of) intermediate input share of output $ln(S^M)$,

$$\ln(S_{ijt}^M) \;=\; \phi_{jt} + \ln\left(\widetilde{\mathcal{E}} * f_{ijt}^{m,\mu}\right) - \widetilde{\epsilon}_{ijt} \tag{7}$$

with $\phi_{jt} = \ln(1/(1+1/\sigma_{jt})) + \mu$; $\widetilde{\mathcal{E}} = \mathbb{E}_t\left\{e^{(1+1/\sigma_{jt})\epsilon_{ijt}}\right\}$; $\widetilde{\epsilon}_{ijt} = (1+1/\sigma_{jt})\epsilon_{ijt}$; and $f^{m,\mu}$ is the input elasticity, $\partial Ln(F(\cdot))/\partial Ln(M)$, up to (exponential of the negative value of) a constant μ.

As Gandhi et al. (2020) show, equation (7) is nonparametrically identified. There is only one unobserved component, ϵ, which by assumption has mean $\mathbb{E}\{\epsilon_{ijt}|\mathcal{I}_{ijt}\} = 0$. Thus, it is possible to estimate equation (7) using, for instance, a nonparametric approach for the elasticity $f^{m,\mu}$, dummy variables for ϕ_{jt}, and Nonlinear Least Squares. This first stage would produce estimates for the elasticity of materials up to a constant $(\widehat{f^{m,\mu}} \equiv \widehat{f^m e^{-\mu}})$, the residuals $(\widehat{\widetilde{\epsilon}}_{ijt})$, and hence, the constant $\widehat{\widetilde{\mathcal{E}}}$.

The next step uses the estimates from the previous regression, in a combination with arguments from the Fundamental Theorem of Calculus and the Markovian-timing assumption, to recover the production function.

First, $f_{ijt}^{m,\mu}$ defines a partial differential equation, thus from the Fundamental Theorem of Calculus

$$\int f_{ijt}^{m,\mu}\, dm = e^{-\mu} \int f_{ijt}^{m}\, dm = e^{-\mu}\left[f(k_{ijt}, l_{ijt}, m_{ijt}) + \mathscr{C}(k_{ijt}, l_{ijt})\right] \tag{8}$$

where $f(\cdot)$ is the production function defined in Assumption 1, and $\mathscr{C}(\cdot)$ is the constant of integration.

Second, using Assumption 4, the production function in Assumption 1 can also be expressed in terms of (natural log of) real revenues

$$r_{ijt} = \left(1 + \frac{1}{\sigma_{jt}}\right) f(k_{ijt}, l_{ijt}, m_{ijt}) - \left(\frac{1}{\sigma_{jt}}\right) \bar{y}_{jt} + \left[\left(1 + \frac{1}{\sigma_{jt}}\right) \omega_{ijt} + \xi_{ijt}\right] + \widetilde{\epsilon}_{ijt} \tag{9}$$

thus, replacing $f(\cdot)$ from equation (8), writting $e^{\phi-\mu} = (1 + 1/\sigma)$, and using the estimates from the first stage (NLS), equation (9) becomes

$$\left[r_{ijt} - e^{\hat{\phi}_{jt}} \int \widehat{f^{m,\mu}}\, dm - \widehat{\widetilde{\epsilon}}_{ijt}\right] \;=\; -e^{\hat{\phi}_{jt}-\mu} \mathscr{C}(k_{ijt}, l_{ijt}) + \left(e^{\hat{\phi}_{jt}-\mu} - 1\right) \bar{y}_{jt} + \widetilde{\omega}_{ijt} \tag{10}$$

with $\widetilde{\omega}_{ijt} = \left[(1 + 1/\sigma_{jt})\omega_{ijt} + \xi_{ijt}\right]$.

This is the central equation in the second stage, in which there is only one unobserved variable: $\widetilde{\omega}$. Therefore, by extending the assumption that productivity is Markovian to $\widetilde{\omega}$, we can express equation (10) in terms of only one random component and set moment conditions to identify the remaining parameters in the production function. Specifically, let $\widetilde{\omega}$ be Markovian, such as

$$\widetilde{\omega}_{ijt} = \mathbb{E}\left\{\widetilde{\omega}_{ijt} | \widetilde{\omega}_{ijt-1}\right\} + \eta_{ijt} \equiv g\left(\widetilde{\omega}_{ijt-1}\right) + \eta_{ijt} \tag{11}$$

thus, given the Timing-Information Assumption, it is possible to use the following moment restriction

$$\mathbb{E}\left\{\eta_{ijt} | k_{ijt}, l_{ijt}\right\} = 0$$

to identify the constant of integration $\mathscr{C}(k_{ijt}, l_{ijt})$ as well as μ, and hence the level of the markups.

Remarks. There are two important features in this technique that are worth highlighting. First, it is only possible to recover a linear combination of productivity and demand shocks, $\widetilde{\omega}$ rather than ω. As Gandhi et al. (2020) state, without observing output prices it is not possible to disentangle whether, after controlling for inputs, a firm has higher revenues because it is more productive or because it can sell at a better price. In this regard, Foster et al. (2016) and Garcia-Marin and Voigtländer (2019) discuss in more detail potential differences that may arise in productivity-analyses based on revenue-based productivity measures (TFPR) and physical efficiency measures (TFPQ). Considering the limitations in the data, in which I do not observe firm-level output prices, results in my paper related to productivity will be interpreted with a note of caution. Second, notice that markups are recovered from a combination of estimates for ϕ_{jt} in the first stage, and the estimate for the constant μ in the second stage (i.e., using variations in $\bar{Y}_{ij}$). Thus, time-variant markup measures are at the segment-level rather than firm-level (e.g., as in De Loecker et al., 2016). Although not the same level of disaggregation, estimating markups at 4-digit categories ('classes') is still informative about average firms' responses to market shocks and thus differences between markets over time. Again, although this limitation is mainly related to unavailable output prices and information from demand side, Gandhi et al. (2020) represents a relevant improvement in this direction. As an comparison exercise, Appendix B presents additional results implementing the proxy-variable technique as in De Loecker and Warzynski (2012).

Notes on the empirical implementation. First, the unknown functions $f^m(\cdot)$, $\mathscr{C}(\cdot)$, and $g(\cdot)$ are nonparametric specifications based on log-sieve polynomial approximations. To illustrate,

$$\mathscr{C}(k_{ijt}, l_{ijt}; \boldsymbol{\alpha}) = \sum_{0<\tau_k+\tau_l\leq 3} \alpha_{\tau_k,\tau_l}\, k_{ijt}^{\tau_k} l_{ijt}^{\tau_l}$$

Second, standard errors are computed using wild bootstrap (Horowitz, 2001; Davidson and Flachaire, 2008). Given the panel structure, the resampling process is in i. Moreover, the auxiliary distribution is the Rademacher distribution rather than commonly used two-point Mammen (1993). The former presents better behavior in the second and the fourth moments (Djogbenou et al., 2019).

Finally, in the Appendix B, the De Loecker and Warzynski (2012) estimator, the production function is a translog. Thus, $\boldsymbol{x} = (1, k, m, l, .5k^2, .5m^2, .5l^2, km, kl, ml)'$ is the vector of inputs for equation (2).

2.2 Energy Prices, Markups and Productivity

I now turn to present the two research design for energy prices and the description of the empirical analysis of how energy prices affect markups and productivity. I focus on natural gas induced variations in electricity prices and also on energy-price induced variations in average variable costs. The goal is twofold: to deliver a local average treatment effect of energy cost on markups and productivity, and also to address potential endogeneity problems. To illustrate, the establishment-level energy prices are computed from the ratio of two survey question responses, the total cost of a particular fuel and the total quantity of fuel purchased. Thus, the potential of measurement error can be a concern because the explanatory variables correlate with the error term.

The following two measures of variation in energy prices take advantage of the fact that national changes in the use of natural gas or in the price of a fuel disproportionately affect regions and industries heavily dependent on that fuel. For instance, when the national price of oil rises more than the national price of coal or electricity, industries heavily dependent on oil will be disproportionately affected. These "shift-share" instruments are related to Bartik (1991) and are commonly used in labor and public economics to study.

2.2.1 The Natural Gas Crisis.

Argentina is one of the main producers of natural gas in Latin America, and also shares a land border with Chile. In the late 90's, Chile invested in infrastructure to facilitate the imports of natural gas from Argentina. This led to important changes in the power generation sector in Chile, which represented about 50 percent of the bulk of the gas demand in Chile. To illustrate, figure 1 shows that electricity generation capacity based on natural gas increased from less than 8% in 1997 to nearly 30% in 2001. By 2003 the installed electricity generation capacity mainly relied on four sources: hydro-power generation (35%), natural gas (30%), Oil (16%), and Coal (17%). Thus, the imports of natural gas at lower prices, combined with low international oil prices, contributed to a sharp decrease in electricity prices in Chile by 2001 (figure 3).

In 2004, Argentina experienced an energy crisis. It was a shortage of energy[15] that forced the country to unexpectedly cut off exports of natural gas to Chile. This sharp cut-off happened across several months, but how much gas was supplied varied from day-to-day.[16] Operators of many gas-fired power plants in Chile adapted to this sharp reduction in supply by switching to diesel, nearly four times more expensive than natural gas.[17]

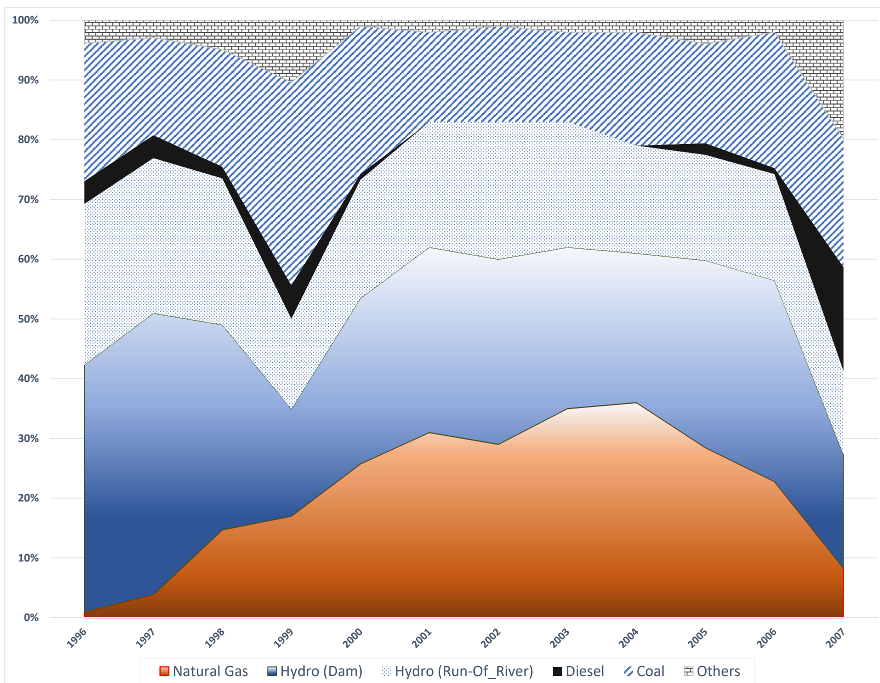
The crisis marked a critical moment in the recent history of the electricity supply

[15] Although there are several explanations for the shortage, two relevant are: (i) the low temperatures during the winter, which increased the requirements for heating in Argentina; and (ii) a decrease in the capacity of production of natural gas after the 1998-2002 great depression.

[16] See, for instance, Honoré (2004).

[17] There were also power outages, though I center the attention on variations in energy prices.

Figure 1: Fuel shares of total electricity generation in Chile.



Notes: The figure shows the mix of fuels used for electricity generation in Chile, 1996-2007. Source: Author's calculations using information from the Comision Nacional de Energia, Chile - CNE.

in Chile, which can work as a natural experiment to study how firms respond to energy shocks. Thus, the first identification strategy in this paper attempts to exploit variations in the use the of natural gas over time and space. In addition, it also takes advantage that in the dataset the Chilean plants report consumption and expenditures of different types of fuels and almost none of them[18] used natural gas as input.

Utilities in Chile supply electricity to one of the following grid-systems:[19] the Great Northern Interconnected Grid (Sistema Interconectado Central del Norte Grande, SING), the Central Interconnected Grid (Sistema Interconectado Central, SIC), Aysen, and Magallanes. Figure 2 illustrates the distribution of these grids, which are divided geographically and cover approximately 22%, 75%, 2%, and 1% of the installed capacity, respectively. I thus construct instruments for electricity prices using the product of the local utility's capacity share of natural gas in each grid-system, for a fixed year previous to the crisis, and the (natural log of) consumption of natural gas per year. In addition, considering that electricity prices are yearly adjusted based on the monomic price in the previous year, in the regressions I use the lagged value of the instrument.

In brief, the first empirical strategy uses exogenous variation in the supply of natural gas, which affected the composition of fuels used by Chilean power utilities in each grid system, and, in this way, the electricity price paid by manufacturing firms.[20]

2.2.2 Instrumental Variables for Average Variable Cost

The Argentine crisis was a relevant energy shock in Chile. However, a potential concern with the instruments obtained in this strategy may be a lack of enough cross-sectional variation from the shock. In other words, only one grid system covers more than 50% of the manufacturing firms, and the instruments may be mainly relying on time series variations. I, therefore, complement the research design with additional instruments that take advantage of the differences in the intensity a which industries

[18] Less than 6%.

[19] The description mainly applies for period of time study in this paper. The configuration of grids is not exactly the same in the present.

[20] Assuming that this was the only channel through which Argentina affected manufacturing firms in Chile may represent a strong assumption. There are other channels through which the 2004 Argentine crisis may affect Chilean manufacturing firms. Namely, a decrease in international trade that may decrease the revenues of Chilean firms, or variations in electricity and natural gas prices may negatively affect Chilean households' budgets, which translates to a lower demand of other locally produced goods. Although the dataset does not contain information on exports, in Appendix C I provide additional information about exports using data from Comtrade, UN. Exports by sector seem to remain constant around the period of the crisis.

Figure 2: Geographical Distribution of the Grid Systems in Chile.

Notes: The figure illustrates a political map of Chile and includes the geographical areas covered by each grid system in 2007. Numbers in parenthesis are share of net capacity. Names on colored areas are Chilean regions with their capitals and national capital. Source: Author's design and calculations using a map from Maps of World (2015; retrieved May, 2017 from *https://www.mapsofworld.com/chile/chile-political-map.html*) and information from the Comision Nacional de Energia, Chile - CNE.

use different fuels.

The second approach follows ideas from the instrumental variables identification strategy in Ganapati et al. (2020), Abeberese (2017) and Allcott et al. (2016). I generate proxies for changes in plant-level energy costs that can be used to instrument a measure of plant-level average variable cost. This source of variation stems from the fact that different manufacturing industries use different energy inputs. In other words, industries whose production process mainly use, for instance, oil will see energy costs increase more when oil prices rise.

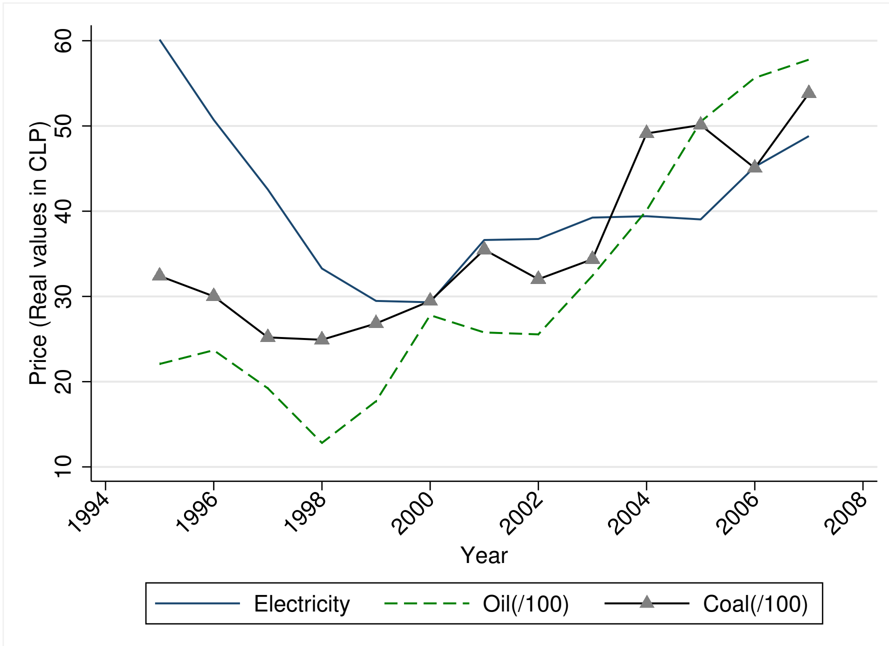
Table 1: Allocation of Energy Input Expeditures by Industry in percentage (%)

	Fuel Oil	Electricity	Coal
Food	1.27	1.07	0.22
Textil	2.41	0.35	0.06
Wood	3.36	0.63	0.00
Paper	5.74	2.12	0.00
Metals	5.56	1.45	3.56
Furniture	1.42	0.37	0.01

Notes: This table presents the variation in the percent of total input costs that come from different fuels for some selected industries. Statistics are calculated by dividing the expenditure on each energy input by the total annual expenditures (salary and wages; materials; electricity; oil; coals; other fuels) in an industry. Source: National Annual Manufacturing Industry Survey - ENIA.

As an illustration, table 1 shows the allocation of energy expenditure across fuels as a percentage of total input expenditures for some selected industries. Total input expenditures are defined as expenditures on salary and wages, materials, electricity, and fuels. Thus, column 1 in table 1 shows that 5.56 percent of the total input cost for metal industry come from fuel oil, but column 2 indicates that 1.07 percent of total input costs in food and beverages come from electricity. In addition, figure 3 shows time-series patterns in the real price of the three primary fuel in the analysis - coal, oil, and electricity. The time series show similar trend, however, each fuel has independent variation.

Figure 3: Fuel Prices, 1995-2007.



Notes: This figure plots time series of national prices from 1995 to 2007. Real values using CPI. Original time series of Oil and Coal are average CIF price reported by the National Comission of Energy, Chile - CNE. These two time series were also adjusted using the real exchage rate and are divided by 100 to facilitate a common axis across the three fuels.

To formalize the relationship between industry fuel prices and industry heterogeneity in fuel inputs used, let z_{jt} be a vector of instruments for a given year t and industry j. Hence, z is obtained from the product of the industry's expenditure shares of electricity, oil and coal and the respective annual average leave-out mean fuel price[21]

$$z_{j,t} \quad = \quad \left[\bar{p}_{(-j,t,f)} \cdot Share_{(j,t_0,f)}\right] \;\; ; \;\; f \in \{electricity, oil, coal\} \tag{12}$$

where $\bar{p}_{(-j,t,f)}$ denotes the national, leave-out mean (natural log of) input price of fuel f for industrial consumers. $Share_{(j,t_0,f)}$ is the share of total expenditures in industry j and year t_0 devoted to fuel f.

[21] As a robustness check exercise, I also explore national average prices. For instance, using the monomic node price of electricity.

2.2.3 Energy Prices, Average Variable Costs, Productivity, and Markups.

I use the constructed energy price variation to estimate the effect of electricity prices and average variable cost on markups and productivity. The main specification is an instrumental variable linear regression model with high-dimensional fixed effects

$$y_{ijt} \quad = \quad \beta_1 \, r_{ijt} + \boldsymbol{x}_{it}'\boldsymbol{\beta} + \alpha_i + \gamma_t + \varepsilon_{ijt} \tag{13}$$

where i and t index plant and year, respectively. The index j refers to an industry if r is the average variable cost, and to a grid-system if r is the (natural log of) of electricity price. y_{ijt} is the outcome of interest, markups or productivity. In the case of electricity prices, for instance, the vector $\boldsymbol{x}$ includes the leave-out mean fuel prices $\bar{p}_{(-j,t,f)}$, separately for each fuel and the industry energy input share $Share_{(j,t_0,f)}$ measured in a fixed year t_0 (e.g., 2003). Equation (13) also includes plant fixed effects α_i, year fixed effects γ_t, and an idiosyncratic error ε_{ijt}. In some specifications, $\boldsymbol{x}$ also includes additional controls, such as a linear time trend for each industry (or region), and industry by time fixed effects. Finally, β_1 is the coefficient of interest and measures the elasticity of the independent variable, markups or productivity, with respect to r (electricity prices or average variable costs).

3 Data

This paper uses as a primary dataset the National Annual Manufacturing Industry Survey (Encuesta Nacional Industrial Anual, in Spanish), henceforth ENIA, collected by the Chilean statistical agency, the *Instituto Nacional de Estadísticas* (INE). Previous studies, such as Levinsohn and Petrin (2003) in the production function estimation literature, Bergoeing and Repetto (2006) in the productivity literature, and Pavcnik (2002) and Alvarez and Lopez (2005) in the international trade literature, have also used the ENIA, though they use different variables and dataframes. I additionally supplement the dataset with information from the National Commission of Electricity of Chile (CNE), on energy prices, consumption of fuels by utilities, and generation.

National Annual Manufacturing Industry Survey (ENIA) I use administrative information on annual plant, or establishments, from the INE.[22] The ENIA is representative of the universe of Chilean manufacturing plants with ten or more workers, which have developed activities for six months or more. The survey contains detailed information about plant characteristics, such as the number of workers, the average of working days, remunerations, taxes, intermediate outputs, electric power consumption (in thousands of KW per hour) and bill, fuel consumption and total bill, aggregate value, among other information. I use the data to construct an unbalanced panel for the period 1995-2007, and compute plant-level measures of relevant variables, such as labor, capital and materials.[23] The ENIA does not report plant-level prices, but it does contain information on prices at the 4-digit ISIC level. I also construct additional deflators from INE's wholesale price indices and use other standard price deflators, such as the CPI from the Central Bank of Chile. As in Bergoeing and Repetto (2006), I exclude the tobacco industry and petroleum refineries from the analysis, because they are organized as monopolies.

the establishment-level energy prices are computed from the ratio of two survey question responses, the total cost of a particular fuel and the total quantity of fuel purchased

Table 2: Number of Plants per Year in the ENIA

Year	Number of Plants Original	Number of Plants Final Dataset
2001	5,088	4,492
2003	5,377	4,662
2005	5,516	4,437
2007	5,037	3,827

Notes: This tabla illustrates the number of observations in the dataset per year. Selected years (Other years show similar figures and are excluded). Column 2 shows the number of observations after constructing the panel. Source: Author's calculations using the ENIA.

[22]The structural model describes firms, rather than establishments or plants. The paper presents these words as synonyms. Some researchers have reported than only less than 10% of the Chilean manufacturing firms are multi-plants (see, for instance, Micco and Repetto, 2012).

[23]There are several survey questions that can be linked to a single variable in the model, for instance, labor. Thus, to guide the construction of the final variables to use in the analysis, I first replicated statistical reports prepared by the INE. For instance, one report is the Annual Report 2007 prepared by INE La Araucania (Análisis: Encuesta Nacional de la Industria Anual; ENIA Regional La Araucania).

Table 2 presents the number of observations in the original sample and after constructing the variables of interest.[24] There is information for nearly 5,000 manufacturing plants per year. Table 3 presents some descriptive statistics for the main variables. In this table I compute the mean and the standard deviation aggregating plants at the 2-digit ISIC level. Gross output, capital stock and materials are expressed in (natural log of) 2003 Chilean pesos. In addition, as in Bergoeing and Repetto (2006), labor inputs are measured as the annual average of employees working at the firm, corrected by the number of days the firm operated in any given year.

Table 3: Descriptive Statistics: Mean and (Standard Deviation)

Industry	y	k	l	m
Food	13.51	11.79	3.50	12.62
	(1.82)	(2.41)	(1.19)	(1.92)
Apparel	12.74	10.97	3.41	11.61
	(1.43)	(1.83)	(1.01)	(1.65)
Wood	13.51	12.14	3.68	12.63
	(1.73)	(2.16)	(1.16)	(1.87)
Paper	14.36	13.05	3.88	13.45
	(1.97)	(2.41)	(1.20)	(2.03)
Chemicals	14.76	13.25	3.78	13.59
	(1.83)	(2.21)	(1.25)	(1.99)
Metals	15.42	14.18	4.22	14.47
	(2.64)	(2.82)	(1.46)	(2.80)
Machinery	13.24	11.79	3.39	12.25
	(1.45)	(1.81)	(0.97)	(1.44)
Overall	*13.48*	*11.99*	*3.50*	*12.51*
	(1.77)	(2.23)	(1.14)	(1.91)

Notes: This tabla presents descriptive statistics, mean and standard deviation (in parenthesis), of the main variables constructed using the ENIA. y is the gross output expressed in (natural log of) 2003 Chilean pesos. Similarly, k, l and m are the (natural log of) inputs capital, labor and materials.

[24] I only present some selected year. Results are similar for other years.

The National Commission of Electricity of Chile (CNE) I also use information from the National Commission of Electricity of Chile. Specifically, I use annual reports and statistical data from the CNE's website[25] to compute additional variables, such as net installed capacity by grid-system and year, electricity prices (Monomic - energy and power, node price in local currency - CLP, per kWh), consumption of natural gas by grid-system and imports of natural gas. Nominal values, such as electricity prices, were deflated using the CPI.

4 Results

This section first presents the estimation results for the production function, in terms of elasticity and productivity, and markups by industry. It then presents results for the empirical relationship between energy prices, average costs, productivity and markups.

4.1 Markups and Productivity

Production functions and productivity As it is common in the literature on estimating production functions, results are summarized in terms of the output elasticities and the sum of these elasticities, which is a measure of the local returns to scale (RTS). Columns 2 to 4 in Table 4 show the estimates of the average output elasticities for each industry, and column 5 reports the RTS. Consistent with previous findings in the literature, and in line with the assumptions made in section 2, the output elasticity of the input materials is larger than the output elasticity of capital. The reported elasticities exhibit wide variation across sectors. Also, the table shows that the values of RTS are close to one, which may be interpreted as statistical evidence of constant returns to scale.

Figure 4 presents box-plots of estimates of revenue total factor productivity (TFPR) for each industry. The figure summarizes the entire set of firms' productivity data points, disclosing differences within and between industries. For instance, results show more dispersion in Textiles, Metals, Machinery, and Motors. The differences in productivity, especially between narrowly related sectors, may also be related to the presence of distortions and allocative inefficiency. This result is something already reported and studied in more detail in the literature on misallocation (Hsieh

[25] Retrieved in May, 2017 from https://www.cne.cl/en/estadisticas/electricidad/.

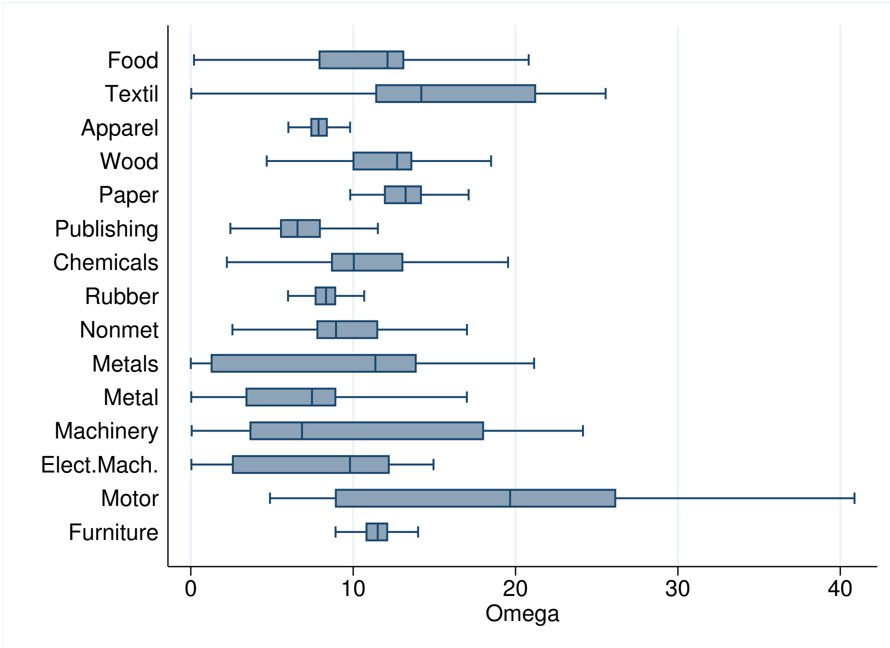
and Klenow, 2009).

Table 4: OUTPUT ELASTICITIES AND RTS

	(Observations)	f^m	f^l	f^k	**RTS**
Food	(31%)	0.48	0.54	0.16	1.18
Apparel	(6%)	0.29	0.84	0.2	1.33
Wood	(7%)	0.55	0.74	0.25	1.54
Paper	(3%)	0.38	0.34	0.2	0.92
Publishing	(5%)	0.33	0.37	0.24	0.95
Chemicals	(6%)	0.68	0.8	0.36	1.84
Rubber	(6%)	0.43	0.54	0.18	1.15
Metals	(2%)	0.4	0.54	0.2	1.15
Machinery	(5%)	0.46	0.66	0.27	1.39
Elect.Mach.	(2%)	0.69	0.88	0.27	1.84
Overall	(100%)	**0.47**	**0.5**	**0.19**	**1.16**

Notes: This table presents the output elasticities for each input: materials, labor and capital. f^j denotes the output elasticity of input j, $\partial Ln(F)/\partial Ln(j)$ with $j \in \{k, l, m\}$.

Figure 4: Estimates of (Revenue) Productivity. Box-Plot of $\widetilde{\omega}$ by Industry.



Notes: This figure shows Box-Plot graphs for the estimates of productivity by sector.

Markups Table 5 reports average values for the estimates of markups for each industry. Overall, the median value of the estimated markups is about 1.36, and the mean is 1.05, which is close to what it is expected in a perfectly competitive market (a markup of one). The results are also comparable to previous findings in the literature for other developing economies. For instance, De Loecker (2007) using Slovenian manufacturing data reports a median value of 1.22.

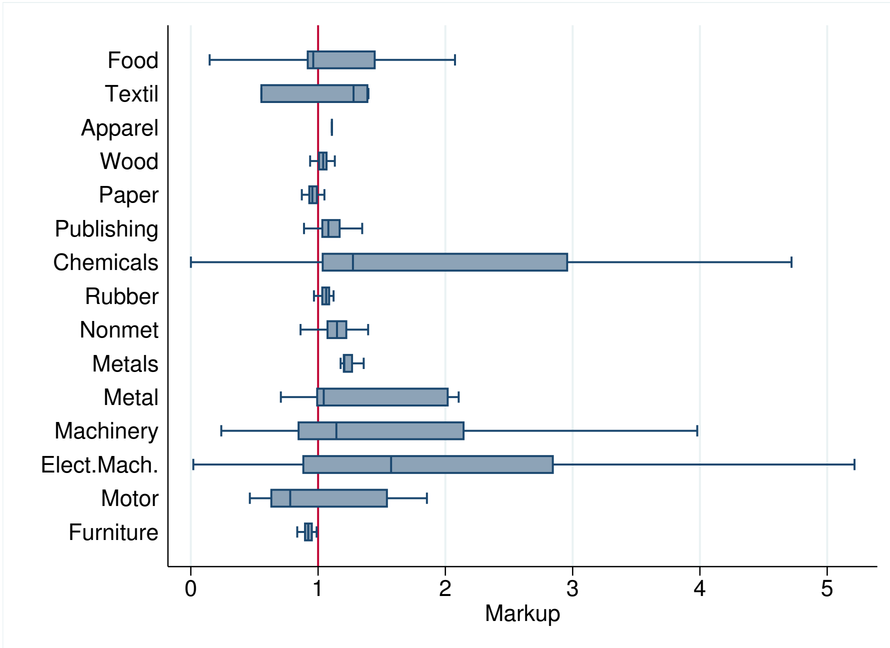
Figure 5 presents a box-plot of the estimates of markups for each industry. The vertical red line represents a perfectly competitive market. Most industries have markups greater than one and there are significant differences between industries. For instance, Chemicals and Electric Machinery are the two industries with the highest values of markups. Conversely, Food and Beverages, the largest industrial sector in Chile, presents less dispersion. The markups for this industry are in a range between 1 and 1.4.

Table 5: Markups by industry.

	Median	Mean
Panel A. Overall.		
Total	**1.05**	1.36
Panel C. By Industry.		
Food	0.96	1.22
Textiles	1.28	2.25
Wearing	1.11	1.11
Wood	1.04	1.46
Paper	0.96	0.96
Chemicals	1.27	2.01
Rubber and plastics	1.03	1.19
Fabricated metal prod.	1.21	1.23
Motor vehicles	0.78	1.03
Furniture	0.92	1.19

Notes: This table reports summary statistics for markups by industry. Selected sectors. Markups are computed at the sector level (ISIC 4-digit) and statistics in this table are at the industry level, ISIC 2-digits.

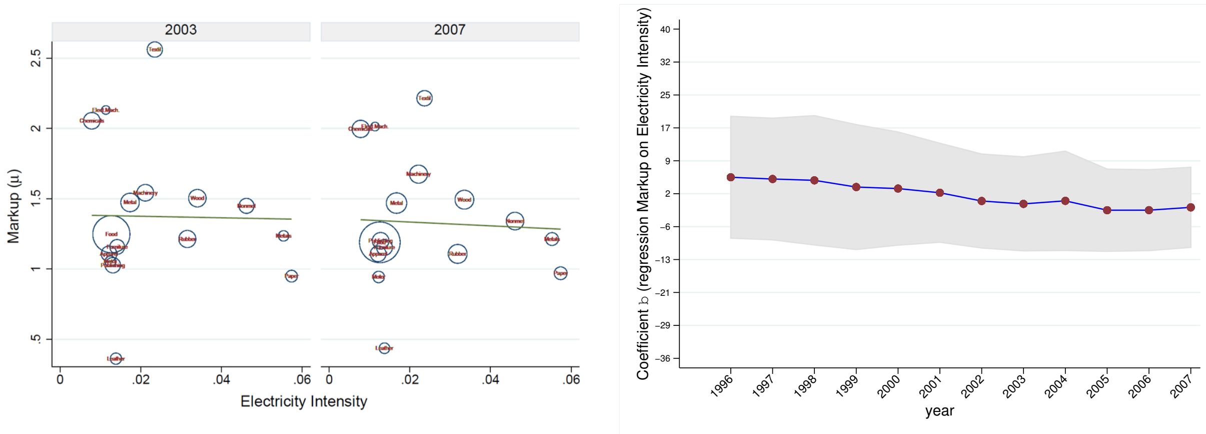
Figure 5: Estimates of Markups. Box-Plot of μ by Industry.



Notes: This figure shows box plot graphs for the estimates of markups by industry. Selected sectors.

Energy intensity and markups (Placebo Test) According to the framework in this paper, firms operating in regions or industries that use more energy are those who are more exposed to energy shocks. I now explore for a potential relationship between the industries' expenditures shares and the outcomes of interest that may affect the identification strategy. Figure 6 examines for patterns between the markups and each industries' electricity intensity. Panel (a) presents two scatter plots for two different years, 2003 and 2007. The size of a circle illustrates the number of firms in an industry. Overall, the location of a particular industry in each graph is about the same for the two years. Also, the regression lines show similar slopes in each scatter. Panel (b) shows a time series of the slope coefficients computed for several years, $Cov(\mu_{jt}, Intensity_{jt})/\sigma_{intensity}$. These coefficients are about the same over the years.

Figure 6: Placebo Test. Markups (μ) and Electricity Intensity by Industry.



(a) μ vs Intensity in two periods

(b) Coefficient $Cov(\mu_{jt}, Intensity_{jt})/\sigma_{intensity}$

Notes: This figure has two panels. Panel (a) presents two scatter plots between markups and electricity intensity. Each scatter also shows a regression line. Electricity Intensity means the intensity a which industries use electricity as expenditure shares. Panel (b) is a time series plot of the regression coefficients. The shaded gray area is the 95% confidence interval.

4.2 Energy Prices, Average Variable Cost, Markups and Productivity

Table 6 presents estimates for equation (13) with the electricity prices as the explanatory variable r_{ijt}. In columns 1 and 2, the dependent variable is the productivity. In columns 3 and 4, the dependent variable is the markups. Both variables are in logs and, thus, the estimates represent elasticities. Column 5 reports the estimate for the first-stage when the price of electricity is instrumented with the natural gas (the multiplication between the natural log of imports of natural gas and the share by grid-system, as described in the empirical strategy). Estimates for productivity in columns 1 and 2 are not statistically significant, suggesting that there is no effect of variations in electricity prices on productivity. Conversely, the estimates for markups in columns 3 and 4 are statistically significant. This result suggest that there is a negative relationship between electricity prices and markups. The value in column 4 indicates that a ten percent increase in electricity prices leads to a one percent reduction in markups. However, given the low value of the first stage F-test, this does not seem to be a good instrument.

Table 6: Relationship between electricity prices, markups and productivity: Natural Gas.

	Productivity		**Markups**		**Electricity**
	OLS	IV	OLS	IV	**Price**
	(1)	(2)	(3)	(4)	(5)
Electricity Price	-0.0014	0.0419	-0.0028 ***	-0.1054 *	
	(0.001)	(0.050)	(0.001)	(0.056)	
Natural Gas					-0.136***
					(0.025)
First Stage F					7.07
Observations	46,320	42,468	46,320	44,104	44,468

Notes: This table presents regression coefficients from 5 separated regressions. The first row describes the dependent variable. Electricity Prices are in logs. Natural Gas means the instrument from the multiplication between the (natural log of) imports of natural gas and the share by grid-system, as described in the empirical strategy. Last column reports the first stage for the Instrumental Variable (IV) research design. The regressions include the (natural log of) consumption of natural gas, capacity share, year and firm fixed effects, and industry time trends as controls (no reported). Standard errors are in parentheses and are clustered by grid-system. *Key*: *** significant at 1%; ** 5%; * 10%. Source: Author's calculations using data from the CNE and the ENIA, Chile.

Similarly, Table 7 presents estimates for equation (13), but using the (natural log of) average variable costs as the explanatory variable. In columns 1 and 2, the dependent variable is the (log) productivity, while in columns 3 and 4 is the (log) markups. Column 5 reports the estimate for the first-stage when the average variable cost is instrumented with the fuels shift-share instruments. Column 2 suggests that there are no significant effects on productivity. Conversely, results in columns 3 and 4 suggest that there is a statistically significant impact of the energy-price induced variations in average variable cost on markups. Specifically, the estimates in column 3 suggest that a 10 percent increase in the average variable costs, due to a negative shock in energy-prices, leads to a 2.5 percent decrease in markups. To put this effect into perspective, if the average value of markups is about 1.05, thus, a decrease in markups of 2.5 percent would mean a new markup of approximately 1.0, which is the reference value for a competitive market.

Table 7: Average variable costs, markups and productivity: Fuel Instrument.

	Productivity		**Markups**		**Average**
	OLS	IV	OLS	IV	**Costs**
	(1)	(2)	(3)	(4)	(5)
Average Variable Costs	-0.211***	-0.291	0.017***	-0.247***	
	(0.009)	(0.198)	(0.003)	(0.050)	
Electricity Price × Electricity Share					1.964**
					(0.943)
Coal Price × Coal Share					1.497***
					(0.246)
Oil Price × Oil Share					3.870***
					(0.560)
First Stage F					171.8
Observations	45,661	45,661	49,091	49,091	49,091

Notes: This table presents regression coefficients from 5 separated regressions. The first row describes the dependent variable. Average variable costs in logs. Last column reports the first stage for the Instrumental Variable (IV) research design. The regressions include the uninteracted (natural log of) fuel price, fuel share, year fixed effects, firm fixed effects, and industry time trends as controls (no reported). Standard errors are in parentheses and are clustered by region. *Key*: *** significant at 1%; ** 5%; * 10%. Source: Author's calculations using data from ENIA and CNE.

The main result for markups in Table 7 may hide important cross-industry heterogeneity. Table 8 reports estimates of equation (13) separately for the industries in the sample. The average variable cost here is instrumented using the fuel shift-share instruments. The table reveals cross-industry heterogeneity in the estimates. The elasticities vary from a high of -0.55 for Clothing (Textil, Apparel, and Leather) to a low of -0.01 for Metals and Machinery Equipment. Thus, these estimates suggest that a 10 percent increase in the average variable costs, due to negative energy shocks, leads to a 3 percent in markups for Food and Beverage, the most representative industry in Chile. For other industries, such as Wood (related manufacturing products), the same variation in the average variables costs can be associated with a 1 percent decrease in markups.

Table 8: Average variable costs and markups, by industry. IV estimates.

	Food & Beverages (1)	Clothing (&) (related) (2)	Wood (3)	Paper & Publishing (4)	Metals & Machinery (5)
Average Variable Costs	-0.329***	-0.550	-0.104***	0.353	-0.010***
	(0.112)	(0.056)	(0.019)	(0.237)	(0.002)
Observations	15,101	7,327	3,340	2,880	8,345

Notes: This table presents regression coefficients from 5 separated regressions. The first row describes industry. The dependent variable is the (log) markups. Average variable costs in logs. The regressions include the uninteracted (natural log of) fuel price, fuel share, year fixed effects, firm fixed effects, and industry time trends as controls (no reported). Standard errors are in parentheses and are clustered by region. *Key*: *** significant at 1%; ** 5%; * 10%. Source: Author's calculations using data from ENIA and CNE.

5 Conclusions

In this paper, I study how input-cost shocks affect firms' markups and productivity. These two variables are unobservable outcomes that are closely related to the estimation of a firm's production function. I first present two arguments about why the commonly applied *proxy-variable* technique to recover these outcomes may fail. I then introduce a novel estimator. The rest of the paper presents an instrumental variables research design that uses variations in energy prices. The two primary sources of exogenous variations are: (1) a natural experiment, the 2004 Argentine energy crisis; and (2) a set of shift-share type instruments.

The results in this paper suggest that firms respond to negative cost-shocks by changing markups. In the case of the empirical application in this paper, the Chilean manufacturing firms, estimates suggest that energy cost-shocks increase firms' average variable costs, and that a 10 percent increase in this variable, leads to a 3 percent decrease in markups. Conversely, productivity does not seem to be affected by short-run energy cost-shocks.

The novel econometric technique and also the instrumental variable research design in this paper may provide an empirical tool to the literature in the Industrial

Organization interested in market power. Although markups may be larger than one (perhaps signaling market power), it may be the case that the variations in this variable inform us about the industrial organization environment in which firms operate. In other words, if, after a negative shock that affects firms' variable costs, markups remain constant, it may be the case that firms have the power to fully pass the negative shock to the final prices that consumers pay. However, due to limitations in the data, these kinds of detailed explanations escape to the analysis in this paper, and are left for future research.

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Appendix A Markups as in De Loecker and Warzynski (2012) and the *proxy-variable* technique.

A.1 Markups

This section describes the methodology for calculating markups following De Loecker and Warzynski (2012). Let Q_it denote the physical output Q of plant i in year t and let P_{it}^x be the input prices with $x \in \{K_{it}, L_{it}, M_{it}\}$. The associated Lagrange function for a cost-minimizing firm that makes decisions based on observed $Q(K_{it}, L_{it}, M_{it}, \omega_{it}) = F(K_{it}, L_{it}, M_{it})e^{\omega_{it}}$ is

$$\mathscr{L} = \sum_{x \in \{K,L,M\}} P_{it}^x x_{it} + \lambda_{it} \left(Q_{it} - F(K_{it}, L_{it}, M_{it})e^{\omega_{it}}\right) \tag{14}$$

The firm's first-order condition for the variable input M is

$$\frac{\partial \mathscr{L}}{\partial M_{it}} = P_{it}^M - \lambda_{it} \frac{\partial F(\cdot)}{\partial M_{it}} e^{\omega_{it}} \tag{15}$$

Rearranging terms for an optimum where $\frac{\partial \mathscr{L}}{\partial M_{it}} = 0$, and multiplying by (M_{it}/Y_{it})

$$\left(\frac{P_{M,it} M_{it}}{P_{it} Y_{it}}\right) \left(\frac{P_{it}}{\lambda_{it}}\right) = \left(\frac{\partial Q_{it}(\cdot)}{\partial M_{it}} \frac{M_{it}}{Q_{it}}\right) \left(\frac{1}{e^{\epsilon_{it}}}\right) \tag{16}$$

Here, λ_{it} is the marginal cost of production. Therefore, $\mu_{it} = P_{it}/\lambda_{it}$ would be the firm-specific markup. Additionally, $S_{it}^m = (P_{it}^M M_{it})/(P_{it} Y_{it})$ is the share of materials in the value of output, and $f_{it}^m = (\partial Q_{it}/\partial M_{it})(M_{it}/Q_{it})$ the output elasticity of materials. Thus,

$$\mu_{it} = f_{it}^m \left(S_{it}^m\right)^{-1} exp(-\epsilon_{it}) \tag{17}$$

Thus, it is possible to compute a time-varying, plant-level markup by using the output elasticity of a variable input f_{it}^m and the revenue share of that input S_{it}^m. The share S^m can directly be observed in the data and the only unknown variable in this equation would be the elasticity, f^m.

A.2 Recovering f_{it}^m by using the *proxy-variable* technique.

To simplify exposition, the general idea in Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) is to follow a two-step process.[26] First, the unknown (productivity) ω is replaced by a nonparametric function on observables. Second, using the markovian assumption for ω, one can set moment conditions to find the parameters in the production function.

Step one calls for the possibility of inverting a intermediate inut demand function, and, therefore, ω_{it} can be 'proxied' by a function on k_{it}, l_{it}, m_{it}

$$\begin{aligned} y_{it} &= f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{it} \\ &= f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) + \mathbb{M}^{-1}(k_{it}, l_{it}, m_{it}; \boldsymbol{\gamma}) + \epsilon_{it} \\ &= \Phi_t(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}, \boldsymbol{\gamma}) + \epsilon_{it} \end{aligned}$$

which can be estimated using, for instance, OLS to obtain $\hat{\Phi}_{it}$.

Step two calls for the assumption $\omega_{t+1} = \mathbb{E}(\omega_{t+1}|\omega_t) + \xi_{t+1} \equiv g(\omega_t; \boldsymbol{\alpha}) + \xi_{t+1}$ or

$$\left(\hat{\Phi}_{it+1} - f(k_{it+1}, l_{it+1}, m_{it+1}; \boldsymbol{\beta})\right) = g\left(\hat{\Phi}_{it} - f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}); \boldsymbol{\alpha}\right) + \xi_{it+1}$$

and allows to set the identification moment conditions. For instance,

$$\mathbb{E}\left\{\xi_{it+1}|\mathcal{I}_{it}\right\} = 0 \quad \Rightarrow \quad \mathbb{E}\left\{\xi_{it+1}(\boldsymbol{\beta})\begin{pmatrix} k_{it+1} \\ l_{it+1} \\ m_{it} \\ \vdots \end{pmatrix}\right\} = \mathbf{0}$$

Hence, it is possible to recover estimates of $\boldsymbol{\beta}$, and ,therefore, the elasticity f_{it}^m.

[26] Wooldridge (2009) reviews the efficiency of the two steps process.

Appendix B Results using the *proxy-variable* technique.

Table 9: Production Function Estimation based on the *proxy-variable*.

ISIC		θ_k	θ_m	θ_l	RTS
15	Food products and beverages	0.059	0.521	0.412	0.99
18	Apparel	0.063	0.482	0.373	0.92
20	Wood and of products of wood	0.038	0.560	0.426	1.02
21	Paper and paper products	0.061	0.589	0.459	1.11
22	Publishing, printing and repr.	0.048	0.517	0.389	0.95
24	Chemicals and chemical produc.	0.045	0.624	0.471	1.14
25	Rubber and plastics products	0.044	0.567	0.431	1.04
27	Basic metals	0.044	0.652	0.490	1.19
28	Fabricated metal products	0.046	0.536	0.404	0.99
29	Machinery and equipment n.e.c	0.036	0.537	0.392	0.97
Overall		0.05	0.54	0.41	**1.00**

Notes: This table presents estimates of revenue production function following the *proxy-variable* technique. Source: Author's calculations using data from ENIA and CNE.

Table 10: Markups based on the *Proxy-variable*.

	(% Obs)	Median	Mean
Panel A. Overall			
Total	100	**1.15**	1.38
Panel B. Export Status			
Non-exporters	(78)	1.07	1.29
Exporters	(22)	1.44	1.68
Panel C. By 2-Dig ISIC			
Food products and beverages	(30.5)	0.94	1.13
Textiles	(5.5)	1.25	1.46
Wearing apparel	(5.5)	1.22	1.42
Wood and of products of wood	(6.6)	1.11	1.30
Paper and paper products	(3.0)	1.22	1.30
Chemicals and chemical produc.	(5.6)	1.26	1.51
Rubber and plastics products	(6.3)	1.22	1.37
Motor vehicles	(1.6)	1.46	1.67
Furniture	(4.7)	1.31	1.51

Notes: This table presents estimates of markups following De Loecker and Warzynski (2012) and the *proxy-variable* technique. Source: Author's calculations using data from ENIA and CNE.

Appendix C International Trade Chile-Argentina