Do Energy Price Increases Impact Firm Competitiveness: Evidence from Chile*†

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May 2025

Abstract

Using the Chilean Annual National Industrial Survey data, we examine how manufacturing firms in Chile respond to changes in energy prices. We find that *first*, increases in energy prices generally do not hurt firm competitiveness. *Second*, the impact of energy prices depends on the fuel type—while electricity price increases are negatively correlated with firm outcomes, fossil fuel price increases have a positive association with investment and firm productivity. *Third*, these effects are heterogeneous and vary by firm attributes such as size, ownership and location. *Fourth*, investigating non-linear patterns in firm outcomes based on the level of energy prices, the findings show that the positive relationship between fossil fuel price increases and capital upgrading is particularly pronounced when energy prices are relatively low.

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†This research was completed under the guidance of Marianne Fay, Country Director for Chile. The authors are grateful to Doerte Doemeland and Yira J. Mascaro for their strategic guidance, and to Esperanza Lasagabaster, Vincent Palmade, Richard Record, Erik von Uexkull and several colleagues from the Ministry of Finance in Chile for their useful comments.

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JEL Classification: D21; D24; L60; O14; Q41; Q55.
Keywords: Energy prices; Fossil fuels; Firm productivity; Firm-level technology adoption, Competitiveness.

1 Introduction

Green growth hinges on adopting technologies that use fewer nonrenewable resources and produce lower greenhouse gas emissions. However, investment in these technologies is constrained because carbon, often shorthand for greenhouse gases (GHGs), is significantly underpriced. Political and strategic considerations have historically aimed at reducing the cost of GHG-emitting fuel sources, often in the form of energy fuel subsidies.[1] This has made it challenging to reflect their true societal costs and has resulted in technological path-dependence, hindering energy-efficient innovation (Ley et al., 2016).

As many countries have recently liberalized energy prices and adopted automatic pricing mechanisms (Coady et al., 2019), there is a pressing need to examine this issue in developing economies, where research remains limited compared to developed nations (Burke et al., 2016). Well-designed policy interventions combining carbon pricing instruments with targeted adjustment support to overcome initial obstacles to adopting new technologies have been shown to yield a win-win outcome of higher productivity and lower emissions in many countries.[2] However, the current evidence base for policy design in emerging economies is limited and, to the best of our knowledge, as empirically assessing the effects of energy price variation on firm-level outcomes using microdata has furthermore been challenged by extensive data requirements and identification issues (Coste et al., 2018; Amann et al., 2024, among others).

This paper contributes to understanding the effects of energy price increases on manufacturing firm-level outcomes in Chile, an emerging economy, which has undergone fast-paced economic development in recent years.[3] Chile is an interesting case as the country has experienced a substantial variation in primary energy inputs, including

[1]Industrial policies have historically supported the provision of subsidized energy, a major input in manufacturing, especially in markets where cost-competitiveness is particularly important (El-Katiri and Fattouh, 2017). Consequently, policymakers may fear the adverse reactions of interventions targeting greenhouse gas emissions reduction through price-setting mechanism changes. Climate change mitigation in emerging and emerging economies might pose a challenge from a development perspective if it requires more costly, low-carbon energy sources (Jakob and Steckel, 2014).

[2]See, among others, meta-studies and reviews of the evolving literature such as Arlinghaus (2015),Cohen and Tubb (2018), Ellis et al. (2019), Dechezleprêtre and Sato (2020), Couharde and Mouhoud (2020) or Amann et al. (2024).

[3]Following the historic World Bank Country and Lending Groups classification (last access: November 2024), Chile was an upper middle-income country at the beginning of our sample period in 1995 and became a high-income country in 2012.

hydro, coal and gas, as a primary source of energy production in the past; see Figure A.1.[4] The country has also committed to carbon neutrality by 2050 while its industry continues to depend heavily on fossil fuels despite some progress. In the context of its broader tax reform agenda, the Boric administration that took office in March 2022 has considered corrective taxes and subsidy reforms to incentivize the use of fossil fuel-saving technologies while also pursuing policies to promote investment, innovation and inclusive growth (OECD, 2023).

We assess the effects of energy price changes on firm outcomes using the publicly available version of the Chilean *Annual National Industrial Survey* from 1995 to 2015.[5] We estimate separate elasticities of electricity and fossil fuel for various firm-level outcomes such as productivity, energy efficiency, employment, wages, and profits employing fixed-effects (FE) panel estimations.[6] We also estimate the heterogeneity in responses by firm attributes and non-linearities conditional on energy price levels. We add to the robustness of our results through an Instrumental Variable (IV) approach utilizing the regional energy distribution cost to account for unobserved reverse causality.

This paper makes the following broad contributions: *First*, it finds that overall increases in energy prices generally do not hurt firm competitiveness. *Second*, it confirms notable heterogeneity in how energy price surges affect Chilean manufacturing firms' performance in line with other recent works. These depend on the type of energy input, i.e. electricity vs fossil fuels, (Amann et al., 2021; Calì et al., 2022, among others) and hint at various degrees of substitutability between distinct production inputs conditional on firm characteristics (Brucal and Dechezleprêtre, 2021, among others). In particular, a 10% rise in fossil fuel prices correlates significantly with a capital investment increase of 3.1% and an increase in output per worker of 0.8%. *Third*, our work points out extensive heterogeneities of energy price hikes along many dimensions. We find heterogeneous effects based on firm attributes such as size, ownership, and location. The heterogeneity analysis suggests that positive innovation

[4]Between 1995-2013, more than 95% of Chilean manufacturing firms used electricity, followed by diesel, with 35%-54% using this fuel type. The consumption of other fuels such as LPG and petrol is lower; on average, 20%-30% firms use these fuels. A relatively smaller share of firms uses natural gas, coke, kerosene and pipe gas.

[5]As outlined in Appendix B, we construct a panel data set containing 100,803 observations on 12,169 plants, with an average of 4,200 unique firms observed across survey years from 1995 to 2015.

[6]Note that in this study, we combine various types of fossil fuels which may vary notably in the amount of GHG emissions. In particular, we construct a harmonized unit price index for fossil fuels by combining information on coal, gas, diesel, petrol, LPG and kerosene use of Chilean manufacturing firms.

and productivity effects can only be observed for large firms (with 50 employees or above). By comparison, small firms observe a negative correlation with surges in energy prices in general and electricity prices in particular. In line with existing work, our results highlight firm-level heterogeneity concerning their degree of global market integration.[7] In particular, we find that the innovation-led adoption mechanism is more pronounced for exporting firms and firms under foreign ownership, while firms that only operate domestically and are under domestic ownership are more adversely affected by hikes in electricity prices. *Fourth*, it presents explanatory evidence suggesting a notable change in the relationship between competitiveness indicators and fossil fuel price changes conditional on the price level. The positive correlation between fossil fuel price increases and capital upgrading is more pronounced when fuel prices are low. At higher fuel price levels, this effect becomes smaller and eventually insignificant. Similar non-linear effects cannot be observed for electricity prices.

The structure of this paper is as follows: section 2, provides an overview of the empirical firm-level literature on the energy prices-productivity nexus, while section 3 sets a background on the institutional changes concerning energy prices for Chilean manufacturing firms. We then introduce the *Estructura de la industria manufacturera* data (INE, 2015) in section 4, after which we turn to our empirical strategy and the results in sections 5 and 6, respectively, before concluding in section 7.

2 Literature

The literature identifies four main transmission channels for how firms may respond to energy price interventions:[8] Firms typically respond to policy-induced energy price changes by (i) passing the price increase on to customers, (ii) absorbing the price increase, (iii) substituting inputs, or (iv) using firm-level capacities to innovate or improve productivity.

[7] For example, Banerjee et al. (2021) find that exporting encourages greater pollution abatement in Indonesian firms, while Forslid et al. (2018) and Kwon et al. (2023) shed light on the abatement mechanism of globally engaged enterprises in Sweden and China, respectively. Albrizio et al. (2017) show that introducing more stringent environmental policy is associated with industry-level productivity growth in technologically advanced countries in the short run in a panel of OECD countries, with diminishing effects at lower productivity levels. The authors find no evidence of the strong version of the Porter Hypothesis.

[8] See, among others, Ambec et al. (2013), Arlinghaus (2015), Rentschler et al. (2017), Cohen and Tubb (2018), Coste et al. (2018), André et al. (2023) or Amann et al. (2024) for a more extensive discussion and meta-analysis of the field.

The one strategy, where firms *innovate* by adopting more efficient technologies and reap economic benefit while simultaneously adopting more environmentally friendly policies following a *policy intervention*, is often referred to as the Porter Hypothesis (Porter, 1991; Porter and Van der Linde, 1995).[9]

In the subsequent review of the literature, we concentrate on recent empirical studies conducted in the context of developing economies. Specifically, we examine both policy-induced price changes and market-driven adjustment mechanisms arising from exogenous shocks, insofar as firm-level responses are analyzed with respect to energy-type-specific price fluctuations. This analytical framework is particularly relevant to the case of Chile during the sample period under investigation in this study.[10]

The empirical firm-level literature on emerging economies finds broad support for the Porter-type *innovation* hypothesis, where policy-led price interventions lead to innovation and notable business upgrading. Brucal and Dechezleprêtre (2021) show that large and energy-intensive sectors in Indonesian manufacturing tend to reduce energy consumption most significantly in response to an energy price hike. Plants react to higher energy prices by updating their capital stock and investing in new and presumably more energy-efficient technology. Using firm-level data of small and micro enterprises from Indonesia for 2013, Rentschler and Kornejew (2018) explore the impact of input price changes of electricity and various fossil fuels on firm performance. The authors find that higher prices for all energy types are associated with higher energy efficiency. Calì et al. (2023) evaluate energy prices' direct and indirect impact on firms' economic performance for eleven developing countries between 2002 and 2013. Using World Bank firm-level survey (WBES) data, the authors find that higher energy prices do not necessarily hamper economic performance. They also report considerable heterogeneities, as energy-intensive firms report a smaller performance effect in response to a rise in energy prices than their less energy-intensive

[9]The literature distinguishes between different forms of the Porter Hypothesis (Ambec et al., 2013): Under its *"weak"* form, environmental regulations spur innovations, while under the *"strong"* version, environmental regulations will lead to increases in firm competitiveness. The *"narrow"* interpretation states that more flexible regulations may be better at providing the preferable incentive structures to firms than more prescriptive forms; see Jaffe and Palmer (1997) for a discussion on the different variants of the *Porter Hypothesis* in the literature.

[10]We acknowledge that policy-induced price changes, as planned interventions announced in advance, are quite different from abrupt energy price changes brought about by exogenous price shocks. In addition, the duration of price changes associated with exogenous shocks can be rather uncertain; policy-induced price changes are expected to be long-lasting, at least in principle, even though policy reversals are not uncommon. In contrast, exogenous energy price shocks are unexpected and uncertain and are either the result of shocks, for example, geopolitical, technological, or climate-related shocks, or result from supply- or demand-driven market dynamics.

counterparts. Calì et al. (2022) focus on medium- to large-sized manufacturing firms in the two emerging economies Mexico and Indonesia. They find that while surges in electricity price harm plants' performance, increases in fuel prices yield positive outcomes for labor and total factor productivity and profits. The effects are particularly pronounced for capital-intensive manufacturing sectors. In the same vein, Amann et al. (2021) analyze the effects of energy price hikes on manufacturing firms in Oman. They show that increases in fossil fuel prices are causally linked to improvements in productivity and efficiency and lead to notable business upgrading. As Calì et al. (2022), the Oman study only observes such innovation effects for fossil fuel price increases but not for electricity hikes, which are more detrimental to firm performance. Qi et al. (2023) present evidence that the VAT reform policies in China aimed at reducing sulfur dioxide (SO2) emissions encouraged investment in production technologies. Their analysis also highlights that the joint impact of the Chinese VAT reform and environmental regulation resulted in Chinese firms' substitution towards cleaner energy inputs.

The degree to which different energy carriers can serve as *substitutes* remains relatively unexplored for emerging economies. Rentschler and Kornejew (2018) find that while electricity can be substituted away by a blend of other energy sources, it plays a minor role in replacing fossil-based energy sources. Amann et al. (2021) evaluate the substitutability of electricity and aggregated fossil fuels and report that Omani firms significantly increase their kWh consumption of electricity in response to rising fuel prices. Greve et al. (2023) show that firms react to energy price shocks by substituting labor for energy and self-employed firms increase their own labor input in a 2012 cross-section of Mexican micro and small enterprises.

Firm-level evidence suggests that the effectiveness of the *absorption* channels depends on firm characteristics and sectoral attributes. Particularly, firms in energy-intensive sectors respond more strongly to price hikes. Rentschler and Kornejew (2018) highlight that firm-level response patterns of Indonesian micro-firms are very different depending on the analyzed sector. Brucal and Dechezleprêtre (2021) report that for Indonesian manufacturing firms, energy price increases are causally linked to upticks in plant exit and employment contraction, particularly for energy-intensive and large firms. The authors also report job reallocation from energy-intensive to energy-efficient firms and sectors. Kumar and Prabhakar (2020) analyze how Indian energy-intensive exports react to changes in energy prices and find adverse trade effects, asserting that carbon leakage concerns are not necessarily unfounded. Furthermore, energy-intensive sectors, most notably the non-ferrous metal and machinery industry, are affected more severely by energy price hikes. Further evidence of emission outsourcing in emerging economies is presented in Han et al. (2024) for the case of China In turn, Calì et al. (2023) do not find statistical evidence that price hikes lead to employment losses across eleven developing economies between 2002 and 2013. Greve et al. (2023) find that fuel price changes have a stronger immediate impact on Mexican micro and small enterprises than electricity price changes, with effects varying by sector and firm status. Formal firms are more vulnerable due to their higher energy cost share, pointing to transitional risks for low-profit, energy-intensive businesses during abrupt price shifts. Similarly, Zarepour and Wagner (2023) examine the 2010 energy subsidy reforms in Iran using sector-level data (2009–2013) and report a notable drop in posted profits and a rise in direct energy costs, alongside a significant increase in cost *pass-through* from upstream firms.

Firm-level evidence on cost pass-through remains relatively scarce for emerging economies except for Indonesia (Rentschler and Kornejew, 2018) and Mexico (Greve et al., 2023). Calì et al. (2023) find significant evidence for an aggregated cost pass-through effect for firms experiencing power outages based on a cross-country study using WBES data.

3 Institutional Setting

Three distinctive characteristics of Chile's energy sector generate the regional variation in energy prices that is central to the empirical analysis presented in this paper.

First, Chile underwent a comprehensive privatization of its electricity sector in the 1980s, resulting in private ownership and operation across all segments of the electricity supply chain for generation, transmission, and distribution. Second, during the period under study, the country's electricity infrastructure was organized into four principal grids: the Northern Interconnected System (SING), the Central Interconnected System (SIC), the Aysén System (SEA), and the Magallanes System (SEM). Notably, SING and SIC were eventually merged to form the National Electricity System (SEN). Within these networks, electricity generation was carried out by a mix of state-owned and private energy producers (Serra, 2022).

Third, the Chilean energy sector experienced significant fluctuations over time, particularly in the composition and availability of primary energy inputs.[11] In particular, Chile suffered a severe drought in 1998, which had a notable impact on the energy generation of the Central Interconnected System (SIC) network. This event, in conjunction with disruptions in three natural gas plants, caused blackouts between

[11]These variations, especially in the supply of natural gas, also manifested in the mix of direct energy inputs used by firms, contributing to firm-level exposure to energy-type-specific price changes (Figure A.1).

November 1998 and April 1999, forcing the government to ration supply (Serra, 2022). The subsequent period of the late-1990s to mid-2000s was characterized by heavy use of natural gas in electricity generation and massive natural gas imports from Argentina (Cansino et al., 2018). However, the gas-heavy energy production episode abruptly stopped in 2005 when Argentina began restricting and taxing natural gas exports due to domestic deficits, leading to a notable price surge in Chile. In response, Chile saw the construction of new coal plants to close the wedge between reduced energy supply and growing demand. Coal plants played a crucial role in this endeavor, given their comparably lower cost of electricity generation (Serra, 2022). The country also diversified its energy mix in terms of energy type and destination. For example, in 2009/2010, Chile imported natural gas from Algeria, Equatorial Guinea, the Arab Republic of Egypt and Indonesia and constructed large-scale liquefied natural gas terminals (Mundaca et al., 2015), leading to an overall reduction in the relative weight of hydropower (Cansino et al., 2018). Technological advancements and growing environmental concerns have led to a stronger focus on green and renewable energy in recent years. By the 2010s, increasing public opposition and stricter environmental requirements halted the construction of additional coal-fired plants (Serra, 2022), and new policy measures promoting non-conventional renewable energies were put into practice (MEFR, 2008; Cansino et al., 2018). The year 2014 also saw the passing of carbon tax legislation with the *General Tax Reform Bill*.[12]

4 Data

The Chilean *Annual National Industrial Survey* (ENIA from now on) is made available by the *National Statistical Institute* (INE, 2015). ENIA data is publicly available and spans the period 1995-2019. From 1995 to 2007, ENIA offers a harmonized panel data set (referred to as the *combined* data) which identifies the same manufacturing firm with a unique ID linking plants over time. At the time of this study, unique firm IDs linking panel data were unavailable and, until recently, ENIA had microdata available from 2016-2019 in separate annual waves (without a unique firm ID over time).[13] We refer to these separate waves as the *raw* version on ENIA.

The combined ENIA data set suffers from a lack of regional and manufacturing sector-level identifiers. To recover information on the location and the ISIC 4-digit

[12]With its inception in 2014, the tax reform (Ley 20.780) falls too close to the end of the sample period to merit an empirical analysis. At the time of writing, the implementation of the policy remains an ongoing process; see the World Bank's Results Brief 15 February 2021 and project Market Instruments for Climate Change Mitigation in Chile (last access: October 2024).

[13]For reference, see the ENIA manual (last access: September 2022).

codes for each plant, we resort to the raw data version of ENIA, which contains both desired variables. We match plants in the combined and raw data by their common characteristics and apply the same matching techniques to expand the panel structure in the post-2007 period. This procedure yields a final data set containing 100,803 observations on 12,169 plants, with an average of 4,200 unique firms observed across survey years. We provide a more extensive discussion on the matching algorithm in Appendix B. As illustrated in Figure A.2, the matching algorithm achieves a stable firm sample over the entire sample horizon and a low attrition rate.

The combined data also exhibit irregularities potentially stemming from misreported electricity and fossil fuel profiles. We address this issue by employing a simple cleaning algorithm, which provides a rule-based procedure to identify and correct inter-temporal changes in reported quantities and unit prices of pre-defined magnitudes. We provide a more extensive discussion on the cleaning algorithm in Appendix C.

5 Empirical Methodology

5.1 Baseline Estimation

Model Structure. Our empirical setup is similar to that of other works in the literature, such as Amann et al. (2021) and Calì et al. (2022). We estimate:

$$y_{it} = \boldsymbol{\beta}_i \mathbf{x}_{it} + \varepsilon_{it}, \tag{1}$$

where $\mathbf{x}_{it} = \left[up_{it}^{EL}, up_{it}^{FF}\right]'$ denote the unit prices for electricity (EL) and fossil fuels (FF) for firm i and period t, respectively. The calculation of the electricity unit prices is straightforward:

$$up_{it}^{m} := \frac{value_{it}^{m}}{quantity_{it}^{m}}, \tag{2}$$

where *value* denotes the purchased value (in real LCU) and *quantity* denotes the purchased quantity of energy type $m = \{EL\}$.[14] For the fossil fuel aggregate, we calculate kWh-equivalent quantities for all $n = \{$*coal, gas, diesel, petrol, LPG, kerosene*$\}$ fossil fuel types according to the conversion rates in Table A.1 as follows:

[14] All monetary series are deflated using ISIC 2-digit industry-level following Haraguchi and Amann (2023).

$$up_{it}^{FF} = \sum_{n} w_{it}^{n} \times up_{it}^{n}, \quad w_{it}^{n} = \frac{\tilde{q}_{it}^{n}}{\sum_{n} \tilde{q}_{it}^{n}}, \tag{3}$$

where $\tilde{q}_{it}^{n}$ denotes the quantity (in kWh equivalents) of fossil fuel type n for firm i and period t, and w_{it}^{n} corresponds to its fixed-quantity weight, respectively. The calculation of the individual up_{it}^{n} series is identical to Equation 2 for $m = n$. The two energy unit price series we derive in this way are visualized in Figure A.3.

Dependent Variables. We analyze the effect of energy price variations on firm-level outcomes, y_{it}. To this end, we compartmentalize the outcome variables by applying the framework introduced in section 2 to the extent to which this is possible with the open-access version of ENIA.[15] We define these domains as: *investment* and *productivity/survival*, *substitution* and *absorption*. On the *competitiveness/innovation* effects, we evaluate the strong and weak form of the Porter Hypothesis by computing various measures of productivity, including labor productivity and Total Factor Productivity (TFP) using the Ackerberg-Caves-Frazer (ACF) method (Ackerberg et al., 2015). *Substitution* effect is measured by the elasticity of substitution across various energy sources due to changes in their prices. *Absorption* effect is measured through the impact of energy prices on firm size (employment), other input costs (e.g., wages), profit margins, and return on sales, normalized by net income, costs and the changes of fixed assets. We provide a complete list of analyzed firm-level outcome variables y_{it} alongside their definition and descriptive statistics in Table A.2 as well as a list of dependent variables analyzed by comparable work using firm-level microdata in Table A.3.

5.2 Heterogeneity in Responses

To analyze heterogeneity in the response patterns, we adjust Equation 1 employing a dummy identifier of the form:

$$y_{it} = (\boldsymbol{\beta}_i' \mathbf{x}_{it}) \times I_{(z_i \in Z)} + \varepsilon_{it}, \tag{4}$$

[15] A more detailed analysis of additional variables of interest, such as TFPQ or other coping mechanisms, particularly the cost *pass-through* dimension, was not possible due to current data limitations. This leaves numerous highly policy-related questions unanswered. For example, one of the most direct measures of cost pass-through is the unit price of final products sold to the market; however, this is not observed in the open-access version of ENIA. A more extensive analysis could be conducted in the presence of access to the full data.

where $I(\cdot)$ is an indicator function which takes the value one if condition Z is met for a particular observation in our data z_{it}. We analyze heterogeneities in firm-level responses by breaking down the sample based on the firm-level characteristics of firm size (small, medium, large; see panel I in Table A.4 for a summary statistics and definition of the respective cut-offs), ownership (foreign and domestic; see panel II), export status (exporter and non-exporter; panel III) and energy intensity (intensive and non-intensive; panel IV).

5.3 Non-linearity in Responses

We investigate non-linear patterns by extending the model in Equation 1 and estimating a panel quantile regression model as proposed by Machado and Silva (2019) to evaluate how the correlation between firm-level outcomes and energy price changes varies depending on the actual observed price level. The implication is that a firm's optimal response to energy price hikes may vary depending on the energy price it observes. For example, firms may be more wasteful in their energy use at lower energy price levels and retain less efficient production processes because of low opportunity costs. Conversely, they might find it more difficult to adjust their production at higher price levels as they may have already exhausted some of the more straightforward energy-saving strategies when transitioning away from an initially low energy-price regime. The linear specification for the conditional quantile of dependent variable y and explanatory variables $\boldsymbol{x}_{it}$ is given by:

$$Q(\tau|\boldsymbol{x}_{it}, \beta(\tau)) = \beta(\tau)\ \boldsymbol{x}_{it}, \tag{5}$$

where $\beta(\tau)$ is a vector of the coefficients related to the τth quantile.

5.4 Endogeneity Issues

Endogeneity in estimating the impact of energy prices on firm outcomes can emerge due to omitted variables bias, selection effects, and reverse causality. We address the various sources as much as possible in the current setup.

First, omitted variable bias can be due to time-invariant variables (e.g., access to specific energy sources due to regional or industry-specific attributes or policies contingent on such criteria). It can also vary over time and be either idiosyncratic (e.g., managerial ability to adjust energy use based on prices optimally) or more systemic (e.g., time-trends such as structural changes due to global market shocks or technological change). Issues of reverse causality arise in our context because energy prices are measured at the firm level. Firms with higher productivity or other outcomes are likely the ones with better capabilities, e.g., management. In turn, these can affect energy prices at the firm level through several channels. For example, by easing information and coordination frictions, management may help reduce "hidden" administrative and time costs associated with energy use through efficiency-enhancing investments in programs or equipment that can affect firm-level energy prices per unit (Gillingham and Palmer, 2014). Management may also help firms overcome uncertainty, for instance, in energy price fluctuations or the magnitude of future cost savings, by enabling firms to target and track historical energy use and accurately forecast future needs and payoffs. In particular, savvy firms may be able to optimally time energy purchases when prices are low, e.g., by employing forecasting tools or using financial vehicles.[16] Productive firms also implement more energy-centric management practices (Grover and Karplus, 2020), which may raise energy efficiency and thereby reduce the per-unit price.

Fixed-effects Specification. *First*, we use a fixed-effects (FE) setup to capture endogeneity arising from variations in time-invariant firm attributes, regional and industry-specific market conditions and technology-related developments (Mundlak, 1978; Wooldridge, 2005). To this end, the error term in Equation 1 has the following structure:

$$\varepsilon_{it} = \alpha_i + D_{st} + \tau_{rt} + e_{it}, \tag{6}$$

where α_i denotes firm-specific intercepts while industry-year interactions (D_{st}) capture industry-specific market conditions and technology-related developments. We also include region-year interactions (τ_r) to capture the evolution of region-specific long-run development dynamics in local governance, infrastructure, development, innovation, etc.

Second, we rule out endogeneity resulting from autocorrelation or heteroscedasticity by using clustered standard errors at the plant-year level as residuals in Equation 6 (Petersen, 2009), which can be estimated consistently with a sufficiently large number of clusters (Wooldridge, 2010; Cameron et al., 2011). We employ this FE specification for all baseline estimations, including the heterogeneity and non-linearity analysis.

[16] Even difficult-to-store energy carriers such as electricity are often subject to differences in fixed costs based on use and time-of-day pricing, including in developing countries, creating opportunities for arbitrage by shifting production to off-peak hours.

Instrumental Variables. We address time-varying unobserved variation at the plant level remains a source of endogeneity by employing an Instrument Variable (IV) design commonly used in this field (e.g., Amann et al., 2021; Calì et al., 2022) to exploit the geographical variation in energy prices resulting from the cost of distributing energy to a particular province. We derive our spatial/leave-one-out instrument by calculating the normalized cost of geographical energy distribution for firm i in year t and unit energy price index of type m, up_{it}^{m}, from the average unit price paid by all other firms, i', $i \neq i'$, in the same region r and year t. The first stage IV estimating plant-level energy prices is:

$$up_{it}^{m} = \alpha_0 + \alpha_1 inst_{it}^{m} + D_{st} + \tau_{rt} + \eta_{it}, \tag{7}$$

where $inst_{it}^{m}$ refers to the instrument of energy unit price up_{it} of energy source m. For the validity of our instrument, we require it to be correlated with plant-level energy prices without directly affecting performance.

Spatial instruments of this sort have been criticized for various reasons (Betz et al., 2018). Spatial instruments are effective if the unit prices of other plants i' do not directly or indirectly affect the outcome variables of plant i. However, as energy prices drive firm performance, they can indirectly feed into the outcomes of other plants through *spillover effects*. To minimize this effect, our spatial instrument considers energy prices of i' plants within a region that are *not* operating in the same ISIC 2-digit sector as plant i in IV specification 1 (IV_1). At the same time, energy prices of firms within the same sector can be aligned due to policies pertaining to subsidies in a given sector. If we consider the prices of firms in other ISIC 2-digit sectors as instruments, they may not be strongly correlated with the energy prices of a firm in another sector. At the same time, spillover effects may be most prominent in industries that are most closely related in terms of activity and location. Consequently, and as a robustness check, we provide an alternative IV specification (IV_2), which considers the energy prices for i' plants within a region that are *not* operating in the same ISIC 4-digit sector as plant i but can operate in the same broader ISIC 2-digit aggregate.

We recover the cost of regional energy distribution as follows: *In step one*, for firm i unit price index for fuel type m, up_{it}^{m}, we calculate the average unit prices paid by all *other* firm i' in the same region r in a given year. The instrumented energy unit prices are calculated as:

$$IV_1: \qquad \bar{up}_{it}^{m,2} = \sum_{i \in r, i \neq i', s_i^2 \neq s_{i'}^2}^{N_{rts}} \omega_{it} \frac{up_{it}^m}{(N_{rt}-1)}, \tag{8}$$

$$IV_2: \qquad \bar{up}_{it}^{m,4} = \sum_{i \in r, i \neq i', s_i^4 \neq s_{i'}^4}^{N_{rts}} \omega_{it} \frac{up_{it}^m}{(N_{rt}-1)}, \tag{9}$$

where N_{rts} denotes the number of plants in period t populating the same region as firm i, $i \in r$ that are not engaged in the same manufacturing activity, i.e., the same ISIC k-digit sector s^k, $s_i^k \neq s_{i'}^k$, $k = \{2, 4\}$. Finally, ω_{it} corresponds to plant- and time-specific similarity weight for a set of observations.[17] *In step two*, we normalize this unit price in equations 8 and 9 by the national average of the same year to minimize the potential correlation of plant-level outcomes with aggregate shocks affecting each energy type:

$$inst_{it}^{m,k} = \frac{\bar{up}_{it}^{m,k}}{\bar{up}_t^{m,k}}, \qquad \bar{up}_t^{m,k} = \sum_i^{N^k} \frac{up_{it}^{m,k}}{N^k}, \tag{10}$$

where $\bar{up}_t^{m,k}$ is the average, national unit price of energy source m in year t and instrument of type k. This instrument can be interpreted as a proxy for the cost of energy distribution for plant i to a particular region as the weighted average of the energy prices of the other plant, i': it is correlated with plant-level energy prices while mitigating the effect of idiosyncratic plant-level attributes by excluding the plant itself when calculating regional averages in equations 8 and 9.

Some concerns about the validity of spatial instruments may remain. *First*, it is possible that the energy unit price of firm i can, at least partially, be influenced by the unit price of other firms. Given the market structure of the Chilean energy sector, we argue that firms typically enter the market as price takers. Consequently, they cannot negotiate lower prices based on other firms' energy bills, even if they know the energy bills of their competitors. *Second*, not all of our analyzed outcome variables are subject to the same endogeneity concerns. For example, if firms in i' become more efficient and consume less coal, it is unlikely that this will affect the coal consumption of firm i. However, spatial instruments may be more of a concern

[17] A similar weighting approach is adopted in Singer (2024).

in cases where the substitutability of inputs is highly dependent on local conditions. For instance, the hiring practices of firms in i' may influence the bargaining power of job seekers and, therefore, affect the wage bill of other firms, including firm i. While we cannot rule out all such dynamics, the consistency in our findings across model specifications (including both IV designs) may indicate that our empirical setup accounts for most of these effects. *Finally*, as an additional check for our instrumental variable design, we follow the recommendations in Chao and Swanson (2005) and provide test statistics as part of the regression tables to illustrate that none of our models suffers from weak identification.

6 Results

6.1 Baseline FE Estimates

Table 1 present results from baseline estimation, which we discuss along with the identified firm-level coping mechanism.[18]

Investment & productivity/survival. In line with global evidence, our FE estimations suggest a positive correlation between productivity and investment with fossil fuel prices (panel I) and a small trade-off between productivity and energy prices (panel II). There are some noteworthy differences in firm-level responses by fuel types. Higher electricity prices do not significantly correlate with a reduction in investment in assets (panel I) and lower productivity (panel II). However, increases in fossil fuel prices correlate positively with investments in machinery (column 1), the balance of net assets (4), output per worker (5) and higher wages (13), and negatively with exit probability (8). Overall, the results on fossil fuel price hikes pertaining to investments support a weak version of the Porter Hypothesis, while those on productivity are in favor of the strong version. These results align with other studies differentiating firm-level coping strategies by energy type and underscore the importance of a disaggregated analysis by fuel type.

Substitution effect. Panel III in Table 1 suggests that increases in prices of electricity correspond to a significant reduction in consumed quantities of electricity (9). In terms of magnitude, the quantified effects for fossil fuel are comparable in magnitude to other studies with a similar estimation setup (Amann et al., 2021). However,

[18]Given the lack of exogenous policy change, we refer to weak (strong) *Porter-type* response mechanisms whenever our results indicate that price variations observed at the plant level are associated with subsequent investment (and productivity) responses. This does not imply that any hypothetical policy change in this scenario would have necessarily brought about the same or similar response mechanisms as the ones we observe.

the results hint at more pronounced price elasticities of both energy types. We also observe similar responses across all energy types in response to a surge in fossil fuel hikes, which are significant. Firms' consumption of fossil fuels correlates positively with a price hike in electricity (9), but the degree of substitution between fossil fuels and electricity varies by fuel type (11 vs 12).

Table 1: Baseline results - FE

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity	-0.009	-0.053	0.027	-0.024
	(0.026)	(0.132)	(0.033)	(0.023)
Fossil Fuel	0.031**	0.102*	0.042*	0.030***
	(0.015)	(0.048)	(0.021)	(0.008)
R^2	0.47207	0.69099	0.69640	0.72267
Adjusted R^2	0.34371	0.34659	0.55930	0.67233
Observations	39,922	2,143	18,719	63,920
# firms	9,097	1,153	6,602	11,609

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Exit (8)
Electricity	-0.017*	-0.018*	-0.004**	0.010***
	(0.009)	(0.009)	(0.002)	(0.004)
Fossil Fuel	0.008**	0.004	0.001	-0.003***
	(0.003)	(0.005)	(0.0007)	(0.0009)
R^2	0.88466	0.74716	0.95606	0.305195
Adjusted R^2	0.86477	0.70221	0.93808	0.18521
Observations	67,982	65,502	13,470	53,887
# firms	12,228	12,232	4,363	9,207

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuel (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity	-0.626***	0.004	0.025	0.082*
	(0.181)	(0.034)	(0.039)	(0.043)
Fossil Fuel	0.173***	-0.584***	-0.512***	-0.501***
	(0.014)	(0.044)	(0.043)	(0.073)
R^2	0.85820	0.76343	0.76835	0.75485
Adjusted R^2	0.83374	0.71868	0.71857	0.69437
Observations	68,242	57,561	42,925	31,197
# firms	12,284	12,285	7,538	6,074

Panel IV *Absorption - workers*	Wages workers (13)	Wages prod. workers (14)	Emp. workers (15)	Emp. prod. workers (16)
Electricity	0.002	-0.014	-0.026***	-0.035***
	(0.006)	(0.020)	(0.008)	(0.011)
Fossil Fuel	0.005**	0.0008	0.004	0.005
	(0.002)	(0.006)	(0.004)	(0.005)
R^2	0.86734	0.75367	0.91187	0.89357
Adjusted R^2	0.84448	0.70288	0.89667	0.87515
Observations	67,967	45,782	68,004	67,575
# firms	12,207	8,955	12,285	12,285

Panel V *Absorption - business metrics*	Profit margin (17)	Sales/output (18)	Costs/output (19)	Return on Sales (20)
Electricity	-0.016*	-0.009**	0.003	-0.043*
	(0.008)	(0.003)	(0.005)	(0.023)
Fossil Fuel	-0.010**	0.001	0.005*	-0.018*
	(0.004)	(0.002)	(0.002)	(0.010)
R^2	0.48955	0.60731	0.54986	0.82711
Adjusted R^2	0.39786	0.53855	0.47223	0.77826
Observations	64,959	64,742	68,228	35,097
# firms	12,277	11,728	12,277	12,255
Fixed-effects				
Plant	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
Region-Year	Yes	Yes	Yes	Yest

Note: Estimates according to fixed-effects model described in equations 1 and 6 include firm-effects and industry-year and region-year effects. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Absorption effect. Panel IV of Table 1 suggests that fossil fuel increases positively correlate with wages (13) but not employment (15 & 16). Wage effects emanate primarily from the non-production worker sub-sample, suggesting some reallocation of workers towards higher skill usage or premium due to changes in fossil fuel prices (Brucal and Dechezleprêtre, 2021; Dechezleprêtre et al., 2020). By comparison, electricity price hikes seem to force firms to shed employment (15) and, more so, production workers (16). Panel V of Table 1 confirms that energy price increases negatively correlate with firms' profit margins. However, absorption and pass-through again vary by energy type. While fossil fuel price hikes are associated with cost increases, electricity surges affect profit margins through a reduction in sales (perhaps through a reduction in firms' production workers). The results for return on sales are consistent with the findings on sales costs and asset evolution, showing a consistent negative correlation with increases in energy prices.

To conclude, while electricity price increases are associated with reduced production and a decline in firm size, fossil fuel price hikes have a positive association with capital investment, possibly manifesting in improved productivity, thereby supporting the *strong* version of the Porter Hypothesis. However, these productivity increases may not translate into higher profitability (at least in the short run), indicating that the pass-through of such price hikes is limited and at least partially absorbed by firms.[19]

6.2 Heterogeneity in Responses

This section highlights the significant heterogeneity in response to energy price hikes across various firm attributes by estimating Equation 4.

Firm Size. Considering three categories of firm sizes: large (more than 50 employees), medium (between 20 and 49) and small (fewer than 20),[20] we draw the following conclusions on the heterogeneity in responses based on the results presented in Table 2: *First*, the overall positive correlations of fossil fuel price changes with firm upgrading and productivity are primarily driven by large firms (panel I).

[19] Evidence suggests firms pass at least parts of the energy costs on to consumers (Chateau et al., 2018), which may not be desirable from the point of the policy design and may have notable welfare implications (Maruejols et al., 2022). Given the current data limitations, it is impossible to quantify this effect in this study.

[20] We provide summary statistics for the size cut-offs used in the analysis in Table A.4. In ENIA the classification by firm size varies between the raw and combined data sets and complicates the firm matching algorithm described in Appendix B slightly; see Table B.12 for more information on the respective cut-offs in the two ENIA data sets.

In response to the withdrawal of fossil fuel subsidies, large firms upgrade both machinery *and* ICT equipment, consistent with the results from Oman, Mexico and Indonesia (Amann et al., 2021; Calì et al., 2022). *Second*, the aggregate negative productivity effects observed for electricity price hikes are primarily driven by small and medium-sized firms (panel II). Large firms seem to be unperturbed by electricity price increases, both in terms of their productivity and profitability. However, large firms also observe negative correlations of fossil fuel price hikes with profit margins. *Third*, firms of all sizes are sensitive to energy prices and substitute away from the energy source whose price increases and towards the alternative source. Intra-fuel elasticities do not notably differ by firm size (panel III).

Foreign Ownership. We differentiate between nationally-owned (domestic) and foreign firms.[21] Results from Table A.7 suggest that although investment correlates positively and significantly with fossil fuel hikes for both firm types, the magnitude is generally higher for foreign firms (panel I). It is not surprising, then, that fuel price increases correspond more strongly to productivity increases for foreign-owned firms than domestic ones (panel II). Furthermore, electricity price hikes are negatively and significantly correlated with domestic firms' productivity and profit margins. Regarding substitution and absorption effects, foreign firms substitute more strongly in response to increases in fossil fuel prices (panel III) while they sharply reduce employment following electricity price hikes (panel IV).

Table 2: Results by firm size - FE

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity × Large	0.003	-0.068	0.002	-0.046
	(0.035)	(0.139)	(0.040)	(0.043)
Electricity × Medium	-0.065	-0.050	0.045	-0.027
	(0.041)	(0.286)	(0.068)	(0.025)
Electricity × Small	0.059	-1.17	0.047	0.004
	(0.062)	(0.723)	(0.070)	(0.022)
Fossil Fuel × Large	0.042***	0.096*	0.039	0.040***
	(0.014)	(0.047)	(0.025)	(0.011)
Fossil Fuel × Medium	0.007	0.211	0.051	0.032**
	(0.030)	(0.154)	(0.035)	(0.013)
Fossil Fuel × Small	0.015	-0.318	0.059	-0.005
	(0.038)	(0.513)	(0.050)	(0.017)
R^2	0.47246	0.69301	0.69771	0.72292
Adjusted R^2	0.34405	0.34796	0.56102	0.67259
Observations	39,901	2,142	18,709	63,920
# firms	9,097	1,153	6,602	11,609

[21] We define a firm as *domestic* if it records a foreign capital formation of zero in all periods; see Table A.4 panel II for the corresponding summary statistics.

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Profit margin (8)
Electricity × Large	-0.013	0.010	-0.002	0.013
	(0.013)	(0.016)	(0.002)	(0.014)
Electricity × Medium	-0.032**	-0.036**	-0.003	-0.020
	(0.013)	(0.014)	(0.003)	(0.012)
Electricity × Small	-0.030**	-0.054**	-0.008	-0.053***
	(0.012)	(0.020)	(0.005)	(0.016)
Fossil Fuel × Large	0.016**	0.007	0.01*	-0.024***
	(0.006)	(0.008)	(0.007)	(0.006)
Fossil Fuel × Medium	0.012**	0.007	0.002	-0.007
	(0.005)	(0.007)	(0.002)	0.006
Fossil Fuel × Small	-0.004	0.004	-0.003	0.015*
	(0.007)	(0.010)	(0.002)	0.008)
R^2	0.88783	0.74942	0.95686	0.49022
Adjusted R^2	0.86847	0.70482	0.93917	0.39854
Observations	67,940	65,462	13,470	64,920
# firms	12,228	12,232	4,363	12,277

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity × Large	-0.652***	-0.077*	-0.103*	0.062
	(0.210)	(0.043)	(0.053)	(0.048)
Electricity × Medium	-0.579***	0.062	0.023	0.105**
	(0.180)	(0.036)	(0.038)	(0.049)
Electricity × Small	-0.609***	0.120**	0.068	0.138**
	(0.139)	(0.047)	(0.052)	(0.055)
Fossil Fuel × Large	-0.154***	-0.596***	-0.468***	-0.535***
	(0.015)	(0.045)	(0.038)	(0.072)
Fossil Fuel × Medium	-0.174***	-0.550***	-0.496***	-0.467***
	(0.023)	(0.048)	(0.054)	(0.071)
Fossil Fuel × Small	-0.223***	-0.517***	-0.517***	-0.372***
	(0.020)	(0.051)	(0.059)	(0.067)
R^2	0.86055	0.76631	0.77141	0.75677
Adjusted R^2	0.83646	0.72204	0.72221	0.69667
Observations	68,200	57,525	42,895	31,180
# firms	12,284	12,285	7,538	6,074

Panel IV *Absorption - workers*	Wages workers (13)	Wages prod. workers (14)	Emp. workers (15)	Emp. prod. workers (16)
Electricity × Large	0.013	-0.005	-0.006	0.004
	(0.014)	(0.005)	(0.008)	(0.035)
Electricity × Medium	-0.020	-0.014**	0.001	-0.022
	(0.012)	(0.006)	(0.007)	(0.029)
Electricity × Small	-0.053***	-0.009	0.017**	-0.075**
	(0.016)	(0.006)	(0.006)	(0.032)
Fossil Fuel × Large	-0.024***	0.001	0.010**	-0.008
	(0.006)	(0.005)	(0.003)	(0.017)
Fossil Fuel × Medium	-0.007	0.002	0.002	-0.011
	(0.006)	(0.003)	(0.003)	(0.016)
Fossil Fuel × Small	0.015*	0.0004	0.0008	-0.019
	(0.008)	(0.006)	(0.004)	(0.023)
Adjusted R^2	0.39854	0.53877	0.47258	0.78191
Within Adjusted R^2	0.00351	0.00998	0.00452	0.02166
Observations	64,612	42,433	64,642	64,218
# firms	12,158	8,904	12,235	12,235
Fixed-effects				

Plant	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
Region-Year	Yes	Yes	Yes	Yes

Note: Estimates according to fixed-effects model described in equations 1 and 4 and include firm-effects and industry-year and region-year effects as well as interactions and levels of the respective firm-level heterogeneity variables. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Exporter Status. We separate firms based on their international market engagement.[22] The results presented in Table A.8 can be summarized as follows: Capital upgrading among exporters is more strongly and positively associated with fossil fuel price increases (panel I). Non-exporting firms, in turn, experience a negative correlation between productivity indicators and electricity price increases (panel II). The same effect is absent for exporters. Exporters have a positive association with productivity and fossil fuel hikes. Considered jointly, our results suggest that the strong version of the Porter Hypothesis holds for exporting firms. For non-exporters, the empirical evidence lends support to the weak version of the Porter Hypothesis instead.[23] Energy substitution and absorption are comparable across both firm types (panels III and IV).

Energy Intensity. Finally, we evaluate the impact of energy price variations conditional on energy consumption. We do so by classifying the manufacturing sectors as either energy-intensive or non-intensive.[24] The results presented in Table A.9 suggest that capital upgrading is more prevalent for energy-intensive sectors; however, evidence for the weak Porter Hypothesis exists for energy-intensive and non-intensive sectors in response to fossil fuel price surges (panel I). Further evidence in support of the strong version of the Porter Hypothesis is again observed, primarily for the energy-intensive sub-sectors (panel II). Intra-fuel substitution and absorption of energy price hikes are also more prevalent for energy-intensive sectors (panels III) and IV).

[22] We define a firm as an exporter if it reports a positive net value of export earnings of self-made products during any period. For more information and summary statistics, see Table A.4 panel III.

[23] The estimated signs for non-exporters are also in line with the strong version of the Porter Hypothesis yet remain insignificant.

[24] Energy-intensive sectors are food; pulp and paper; basic chemicals; refining; iron and steel; non-ferrous metals; non-metallic minerals following the sector classification of EIA (2022).See Table A.4 panel IV for a cross-tabulation by groups.

6.3 Non-linearity in Responses

Next, we turn to the issue of potential non-linearities in the firm-level responses to energy price increases. We examine if firms' optimal response to energy price hikes may depend on the energy price it observes. Firms may resort to different energy-saving strategies at low energy price levels compared to higher prices. For example, firms may invest in updated production technologies to increase efficiency at lower price levels. Still, this coping mechanism may not be accessible to firms once they have exhausted the saving potential stemming from capital upgrading, for example, at higher energy price levels. It is, therefore, crucial to analyze to what extent the previously established correlation patterns are themselves determined by the actual price levels of energy.

The results of this analysis are summarized in Figure 1 and show that the positive correlation between fossil fuel price increases and capital upgrading is more pronounced when fuel prices are low (panel I). At higher fuel price levels, this effect becomes smaller and eventually insignificant. Similar effects cannot be observed for electricity prices.[25] These patterns may be suggestive of the cost of upgrading electricity-based technology relative to fuel-based machinery (panel I, Figure 1a). Furthermore, the previously identified Porter-type innovation hypothesis for fossil fuels seems most pronounced at low(er) energy price levels but becomes statistically insignificant at higher fuel levels (panel II). By comparison, the *substitution* channel does not exhibit a non-linear relationship as correlations between electricity and fossil fuel prices and consumed quantities of either energy source are similar during low- and high-price energy regimes (panel III). Lastly, the positive wage effect correlating with a surge in fossil fuel prices becomes smaller and insignificant at higher fuel price levels (panel IV).

These findings suggest that firms may resort to different coping strategies depending on energy price levels. At lower energy price levels, adjustment is notably through the *innovation* channel, while other mechanisms, such as *absorption*, may become more relevant at even higher energy price levels.

[25] The correlations between machinery investment and electricity price increases follow a less pronounced yet still non-linear pattern. A positive correlation with innovation is observed at higher electricity prices, while lower electricity prices correspond to a negative correlation with investment in machinery.

Figure 1: Non-linear Correlations

Panel I: Investment

(a) Machinery/output

(b) Asset balance/output

Panel II: Productivity/Survival

(c) Gross output/worker

(d) TFP

Panel III: Substitution

(e) Quantity Electricity

(f) Quantity Fossil Fuel

Panel IV: Absorption - workers

(g) Wages all workers

(h) Wages production workers

(i) Employment all workers

(j) Employment production workers

Note: Y-axis plot the coefficients of the non-linear FE regression as described in Equation 5 and baseline FE regression (Equation 1). Scatters and error bars: Percentile FE estimates and 90% confidence interval of non-linear FE regressions. Colored horizontal lines and shaded areas: Point estimates and 90% confidence interval of baseline FE regressions. Dashed horizontal line: Zero line.

6.4 Robustness Checks

Instrumental Variables Estimation. We address potential endogeneity by employing a spatial/leave-one-out instrument to exploit the geographical variation in energy prices from the cost of distributing energy to a particular province to eliminate time-varying unobserved variation in the energy prices faced by firm i. As we discuss in section 5.4, we provide two variations of the spatial instrument where either excluding the same ISIC 2-digit sector (IV_1) or 4-digit sector (IV_2) to address potential spillover effects that could potentially invalidate our IV design.[26]

Results for IV_1 (Table 3) and IV_2 (Table A.10) generally confirm the robustness of our OLS results in the baseline model. In particular, the IV estimators report a slightly higher price elasticity of electricity. Furthermore, wages by production workers are now found to significantly contract in response to an electricity price hike (14) with IV_1. This effect is statistically insignificant in the baseline model and the IV_2 specification. Compared to Table 1, results in Table 3 are typically larger, indicating that OLS is biased towards zero. This is most apparent for output-related variables, indicating that output shocks may be correlated with energy prices and, in particular, electricity prices. This indicates potential energy price interventions in response to output shocks—a strategy not uncommon as recent evidence suggests (Fabra, 2024). The most notable differences are that the effect of fossil fuel increases on ICT capital upgrading (2) and wages (13) are now insignificant in the two IV specifications. The same applies to the negative correlation of electricity price hikes with the profit margin (17).

Table 3: Instrumental Variable Results - IV_1

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity	-0.020	-0.062	0.013	-0.026
	(0.027)	(0.186)	(0.034)	(0.023)
Fossil Fuels	0.028*	0.051	0.045*	-0.032***
	(0.015)	(0.066)	(0.022)	(0.009)
Fit statistics				
Adjusted R^2	0.35121	0.37544	0.56574	0.67408
Within Adjusted R^2	0.00115	0.00139	0.00224	0.01570
Observations	39,922	2,143	18,719	63,920
Weak id. test	59.4	102.0	69.8	110.1

[26] We provide the First Stage estimates for both variations of the instrument in tables A.5 and A.6, respectively. Across all estimated models, the F-statistics lie between 118 and 148, suggesting that the selected instrument is strong. In both cases, the instrument has a positive association with electricity prices, consistent with the results reported for Indonesia in Calì et al. (2022). Since plants' electricity is generated by utilizing fuel, higher fuel prices are implicitly included in electricity prices.

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Exit (8)
Electricity	-0.022**	-0.021**	-0.005*	0.010**
	(0.009)	(0.010)	(0.003)	(0.003797)
Fossil Fuels	0.008**	0.003	-0.0004	-0.003***
	(0.004)	(0.005)	(0.001)	(0.0007308)
Fit statistics				
Adjusted R^2	0.86930	0.71151	0.81888	0.18521
Within Adjusted R^2	0.00397	0.00281	0.00209	0.00622
Observations	67,982	65,502	13,470	53,887
Weak id. test	92.6	83.7	43.7	43.9

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity	-0.860***	0.030	0.0006	0.070
	(0.064)	(0.035)	(0.042)	(0.043)
Fossil Fuels	-0.183***	-0.543***	-0.451***	-0.491***
	(0.012)	(0.044)	(0.039)	(0.063)
Fit statistics				
Adjusted R^2	0.88009	0.75431	0.76921	0.70066
Within Adjusted R^2	0.12624	0.09820	0.07439	0.08329
Observations	68,242	57,561	42,925	31,197
Weak id. test	81.9	73.8	116.3	73.5

Panel IV *Absorption - workers*	Wages workers (13)	Wages prod. workers (14)	Emp. all workers (15)	Emp. prod. workers (16)
Electricity	-0.003	-0.029*	-0.025**	-0.037**
	(0.006)	(0.015)	(0.010)	(0.014)
Fossil Fuels	0.004	0.002	0.002	0.005
	(0.002)	(0.007)	(0.004)	(0.004)
Fit statistics				
Adjusted R^2	0.85280	0.69545	0.90048	0.87769
Within Adjusted R^2	0.00139	0.00848	0.00179	0.00182
Observations	67,967	45,782	68,004	67,575
Weak id. test	111.5	55.9	38.6	62.9

Panel V *Absorption - business metrics*	Profit margin (17)	Sales/output (18)	Costs/output (19)	Return on Sales (20)
Electricity	-0.014	-0.009**	0.002	-0.043*
	(0.008)	(0.003)	(0.005)	(0.024)
Fossil Fuels	-0.010**	0.0006	0.005*	-0.019*
	(0.004)	(0.003)	(0.003)	(0.010)
Fit statistics				
Adjusted R^2	0.40214	0.54410	0.47755	0.77830
Within Adjusted R^2	0.00098	0.00091	0.00064	0.00137
Observations	64,959	64,742	68,228	35,097
Weak id. test	119.5	90.7	95.2	81.2
Fixed-effects				
Plant	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
Region-Year	Yes	Yes	Yes	Yest

Note: Estimates are based on FE model described in equations 1 and 7 and include firm-effects and industry-year and region-year effects. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1 Weak identification test ('Weak id.') test statistic for instrumental variables following Chao and Swanson (2005).

Contemporaneous versus Medium-term Effects. We are concerned that it might take time for firms to make decisions on their investments that would, in turn, translate into productivity effects with further lags. By comparison, substitution and absorption effects could potentially be instantaneous, although they may show further adjustments over the medium to long run.[27]

To this end, we experiment with lags of energy price changes in Equation 1 to analyze the intertemporal component of the response patterns in investment and productivity effects. We estimate the model:

$$y_{it} = \boldsymbol{\beta}_i \mathbf{x}_{i,t-\ell} + \varepsilon_{it}, \tag{11}$$

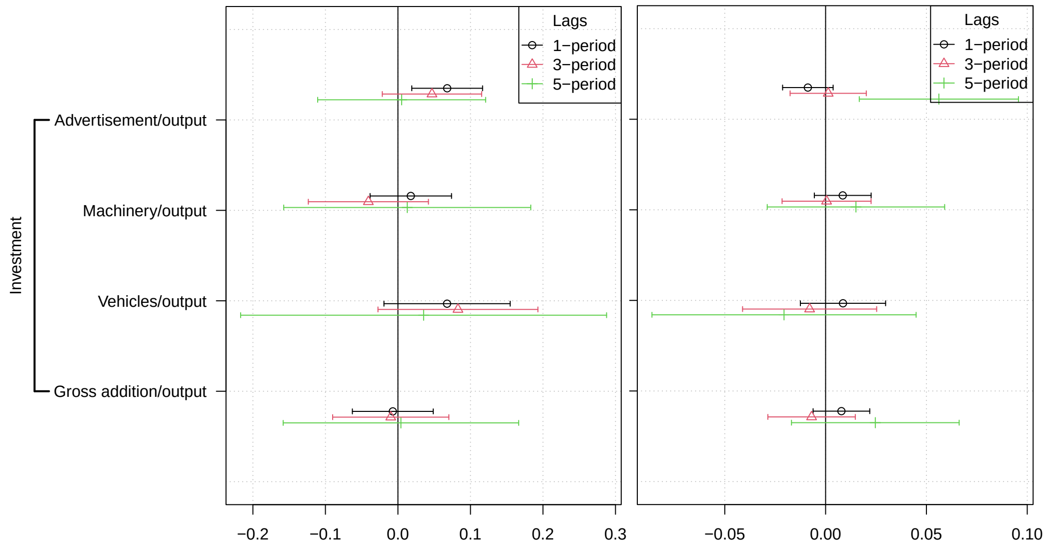
where we compare the contemporaneous effect with the one-, three- and five-year lagged observations of the electricity and fossil fuel prices, respectively, by setting $\ell = \{1, 3, 5\}$. The results presented in Figure 2 suggest that the negative correlation of electricity price hikes on investment indicators is no longer significant for lagged models. At the same time, productivity effects are stronger for a five-year period when considering electricity prices (panels 2a and 2b).[28]

Sensitivity to Sample Period. Finally, we confirm the robustness of our results by providing a sensitivity analysis where we remove the final three years of the sample, where we observe a stronger deviation of the reported raw data sample vis-à-vis our reconstructed data set. We do this to ensure that the results of our analysis are not driven by our matching algorithm while acknowledging that the correlations between the variables may change over time. This implies that a further truncation of the data set may, therefore, pick up intertemporal variations rather than eliminate any potential contagion stemming from our data generation. The results in Table A.11 confirm the previously established relationships between energy prices and firm-level outcome variables.

[27] Historically, lagged values of the explanatory variables are also used as valid instruments, although subject to some criticism. The literature on whether lagged explanatory variables are effective in surmounting endogeneity concerns is scarce. Among the few contributions, Reed (2015) and Bellemare et al. (2017) evaluate the practice of replacing an endogenous variable with its lag. Reed (2015) focuses on situations where endogeneity stems from simultaneity between y and x. In turn, Bellemare et al. (2017) identify the lack of serial correlation in the potentially endogenous explanatory variable and serial correlation among the unobserved sources of endogeneity as conditions that could lead to incorrect inferences when employing lagged variables as instruments. Consequently, we refrain from employing such a lagged IV setup in this study.

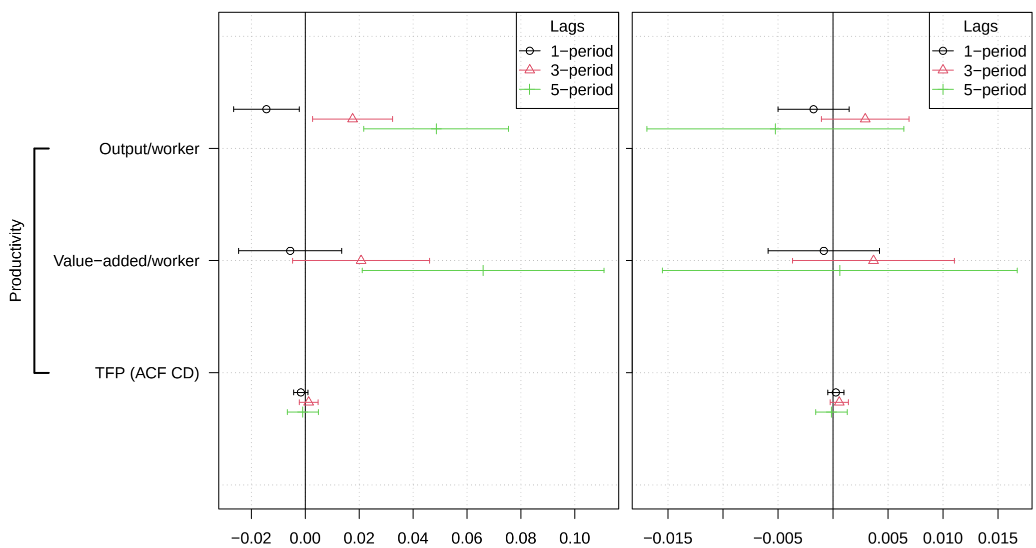
[28] Results pertaining to substitution and absorption effects are instantaneous in most cases with stronger adjustments in five-year periods.

Figure 2: Contemporaneous vs medium-term Effects



(a) Investment effects electricity prices

(b) Investment effects fossil fuel prices



(c) Productivity effects of electricity prices

(d) Productivity effects of fossil fuel prices

Note: Estimates based on Equation 11. Scatters and error bars: FE point estimates and 90% confidence intervals.

7 Conclusion

This paper contributes to understanding the energy price-firm competitiveness nexus in an emerging economy context. Firms use four coping mechanisms to navigate energy price increases: *innovation and competitiveness*, *substitution* across fuel types and other inputs, *absorption* and *pass-through*. Our results indicate that while electricity price increases are associated with reduced production and employment, fossil fuel price hikes result in increased capital investment, manifesting in improved productivity, thereby supporting the *strong* version of the Porter Hypothesis. However, these productivity increases do not translate into higher profitability (at least not in the short run), indicating that such price hikes are at least also partly absorbed by firms.

These broader results mask heterogeneity by firm attributes. The strong version of the Porter Hypothesis can only be observed in large firms. Small firms are more negatively affected by surges in energy prices. Likewise, exporters and foreign-owned firms are also less affected compared to domestically oriented firms. Moreover, energy-intensive firms are also found to experience more extensive Porter-type innovations, and their business and employment metrics are typically more affected by energy price hikes than firms in non-energy-intensive sectors.

Given the firm heterogeneity in outcomes, policy reforms affecting energy prices and accompanying measures are best targeted based on solid micro-level analyses. The most vulnerable firms, such as the smaller and domestically oriented firms, may not have the means to adjust to energy price fluctuations and may need complementary support to undertake the necessary changes and investments. A better understanding of how existing inequalities interact with the risks posed by energy price policies, taking into account firm capabilities and management skills, will inform a more efficient policy design.

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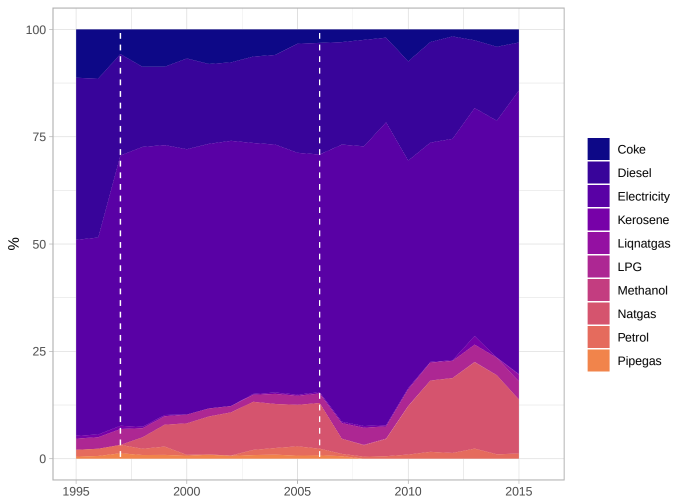
Appendix

A Supplementary Figures and Tables

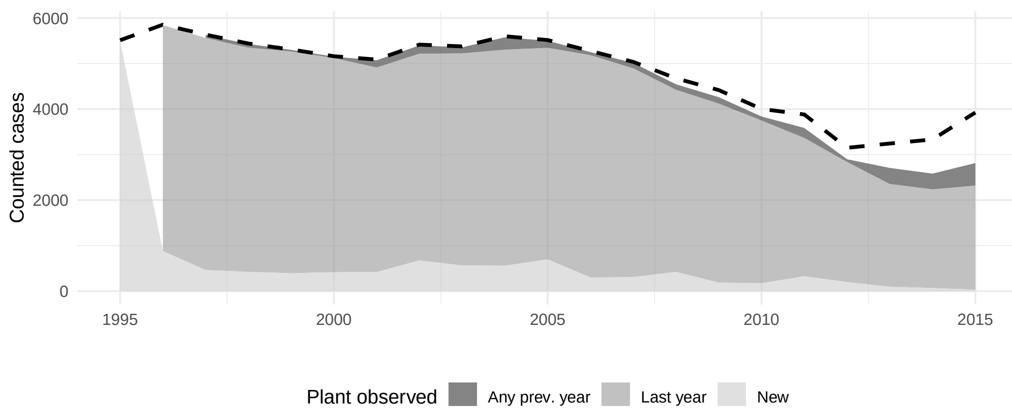
A.1 Supplementary Figures

Figure A.1: Energy Composition



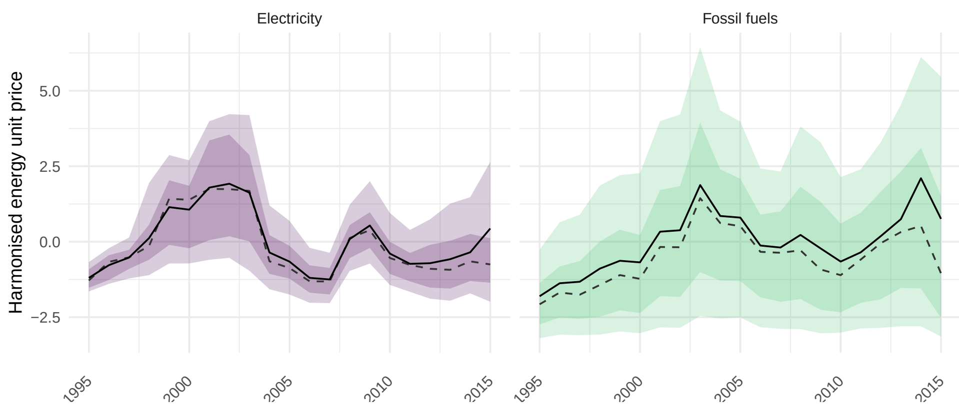
Note: Purchased quantities by energy type. Years 2007 and 2006 highlighted with dashed lines.
Source: Authors' calculations based on ENIA data (INE, 2015).

Figure A.2: Distinct Plants over Time



Note: Dashed line: number of unique plants reported in raw data.
Source: Authors' calculations based on ENIA data (INE, 2015).

Figure A.3: Harmonized Unit Prices by Energy Type



Note: ISIC 2-digit industry-level deflators following Haraguchi and Amann (2023). Dashed line: median. Shaded area: $10^{th}/90^{th}$ (light); $25^{th}/75^{th}$ (darker) percentile.
Source: Authors' calculations based on ENIA data (INE, 2015).

A.2 Supplementary Tables

A.2.1 Descriptive Statistics

Table A.1: Fossil Fuel Conversion Rates

		Unit conversion		
Fossil fuel	Unit measure (um)	um/kg	um/m^3	um/kWh
Coal	kg	1	850	7.00
Diesel	liter	0.85	0.001	9.10
Gas	cubic meter (m^3)	0.51	0.270	8.80
Gasoline	liter	0.75	0.001	10.00
Kerosene	liter	0.80	0.001	10.35
LPG	liter	0.51	0.270	6.90

Source: Authors' calculations based on ENIA data (INE, 2015).

Table A.2: Descriptive Statistics

Variable						Responses	
Abbreviation	Description	Mean	Med.	LQ	UQ	N	%
Independent variables							
Electricity (EL)	Electricity unit price	0.1	0.1	0.1	0.1	93868	97.17
Fossil fuel (FF)	Fossil fuel unit price	2.2	1.8	0.9	3.0	69582	72.03
Investment							
Machinery/output	Investment in fixed assets, machinery and equipment/gross value of net production	0.1	0.0	0.0	0.0	51278	53.08
ICT/output	Investment in fixed assets, software and ICT equipment/gross value of net production	0.0	0.0	0.0	0.0	2492	2.58
Vehicles/output	Investment in fixed assets, vehicles/gross value of net production	0.0	0.0	0.0	0.0	22782	23.58
Gross addition/output	Gross addition to fixed assets/gross value of net production. Includes investment in land; buildings; machinery and equipment; vehicles; furniture; software and ICT; other assets.	0.1	0.0	0.0	0.1	61082	63.23
Productivity							
Output/worker	Gross value of net production/average total contract workers	68599.8	23556.5	13481.7	48014.4	95883	99.26
Value-added/worker	Net value-added/average total contract workers	24098.2	8082.3	4409.2	15412.2	95892	99.27
TFP	Total Factor Productivity following Ackerberg et al. (2015) with Cobb Douglas production function	9.6	9.7	8.8	10.5	16189	16.76
Exit	Firm exit probability: 1 if firm remains in sample for at least two consecutive years and drops from the sample (without returning)	91.06	.	.	.	87041	94.70
Substitution							
Qnt. Electricity	Quantity of electricity consumed	10972.0	84.0	27.0	414.0	94724	98.06
Qnt. Diesel	Quantity of diesel consumed	690.2	26.0	8.0	91.0	44022	45.57
Qnt. LPG	Quantity of LPG consumed	155.2	5.0	2.0	18.0	31612	32.72
Absorption - workforce							
Wages all workers	Average remuneration total contract workers	6218.2	4857.2	3126.4	7632.8	95863	99.24
Wages production workers	Average remuneration workers associated with the industrial process	4060.8	2877.8	1155.5	5044.2	60558	62.69
Emp. all workers	Average total contract workers	68.8	26.0	15.0	62.0	95992	99.37
Emp. production workers	Average contract workers associated with the industrial process	51.8	19.0	10.0	46.0	95166	98.52
Absorption - business metrics							
Profit margin	(Total net income from the sale of products and work performed / Total net cost of goods received and work performed under contract - 1)	0.3	0.4	0.2	0.5	96381	99.77
Return on Sales	Total net income from the sale of products and work performed - Total net cost of goods received and work performed under contract - Net balance of fixed assets at the end of the period	-1016851.2	13684.2	-205588.9	129285.1	93748	97.05
Costs/output	Total net cost of goods received and work performed under contract/gross value of net production	0.6	0.6	0.5	0.8	96393	99.79

Note: LQ/UP: Lower and upper quartile. Top/bottom 0.1 per-cent trimmed.
Source: Authors' calculations based on ENIA data (INE, 2015).

A.2.2 Literature Summary

Table A.3: Related Literature

	Amann et al. (2021)
Data	• Oman; Annual Industrial Survey; 3600 manufacturing firms (2012-2017).
Variables	• *Dependent:* value-added/employment; output/employment; TFP; gross profit margin; q^m; machinery and ICT sales and purchases • *Independent:* up^m, various sector- & region-controls.
	Brucal and Dechezleprêtre (2021)
Data	• Indonesia; manufacturing industry; covering all medium and large enterprises (1980-2015).
Variables	• *Dependent:* energy use; CO2 emissions; output; employment; energy and CO2 intensity; energy/worker; capital and capital intensity; purchases/sales of land, buildings, machinery, vehicles. • *Independent:* energy price (firm-level average energy price across energy sources weighted by firm-level consumption-share by energy type), various sector- & region-controls.
	Calì et al. (2022)
Data	• Indonesia; Statistik Industri: manufacturing firms with 20+ employees (1998-2015). • Mexico; Encuesta Anual de la Industria Manufacturera; mfn. firms (2009-2015).
Variables	• *Dependent:* TFP; profitability; value-added/employment; value-added/kWh; energy efficiency; machine turnover • *Independent:* up^m, various sector- & region-controls.
	Calì et al. (2023)
Data	• World Bank's Enterprise Surveys for 11 countries between the years 2002 and 2013
Variables	• *Dependent:* Total employment; sales/(total employment); value-added/(total employment); returns on sales; export share. • *Independent:* Energy price index, interacted with energy export share; firm size; ownership; energy-outage dummy; R&D dummy. The Energy price index (EP) given by $$EP_{cst} = log\left(\sum_j \theta_{jcs,1995} \times p_{jct}\right)$$ where $\theta_{jcs,1995}$ is the share of energy source j (e.g. crude oil, natural gas, electricity, etc.) over total energy use of sector s in country c in year 1995 and p_{jct} is the real price of energy source j in country c and year t.
	Marin and Vona (2021)

Table A.3 continued from previous page

Data	• France; manufacturing industry (1997-2015).
Variables	• *Dependent:* energy consumption; CO2 emissions; employment; annual wage; employment share by occupation group. • *Independent:* energy price (in kWh, firm-level average energy price across energy sources weighted by firm-level consumption-share by energy type), initial capital stock of firm j in $t = 0$, various sector- & region-controls.
	Rentschler and Kornejew (2018)
Data	• Indonesia; 41,402 small and micro mining and manufacturing firms (2013).
Variables	• *Dependent:* cost share • *Independent:* prices of electricity, petrol, diesel, kerosene, LP, sector- & region- controls.

Abbreviations: up^m: unit price of energy type m; q^m: physical quantity of energy type m;
$m = \{Electricity, Fossil\ Fuel\}$; $j = \{electricity, naturalgas, petrol, \ldots\}$.
kWh: Kilowatt hours; TFP: Total Factor Productivity; FE: Fixed effects; IV: Instrumental Variable.

A.2.3 Heterogeneity in Responses

Table A.4: Summary Statistics Heterogeneity Analysis

Panel I: *Firm-size*	N	%	Definition
Responses			
Large	32252	32.26	Large firms: ≥ 50 employees.
Medium	32391	32.40	Medium firms: $\geq 20, < 50$ employees.
Small	35235	35.24	Small firms: < 20 employees.
Non-responses			
No firm-size information	96	0.10	

Panel II: *Ownership*	N	%	Definition
Responses			
Domestic	87215	90.28	Foreign capital formation $= 0$ LCU in all periods.
Foreign	9385	9.72	Foreign capital formation > 0 LCU in any period.

Panel III: *Export engagement*	N	%	Definition
Responses			
Exporter	19714	20.41	Exporter if net value of export earnings of self-made products > 0 LCU in any period.
Non-exporter	76886	79.59	Exporter if net value of export earnings of self-made products $= 0$ LCU in all periods.

Panel IV: *Energy intensity*	N	%	Definition
Responses			
Energy-intensive	64379	64.4	Sectors: Food; pulp and paper; basic chemicals; refining; iron and steel; nonferrous metals; nonmetallic minerals.
Non-intensive	35595	35.6	All other sectors according to EIA (2022).

Source: Authors' calculations based on ENIA data (INE, 2015).

A.2.4 Instrumental Variables

Table A.5: First Stage - IV_1

Model:	Electricity (1)	Fossil Fuel (2)
Variables		
Electricity IV	0.889***	-0.034
	(0.025)	(0.026)
Fossil Fuel IV	-0.115***	0.809***
	(0.037)	(0.045)
Fit statistics		
Adjusted R^2	0.60316	0.77699
Within Adjusted R^2	0.05239	0.01972
F-test	134.43	148.09
Observations	65,058	65,058
Fixed-effects		
Plant	Yes	Yes
Industry-Year	Yes	Yes
Region-Year	Yes	Yes

Clustered (plant & year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.6: First Stage - IV_2

Model:	Electricity (1)	Fossil Fuel (2)
Variables		
Electricity IV	0.785***	-0.041
	(0.023)	(0.045)
Fossil Fuel IV	-0.106***	0.591***
	(0.022)	(0.042)
Fit statistics		
Adjusted R^2	0.62691	0.67030
Within Adjusted R^2	0.04694	0.00930
F-test	117.91	142.66
Observations	65,058	65,058
Fixed-effects		
Plant	Yes	Yes
Industry-Year	Yes	Yes
Region-Year	Yes	Yes

Clustered (plant & year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.2.5 Additional Results

Table A.10: Instrumental Variable Results - IV_2

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity	-0.028	-0.113	0.027	-0.030
	(0.026)	(0.195)	(0.036)	(0.023)
Fossil Fuels	0.027*	0.068	0.052**	-0.034***
	(0.015)	(0.070)	(0.020)	(0.008)
Fit statistics				
Adjusted R^2	0.35031	0.29992	0.56827	0.67441
Within Adjusted R^2	0.00106	0.00235	0.00166	0.01534
Observations	39,922	2,143	18,719	63,920
Weak id. test	42.6	52.9	97.3	107.4
Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Exit (8)
Electricity	-0.017	-0.016	-0.004	0.010**
	(0.010)	(0.011)	(0.002)	(0.003797)
Fossil Fuels	0.007*	0.004	0.0002	-0.003***
	(0.004)	(0.005)	(0.0009)	(0.0007308)
Fit statistics				
Adjusted R^2	0.86884	0.71060	0.88852	0.18521
Within Adjusted R^2	0.00375	0.00267	0.00505	0.00622
Observations	67,982	65,502	13,470	53,887
Weak id. test	102.0	63.2	42.0	43.9
Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity	-0.900***	0.032	0.004	0.077*
	(0.034)	(0.035)	(0.042)	(0.044)
Fossil Fuels	-0.189***	-0.567***	-0.478***	-0.503***
	(0.010)	(0.047)	(0.043)	(0.062)
Fit statistics				
Adjusted R^2	0.88145	0.73719	0.74428	0.69602
Within Adjusted R^2	0.12460	0.09927	0.07439	0.08509
Observations	64,866	54,776	40,567	30,069
Weak id. test	59.3	55.2	67.7	66.7
Panel IV *Absorption - workers*	Wages all workers (13)	Wages production workers (14)	Emp. all workers (15)	Emp. production workers (16)
Electricity	0.003	-0.019	-0.025**	-0.037**
	(0.007)	(0.018)	(0.010)	(0.014)
Fossil Fuels	0.004	0.002	0.007*	0.009*
	(0.002)	(0.007)	(0.004)	(0.004)
Fit statistics				
Adjusted R^2	0.85010	0.69563	0.89863	0.87635
Within Adjusted R^2	0.00150	0.00851	0.00159	0.00173
Observations	67,967	45,782	68,004	67,575
Weak id. test	73.5	95.9	59.8	50.3
Panel V *Absorption - business metrics*	Profit margin (17)	Sales/output (18)	Costs/output (19)	Return on Sales (20)
Electricity	-0.013	-0.012***	0.001	-0.040
	(0.009)	(0.004)	(0.005)	(0.023)
Fossil Fuels	-0.010**	0.0008	0.004	-0.017
	(0.004)	(0.003)	(0.002)	(0.010)
Fit statistics				
Adjusted R^2	0.39903	0.54065	0.47633	0.77868
Within Adjusted R^2	0.00092	0.00088	0.00052	0.00108
Observations	64,959	64,742	68,228	35,097
Weak id. test	96.3	111.9	72.9	106.3
Fixed-effects				
Plant	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
Region-Year	Yes	Yes	Yes	Yest

Note: Estimates are based on FE model described in equations 1 and 7 and include firm-effects and industry-year and region-year effects. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1 Weak identification test statistic for instrumental variables following Chao and Swanson (2005).

Table A.7: Results by ownership - FE

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity × Domestic	-0.013	-0.113	0.050	-0.020
	(0.028)	(0.182)	(0.040)	(0.012)
Electricity × Foreign	0.032	0.204	-0.124	-0.064**
	(0.058)	(0.336)	(0.085)	(0.032)
Fossil Fuel × Domestic	0.022*	0.109	0.045**	0.025***
	(0.013)	(0.073)	(0.019)	(0.006)
Fossil Fuel × Foreign	0.078***	0.055	0.029	0.065***
	(0.026)	(0.166)	(0.036)	(0.013)
RMSE	1.2285	0.95723	0.98320	0.71800
R^2	0.47217	0.69172	0.69654	0.72276
Adjusted R^2	0.34377	0.34621	0.55941	0.67242
F-test, p-value	1.0000	1.0000	0.99939	0.99891
Observations	39,922	2,143	18,719	63,920
# firms	9,097	1,153	6,602	11,609

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Profit margin (8)
Electricity × Domestic	-0.021**	-0.024**	-0.004**	-0.017*
	(0.009)	(0.010)	(0.002)	(0.009)
Electricity × Foreign	0.022	0.051	0.001	-0.008
	(0.033)	(0.039)	(0.003)	(0.028)
Fossil Fuel × Domestic	0.007*	0.004	0.0007	-0.009***
	(0.003)	(0.004)	(0.0008)	(0.001)
Fossil Fuel × Foreign	0.016*	0.004	0.003**	-0.014
	(0.009)	(0.016)	(0.001)	(0.010)
RMSE	0.36361	0.56550	0.03249	0.48342
R^2	0.88475	0.74721	0.95611	0.48955
Adjusted R^2	0.86488	0.70226	0.93813	0.39783
F-test, p-value	0.31509	0.99378	0.00105	1.0000
Observations	67,982	65,502	13,470	64,959
# firms	12,228	12,232	4,363	12,277

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity × Domestic	-0.634***	0.025	0.011	0.085*
	(0.176)	(0.035)	(0.041)	(0.042)
Electricity × Foreign	-0.516**	-0.157*	0.183*	0.070
	(0.245)	(0.076)	(0.088)	(0.121)
Fossil Fuel × Domestic	0.173***	-0.558***	-0.477***	-0.472***
	(0.015)	(0.044)	(0.045)	(0.072)
Fossil Fuel × Foreign	0.161***	-0.666***	-0.566***	-0.631***
	(0.019)	(0.051)	(0.055)	(0.073)
RMSE	0.85190	1.0072	0.95684	0.85131
R^2	0.85823	0.76368	0.76855	0.75529
Adjusted R^2	0.83377	0.71896	0.71879	0.69489
F-test, p-value	0.56986	0.98363	0.97478	0.98616
Observations	68,242	57,561	42,925	31,197
# firms	12,284	12,285	7,538	6,074

Panel IV *Absorption - workers*	Wages all workers (13)	Wages production workers (14)	Emp. all workers (15)	Emp. production workers (16)
Electricity × Domestic	-0.003	-0.019	-0.024**	-0.032**
	(0.006)	(0.017)	(0.009)	(0.012)
Electricity × Foreign	0.048**	0.043	-0.043**	-0.063***
	(0.019)	(0.054)	(0.016)	(0.020)
Fossil Fuel × Domestic	0.006**	0.003	0.003	0.003
	(0.002)	(0.007)	(0.004)	(0.005)
Fossil Fuel × Foreign	-0.002	-0.013	0.015	0.016
	(0.008)	(0.020)	(0.009)	(0.010)
RMSE	0.23635	0.56818	0.33525	0.39468
R^2	0.86744	0.75373	0.91188	0.89359
Adjusted R^2	0.84459	0.70292	0.89668	0.87516
F-test, p-value	0.48889	0.99853	0.09625	0.23316
Observations	67,967	45,782	68,004	67,575
# firms	12,207	8,955	12,285	12,285

Note: Estimates according to fixed-effects model described in equations 1 and 4 and include firm-effects and industry-year and region-year effects as well as interactions and levels of the respective firm-level heterogeneity variables. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A.8: Results by exporter status - FE

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity × Exporter	-0.0004	-0.264	-0.029	-0.035
	(0.034)	(0.213)	(0.043)	(0.034)
Electricity × Non-exporter	-0.014	0.076	0.058	-0.020
	(0.035)	(0.151)	(0.048)	(0.022)
Fossil Fuel × Exporter	0.045**	0.150*	0.040	0.042***
	(0.021)	(0.072)	(0.027)	(0.014)
Fossil Fuel × Non-exporter	0.020	0.064	0.043	0.025**
	(0.019)	(0.065)	(0.025)	(0.009)
RMSE	1.2285	0.95855	0.98298	0.71808
R^2	0.47216	0.69087	0.69669	0.72270
Adjusted R^2	0.34376	0.34441	0.55962	0.67234
F-test, p-value	1.0000	1.0000	0.99938	0.99892
Observations	39,922	2,143	18,719	63,920
# firms	9,097	1,153	6,602	11,609

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Profit margin (8)
Electricity × Exporter	-0.020	0.003	-0.0008	0.026
	(0.014)	(0.018)	(0.002)	(0.016)
Electricity × Non-exporter	-0.015	-0.024**	-0.006**	-0.029***
	(0.010)	(0.011)	(0.002)	(0.010)
Fossil Fuel × Exporter	0.016**	0.005	0.002*	-0.023***
	(0.006)	(0.009)	(0.0008)	(0.007)
Fossil Fuel × Non-exporter	0.004	0.004	0.0003	-0.004
	(0.004)	(0.005)	(0.0010)	(0.005)
RMSE	0.36336	0.56549	0.03243	0.48328
R^2	0.88491	0.74722	0.95627	0.48986
Adjusted R^2	0.86506	0.70227	0.93835	0.39819
F-test, p-value	0.31354	0.99377	0.00103	1.0000
Observations	67,982	65,502	13,470	64,959
# firms	12,228	12,232	4,363	12,277

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity × Exporter	-0.725***	-0.097	-0.132*	0.037
	(0.172)	(0.058)	(0.067)	(0.056)
Electricity × Non-exporter	-0.592***	0.042	0.005	0.104**
	(0.183)	(0.034)	(0.038)	(0.042)
Fossil Fuel × Exporter	0.154***	-0.608***	-0.491***	-0.550***
	(0.012)	(0.043)	(0.038)	(0.075)
Fossil Fuel × Non-exporter	0.180***	-0.555***	-0.491***	-0.461***
	(0.018)	(0.049)	(0.052)	(0.070)
RMSE	0.85080	1.0085	0.95672	0.85131
R^2	0.85860	0.76305	0.76861	0.75530
Adjusted R^2	0.83420	0.71821	0.71886	0.69489
F-test, p-value	0.56640	0.98523	0.97472	0.98616
Observations	68,242	57,561	42,925	31,197
# firms	12,284	12,285	7,538	6,074

Panel IV *Absorption - workers*	Wages all workers (13)	Wages production workers (14)	Emp. all workers (15)	Emp. production workers (16)
Electricity × Exporter	0.004	0.025	-0.032**	-0.044**
	(0.009)	(0.030)	(0.014)	(0.016)
Electricity × Non-exporter	0.001	-0.026	-0.023**	-0.032**
	(0.007)	(0.019)	(0.009)	(0.013)
Fossil Fuel × Exporter	0.007	-0.007	0.001	0.006
	(0.004)	(0.009)	(0.006)	(0.007)
Fossil Fuel × Non-exporter	0.004	0.004	0.005	0.004
	(0.003)	(0.007)	(0.004)	(0.005)
RMSE	0.23635	0.56815	0.33427	0.39391
R^2	0.86744	0.75376	0.91240	0.89400
Adjusted R^2	0.84459	0.70296	0.89728	0.87565
F-test, p-value	0.48888	0.99853	0.09345	0.22952
Observations	67,967	45,782	68,004	67,575
# firms	12,207	8,955	12,285	12,285

Note: Estimates according to fixed-effects model described in equations 1 and 4 and include firm-effects and industry-year and region-year effects as well as interactions and levels of the respective firm-level heterogeneity variables. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A.9: Results by energy intensity - FE

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity × Energy-intensive	-0.008	-0.024	0.004	-0.022
	(0.033)	(0.135)	(0.036)	(0.053)
Electricity × Non-intensive	-0.010	-0.118	0.089*	0.003
	(0.041)	(0.227)	(0.046)	(0.031)
Fossil Fuel × Energy-intensive	0.037**	0.092	0.048**	0.034***
	(0.015)	(0.058)	(0.023)	(0.005)
Fossil Fuel × Non-intensive	0.015	0.126	0.021	0.041***
	(0.029)	(0.106)	(0.035)	(0.011)
RMSE	1.2286	0.95828	0.98331	0.71808
R^2	0.47210	0.69105	0.69648	0.72270
Adjusted R^2	0.34368	0.34477	0.55931	0.67234
F-test, p-value	1.0000	1.0000	0.99939	0.99892
Observations	39,922	2,143	18,719	63,920
# firms	9,097	1,153	6,602	11,609

Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Profit margin (8)
Electricity × Energy-intensive	-0.015*	-0.011	-0.003*	-0.033**
	(0.009)	(0.010)	(0.002)	(0.014)
Electricity × Non-intensive	-0.022*	-0.036**	-0.005	-0.009
	(0.011)	(0.015)	(0.003)	(0.010)
Fossil Fuel × Energy-intensive	0.009*	0.010	0.002***	-0.014*
	(0.004)	(0.007)	(0.0008)	(0.007)
Fossil Fuel × Non-intensive	0.003*	-0.010	-0.003	-0.009
	(0.002)	(0.007)	(0.002)	(0.005)
RMSE	0.36356	0.56550	0.03248	0.48336
R^2	0.88478	0.74721	0.95614	0.48968
Adjusted R^2	0.86491	0.70226	0.93817	0.39798
F-test, p-value	0.31481	0.99378	0.00105	1.0000
Observations	67,982	65,502	13,470	64,959
# firms	12,228	12,232	4,363	12,277

Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity × Energy-intensive	-0.624***	0.002	-0.007	0.085*
	(0.181)	(0.039)	(0.037)	(0.045)
Electricity × Non-intensive	-0.628***	-0.005	-0.102	0.074
	(0.182)	(0.042)	(0.062)	(0.058)
Fossil Fuel × Energy-intensive	0.172***	-0.565***	-0.514***	-0.491***
	(0.015)	0.112)	(0.046)	(0.065)
Fossil Fuel × Non-intensive	0.171***	-0.516***	0.402***	-0.499***
	(0.020)	(0.111)	(0.048)	(0.088)
RMSE	0.85098	1.1555	0.95668	0.85076
R^2	0.85854	0.81396	0.76863	0.75561
Adjusted R^2	0.83413	0.78190	0.71889	0.69529
F-test, p-value	0.56697	0.87892	0.97470	0.98596
Observations	68,242	68,326	42,925	31,197
# firms	12,284	12,285	7,538	6,074

Panel IV *Absorption - workers*	Wages all workers (13)	Wages production workers (14)	Emp. all workers (15)	Emp. production workers (16)
Electricity × Energy-intensive	-0.004	0.037*	-0.050***	-0.063***
	(0.007)	(0.019)	(0.010)	(0.013)
Electricity × Non-intensive	0.004	-0.032	-0.016*	-0.025**
	(0.007)	(0.023)	(0.009)	(0.012)
Fossil Fuel × Energy-intensive	-0.003	0.003	-0.0008	-0.005
	(0.003)	(0.009)	(0.006)	(0.007)
Fossil Fuel × Non-intensive	0.008***	-0.002	0.006	0.008
	(0.003)	(0.008)	(0.005)	(0.006)
RMSE	0.23640	0.56646	0.33467	0.39363
R^2	0.86738	0.75522	0.91218	0.89415
Adjusted R^2	0.84452	0.70472	0.89703	0.87583
F-test, p-value	0.48951	0.99840	0.09459	0.22821
Observations	67,967	45,782	68,004	67,575
# firms	12,207	8,955	12,285	12,285

Note: Estimates according to fixed-effects model described in equations 1 and 4 and include firm-effects and industry-year and region-year effects as well as interactions and levels of the respective firm-level heterogeneity variables. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table A.11: Results Sub-sample

Panel I *Investments*	Machinery/output (1)	ICT/output (2)	Vehicles/output (3)	Asset balance/output (4)
Electricity	-0.027	-0.080	0.002	-0.029
	(0.029)	(0.173)	(0.036)	(0.022)
Fossil Fuels	0.034**	0.074	0.048*	-0.029***
	(0.015)	(0.081)	(0.025)	(0.010)
Fit statistics				
RMSE	1.2359	0.95829	0.97830	0.66044
R^2	0.48196	0.69104	0.71242	0.75643
Adjusted R^2	0.33775	0.34670	0.56107	0.70543
F-test, p-value	1.0000	1.0000	0.99973	0.99859
Observations	29,204	2,143	13,559	46,779
# firms	7,284	1,153	5,146	9,427
Panel II *Productivity/survival*	Output/worker (5)	Value-added/worker (6)	TFP (7)	Exit (8)
Electricity	-0.022**	-0.026**	-0.003*	0.009**
	(0.009)	(0.010)	(0.002)	(0.005)
Fossil Fuels	0.007*	0.002	0.001	-0.004***
	(0.003)	(0.006)	(0.0007)	(0.001)
Fit statistics				
RMSE	0.34847	0.55134	0.03177	0.22433
R^2	0.89978	0.76786	0.96045	0.40215
Adjusted R^2	0.87996	0.72052	0.94321	0.26693
F-test, p-value	0.43245	0.99581	0.00974	1.0000
Observations	49,814	47,875	10,660	36,817
# firms	9,958	9,960	3,535	8,079
Panel III *Substitution*	Qnt. Electricity (9)	Qnt. Fossil Fuels (10)	Qnt. Diesel (11)	Qnt. LPG (12)
Electricity	-0.857***	0.036	0.015	0.082*
	(0.068)	(0.034)	(0.042)	(0.039)
Fossil Fuels	-0.178***	-0.518***	-0.433***	-0.458***
	(0.013)	(0.047)	(0.041)	(0.068)
Fit statistics				
RMSE	0.92019	1.0023	0.95935	0.88167
R^2	0.85004	0.76064	0.76184	0.75881
Adjusted R^2	0.82036	0.70778	0.70264	0.68901
F-test, p-value	0.84734	0.99689	0.99568	0.99631
Observations	50,057	42,373	32,677	22,207
# firms	10,015	10,016	6,447	4,885
Panel IV *Absorption - workers*	Wages all workers (13)	Wages production workers (14)	Emp. all workers (15)	Emp. production workers (16)
Electricity	-0.009	-0.031*	-0.020*	-0.030
	(0.008)	(0.016)	(0.011)	(0.022)
Fossil Fuels	0.003	0.0007	0.008*	0.009
	(0.003)	(0.007)	(0.004)	(0.006)
Fit statistics				
RMSE	0.22853	0.56824	0.32392	0.35748
R^2	0.87331	0.75367	0.92032	0.91481
Adjusted R^2	0.84824	0.70288	0.90454	0.89792
F-test, p-value	0.68804	0.99805	0.21807	0.27194
Observations	49,795	45,782	49,826	49,566
# firms	9,943	8,955	10,016	10,016
Panel V *Absorption - business metrics*	Profit margin (17)	Sales/output (18)	Costs/output (19)	Return on Sales (20)
Fossil Fuels	-0.010**	0.0008	0.005*	-0.021*
	(0.004)	(0.003)	(0.003)	(0.011)
Electricity	-0.016*	-0.009**	0.002	-0.046*
	(0.008)	(0.003)	(0.005)	(0.024)
Fit statistics				
RMSE	0.47850	0.21794	0.23252	0.74621
R^2	0.50904	0.66051	0.57203	0.84141
Adjusted R^2	0.40762	0.59240	0.48739	0.79057
F-test, p-value	1.0000	1.0000	1.0000	0.89491
Observations	47,529	47,238	50,066	26,255
# firms	10,007	9,506	10,008	9,983
Plant	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
Region-Year	Yes	Yes	Yes	Yest

Note: Estimates according to FE model described in equations 1 and 6 include firm-effects as well as industry-year and region-year effects. Clustered (plant & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

B Firm-level Matching Algorithm

ENIA is made available by the National Statistical Institute in two distinct forms. The *combined* data set identifies the same manufacturing firm between 1995 and 2007 with a constant 5-digit ID yet fails to provide information on the firms' location or their ISIC 4-digit classification code. In turn, this information is available in the corresponding *raw* data files of ENIA (available for the years 1995 to 2015); however, these data do use a firm-level identifier which differs (a) from that of the combined data set and (b) varies over time.

We propose a simple algorithm that exploits firm-level characteristics to match firms between the *combined* and *raw* data sets to extract information on the respective firms' location and 4-digit manufacturing sector. Our procedure achieves a successful match of $> 95\%$ and follows the following steps:

- For every year, check if the following characteristics produce an *exact match* between the combined and raw data sets, respectively:
  - Year of the survey.
  - 3-digit ISIC sector.
  - Share foreign/domestic ownership.
  - Firm size. There is some ambiguity between the combined and raw firm data when classifying firm sizes, which requires the harmonization of eight size groups in the raw data to 4 groups as per the harmonized data. This reclassification is 1-to-1 for all but one out of the eight groups identified in the raw data; see Table B.12. If a firm is in category 6 in the raw data, it can be matched to *either* code 3 or 4 in the combined data.
- Furthermore, we enforce a fuzzy match for the value and amount of electricity consumed by firms across both data sets as follows:
  - Quantity electricity purchased ($\pm 5\%$).
  - Value electricity purchased ($\pm 10\%$)
- Because of the fuzzy nature of the match, no exclusive 1-to-1 match outcome is to be expected. Consequently, in case multiple IDs can be matched based on the above match criteria, we identify the best match by:
  - The longest number of matched years between two IDs;

Table B.12: Firm-size Classifications

Raw data ID	Raw data cut-offs	Combined data ID	Combined data cut-offs
0	0 <= *tot. emp.* >= 04	0	< 10 employed
1	05 <= *tot. emp.* >= 09	0	< 10 employed
2	10 <= *tot. emp.* >= 19	1	10-19 employed
3	20 <= *tot. emp.* >= 49	2	20-49 employed
4	50 <= *tot. emp.* >= 99	3	50-249 employed
5	100 <= *tot. emp.* >= 199	3	.
6	200 <= *tot. emp.* >= 499	3.5	.
7	500 <= *tot. emp.* >= 999	4	250+ employed
8	tot. emp. >=1000	4	250+ employed

Note: Firm-size classification according to raw and combined ENIA data sets.
Source: Authors' calculations based on ENIA data (INE, 2015).

  - The lowest average absolute difference between the reported quantity (value) of electricity purchased that falls within an acceptable range between two IDs;
  - In other words, we pick the matched firm that is closest to the reported values in the combined data set as long as the difference does not exceed 5% (10%) of the reported quantity (value) of electricity purchased, respectively.

- This way, we can uniquely identify 90 per cent of all firms in the combined data set as described in Table B.13.

Table B.13: Match Rates Firm-level Matching Algorithm

Matches	Cases	Percent
At most 1 unique ID match	10,538	90.3
At most 2 IDs matched	1,038	8.9
At most 3 IDs matched	84	0.7
Unique ID match after 2^{nd} round	11,156	95.6

Note: Firm matches across raw and combined ENIA data.
Source: Authors' calculations based on ENIA data (INE, 2015).

- Finally, while the outlined algorithm uniquely matches around 90% of firm IDs, the algorithm's nature is such that the same matched firm may satisfy the "closest proximity" requirement of the previous chat. This is the case for around 9.5% of all recorded cases. Given these, we re-iterate the previous step by evaluating the closest proximity *conditional* on the proximity of the other non-unique matches of the identical firm IDs. Through this final step, the match rate between the two data sets is at 95.6%; see last line in Table B.13.

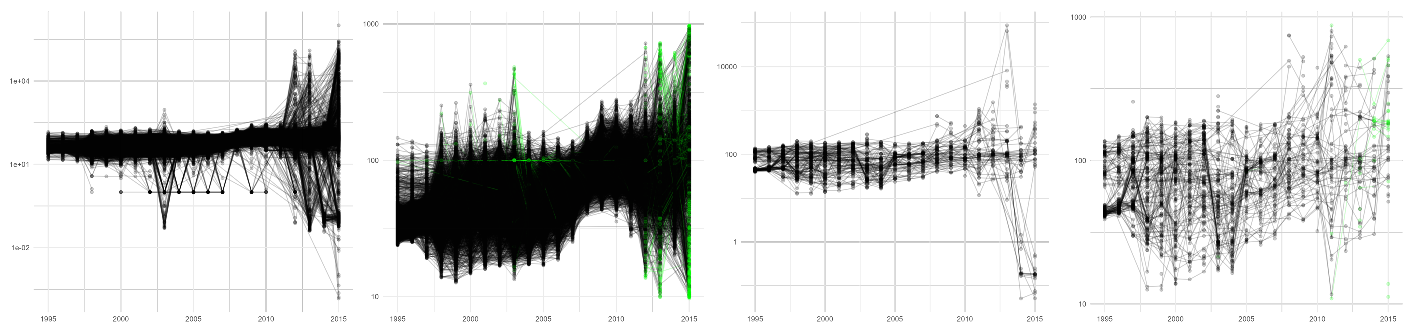
C Energy Unit Price Adjustment Algorithm

The energy and electricity cleaning algorithm described in this section is designed to identify and eliminate artificial jumps in the raw energy data that are the potential result of data imputation or reporting issues. Consider the example where quantities of an unspecified liquid were reported in tonnes in periods t_0 t_1 and t_2, respectively, but the unit of measurement in period t_1 would be wrongfully given in m^3. In such a case, the conversion of m^3 in t_1 to tonnes would lead to an inter-temporal change of reported quantities and unit prices (assuming a not notable change in purchased volumes over the three years) of a factor close to the conversion factor between tonnes and cubic meters. The algorithm we propose identifies jumps of these magnitudes and overwrite the (assumed to be wrongfully reported) quantity information if the corrected measures would not constitute a minimum/maximum in the series. In our example, this means that the quantity measure in t_1 will be adjusted, if the adjusted value would not be smaller (larger) than $min(t_0, t_2)$ ($max(t_0, t_2)$), respectively. More specifically, the cleaning algorithm applied to the respective energy series takes the following steps:

1. For any sequence, i.e., firm and arbitrary energy unit price (up) and arbitrary point in time (t_0) over the time interval $t = 1, \ldots, T$, look at previous/next period ($t_0 \pm 1$) and observe change of unit price:
$$\Delta up_{t_0 \pm 1} = \frac{up_{t_0 \pm 1}}{up_{t0}}.$$
2. Check, if $\Delta up_{t_0 \pm 1}$ is of order of magnitude 1×10^k, $k = \{\ldots, -1, 0, 1, \ldots\}$:
    - If it is, correct up_{t_0} by factor k defined as variable $\widetilde{up}^k_{t0} := up_{t_0} \times k$.
    - If it is not, move to next sequence.
3. Check, if $\widetilde{up}^k_{t0}$ is smaller [bigger] than $\min(up_{t \in T, t \neq t_0})$ [$\max(up_{t \in T, t \neq t_0})$]:
    - If it is, remove observation up_{t0}.
    - If it is not, replace up_{t0} with $\widetilde{up}^k_{t0}$.

Figure C.1 compares the pre- vs post-adjustment energy unit prices. Highlighted data points indicate adjustments made by the adjustment algorithm. Different colors highlight different quantity unites, e.g., cubic meters, tonnes etc.

Figure C.1: Unit Prices Series, pre- and post-adjustment



(a) Electricity, pre-adjustment (b) Electricity, post-adjustment (c) Coal, pre-adjustment (d) Coal, post-adjustment

Note: Unit price series following energy unit price adjustment algorithm described in Appendix C. Highlighted data points indicate adjustments made by the adjustment algorithm. Different colors emphasise different quantity units, e.g., cubic meters, tonnes etc.
Source: Authors' calculations based on ENIA data (INE, 2015).