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AUTHOR

Nada Fadl

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Institute of Energy Economics at the University of Cologne (EWI)
www.ewi.uni-koeln.de

**Institute of Energy Economics
at the University of Cologne (EWI)**

Alte Wagenfabrik
Vogelsanger Str. 321a
50827 Köln
Germany

Tel.: +49 (0)221 277 29-100
Fax: +49 (0)221 277 29-400
www.ewi.uni-koeln.de

CORRESPONDING AUTHOR

Nada Fadl

fadl@wiso.uni-koeln.de

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Examining the impact of differential electricity pricing on industrial development: Evidence from panel VAR

Nada H. Fadl*

University of Cologne, Chair of Energy Economics, Cologne, Germany

Abstract

Significant discrepancies in electricity pricing are observed across countries, particularly between industrial and household rates. Although the literature studies the relationship between electricity prices and economic performance, little empirical evidence exists on how electricity price differentiation between households and industry affects industrial development across countries. This paper addresses this gap by examining the dynamic relationship between industrial development and cross-subsidy electricity price structures. Using panel vector autoregression (VAR) for 17 OECD countries over a period of 25 years, the study assesses the impact of the electricity price ratio (households to industry) on industrial development. To capture the relative price structure between sectors, the analysis incorporates a cross-subsidy electricity price ratio, which reflects differences in electricity pricing across consumer groups. This ratio captures the joint effect of lower industrial production costs and higher household price incentives, thereby reflecting an industry-friendly economic or regulatory environment that supports industrial activity. The analysis is conducted for the full sample as well as various sub-samples. Orthogonalized impulse-response functions are estimated to disentangle the basic factors, such as capital and labor, from the effects of electricity prices on industrial development. The analysis distinguishes between the direct effect of industrial electricity prices on industrial development and an indirect effect operating through the relative electricity price structure. Consistent with existing literature, the results confirm the negative effect of industrial electricity price levels on industrial development. In addition, the results reveal a previously unexplored ratio effect, providing evidence that lower electricity prices for industry relative to households positively affect industrial development in OECD countries. Thus, the results indicate pricing structures that favor production firms and manufacturers. The findings further emphasize the importance of electricity price differentiation between the industry and households, particularly in the context of trade openness.

Keywords: Electricity price ratio; industrial development; panel vector autoregression
JEL classification: C33, Q43, L94, L60

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The contents of this paper reflect the opinions of its author only.

Corresponding author, email: fadl@wiso.uni-koeln.de

1. Introduction

With electricity demand increasing rapidly, a new age of electricity is emerging. Electricity consumption is projected to rise sharply through 2027, and as industries become more electrified, economies are becoming increasingly dependent on electricity (IEA, 2025). Understanding how electricity pricing affects industrial growth has gained importance, with several studies examining its impact on economic growth (Costa-Campi et al., 2018; Narayan and Prasad, 2008).

To transition from a high-emissions energy system to a greener one, economic transformation through a green industrial policy is needed, which can be achieved by decarbonizing the electricity sector and promoting electrification by increasing the share of renewable energy in electricity generation (Blazquez et al., 2018). At the same time, electricity market reforms aimed at promoting competition and efficiency have had mixed effects on electricity prices and cross-subsidies, which vary by country (Erdogdu, 2011).

By examining electricity prices and industrial development, this paper studies the dynamic relationship between industrial development and the differentiation in electricity prices between industries and households. Capital, labor, and energy are the main factors of production, where electricity is a main energy source. Given the interplay between industrial policy and electricity policy (Criscuolo et al., 2022; Aiginger and Rodrik, 2020), lower electricity prices for industry relative to households should have a positive impact on industrial development, where cross-subsidization is measured as the ratio of household to industrial electricity prices. The central question of this paper is: Does a higher electricity price ratio between households and industry matter for industrial development?

Industrial electricity prices directly affect production costs, and several studies find that higher electricity prices reduce industrial output and competitiveness (e.g. Ai et al. (2020); Kwon et al. (2016)). This expected negative channel provides an intuitive baseline. Evidence from the existing literature shows that electricity reforms and regulatory changes influence both overall price levels and the relative pricing structure between households and industrial users (e.g., Hattori and Tsutsui (2004); Nagayama (2007); Erdogdu (2011)). However, these studies largely focus on explaining electricity price outcomes (or price ratios) as consequences of such reforms. This raises the question of whether differences in electricity pricing across consumer groups offer additional insight into industrial outcomes beyond these core factors. Beyond this direct cost channel, this paper examines whether relative electricity price structures generate an additional, indirect effect on industrial development. This study adopts the cross-subsidy electricity price ratio to capture the relative price structure between sectors. The ratio reflects the degree of cross-subsidization, indicating the extent to which industrial users benefit from preferential pricing relative to households. The ratio mainly captures the relative electricity price structure between households and industrial users, reflecting differences in electricity pricing across consumer groups that may arise from regulatory, market, or structural factors. The paper's framework highlights that lower industrial electricity prices reduce production costs and boost competitiveness, while higher household prices encourage efficiency and can reallocate energy to production use. The cross-subsidy ratio captures the joint effect of these mechanisms and reflects an industry-friendly economic or regulatory environment favoring industrial activity.

Without some level of trade openness, subsidizing electricity for industry relative to households will not lead to a positive impact on industrial development (Knoblach and Stöckl, 2020). Thus, the cross-subsidy electricity price ratio is analyzed with trade openness taken into account. A panel vector autoregression (VAR) approach is implemented to examine this connection for 17 OECD countries over a period of 25 years, allowing for country-specific unobserved heterogeneity.[2] Additionally, the response of industrial development to shocks coming from capital and cross-subsidy electricity prices is disentangled using orthogonalized impulse-response functions.

The findings show that a shock in the electricity price ratio of households to industry, along with capital, leads to a positive response of industrial development. Additionally, the indirect effect of cross-subsidy electricity price ratio on industrial development through capital is observed. The analysis reveals a new way of understanding how the ratio of electricity prices can serve as an indicator of a country's stability and the government's focus on supporting the industrial sector. Specifically, when industrial prices are significantly lower than household prices, it indicates that electricity pricing structures are relatively more favorable to industrial users than to households. Therefore, businesses may interpret the ratio of electricity prices as a reflection of an industry-

[2] OECD is the Organisation for Economic Co-operation and Development

friendly economic or regulatory environment. Further, this emphasizes the importance of using the cross-subsidy electricity price ratio as an indicator of a country's level of industrial development. Recognizing this connection highlights how trade openness enhances the beneficial impact of cross-subsidizing electricity on industrial development. Finally, the transition to a low-emissions economy requires significant investments in renewable energy (Herrmann and Savin, 2017), which can lead to rising electricity prices for both households and industries. An effective response to managing these costs can be to subsidize industrial electricity, even if it results in higher household electricity prices. Such pricing structures may influence industrial competitiveness while also interacting with broader energy transition policies. Therefore, this can facilitate the shift to a greener economy while ensuring that industries remain viable despite increasing electricity prices.

The paper is structured as follows: Section 2 reviews the literature and highlights the study's contribution. Section 3 outlines the conceptual framework, Section 4 presents the data, and Section 5 describes the methodology. Section 6 reports the VAR results, including impulse-response functions and variance decompositions. Section 7 discusses the main findings and limitations, followed by the conclusion in Section 8.

2. Literature review

This section first establishes policy and institutional determinants shaping industrial development. It then reviews production factors, emphasizing the role of energy and electricity consumption in industrial activity. Building on this, the review establishes the direct channel through which industrial electricity prices influence industrial development and subsequently examines how electricity reforms affect price structures differently across consumer groups. While existing studies mainly explain these price outcomes as results of reform processes, this motivates analyzing how relative price differentiation between households and industry affects industrial development, leading to the research gap addressed in this paper.

Policy determinants of industrial development. Industrial policy witnessed several phases of development after the post-World War II period. The evolution of industrial policy reflects a shift from traditional government interventions designed to address market failures toward a more market-driven approach. From the early 2000s, the regulator's role became more necessary for fostering systems, establishing institutions, and easing coordination (Naudé, 2010). Governments in OECD countries established industrial policy initiatives as a way to increase their output growth, especially after the 2008/09 economic crisis. Manufacturing is a key potential driver of output growth, where the share of manufacturing in GDP and employment in OECD countries exhibited a falling trend for over decades. This can be attributed to saturated demand for manufacturing goods, productivity growth, and less need for labor, as well as manufacturing internationalization (Warwick, 2013; Aiginger, 2014; Aiginger and Rodrik, 2020).

Industrial policies in OECD countries are characterized by being targeted and demand-side policies (Criscuolo et al., 2022). For instance, France started mobilizing funds for energy, transport, and the health and information technology. Likewise, Japan's new industrial policy targets infrastructure-related exports and infrastructure systems, and environmental and energy problem-solving industries as electric vehicles (Warwick, 2013). Thus, a successful industrial policy should align with other policy areas, such as trade and electricity policy (Aiginger and Rodrik, 2020). Electricity pricing and market regulation therefore become important instruments through which governments can influence industrial competitiveness.

The EU Electricity Directive (1996) required member countries to take substantial measures to set up a unified European electricity market (Robinson, 2007). The UK was one of the early European countries to implement radical electricity reforms. While France has frequently been considered to be more resistant to transitioning away from public monopoly (Fiorio and Florio, 2013). Liberalization of electricity markets should, in a competitive market, achieve efficiency gains that reduce electricity prices. Although theoretically expected, it remains debatable whether this occurred in Europe following the gradual liberalization of its electricity market (Moreno et al., 2012). In the 1990s, the EU introduced liberalization and restructuring to its domestic electricity markets, and by 2000 many EU countries had already opened their retail markets. New Zealand and Japan also introduced liberalization reforms during the 1990s. These reforms included entry of independent power producers, unbundling of generation and transmission, creation of a wholesale spot market, as well as, the establishment of a regulatory agency (Nagayama, 2007). These reforms not only aim at improving market efficiency but also influence electricity price structures faced by industrial producers, thereby affecting industrial competitiveness. In addition, electricity market liberalization promotes competition and market integration, which can contribute to price convergence and reduce persistent differences across industrial and household electricity prices that existed under regulated pricing regimes (Percebois, 2008; Cassetta et al., 2022).

Industrial policy focuses on manufacturing competitiveness, where international trade plays a key role in shaping industrial outcomes. Trade can explain the relationship between capital and labor, where it facilitates the import of labor-intensive intermediate goods that were previously produced domestically as capital-intensive intermediate goods. Hence, the decrease in marginal returns to capital accompanied with capital accumulation is mitigated through trade (Knoblach and Stöckl, 2020). New trade theory holds that international trade promotes growth through two channels: it generates economies of scale and improves the optimal allocation of resources (Krugman, 1994; Chen, 2009). Increasing trade openness improves specialization and therefore increases productivity, manufacturing, and exports, which positively impacts growth (Edwards, 1998; Chandran and Munusamy, 2009). However, this connection should be examined in the context of manufacturing rather than overall growth.

Production factors. Even though energy plays a vital role in the industrial revolution, it only accounts for a small portion of production costs. The "cost-share theorem" disregards energy as one of the main factors of production as capital and labor, where it is evident that capital cannot function without an energy source as fuel or electricity.[3] Incorporating energy as a production factor, the constraint on substituting between capital and labor intensifies and restrains growth more as energy prices increase. Whereas using cost shares underestimates the impact of energy on industrial growth (Ayres et al., 2013; Kümmel et al., 2002, 2010).[4] Kümmel (1982)'s early work implemented

[3]Neoclassical growth models that rely solely on capital and labor are unable to account for the majority of growth using only capital and labor (Santos et al., 2016). The remaining growth that cannot be attributed to capital or labor, is what Solow (1957) referred to as an exogenous residual term or total factor productivity.

[4]Stern and Kander (2012) attempted to answer the question of "How is it possible for energy to have such significance in the industrial revolution but have a relatively minor impact on production expenses in modern economies?" By extending Solow's (1956) neoclassical growth model, their work showed that the expansion of energy services was the most contributing factor to growth until the 1950's. This suggests that the limited availability of energy services significantly restricts the growth of output. Conversely, when there is an abundance of energy, its impact on economic growth is less pronounced (Stern, 2011).

this concept by relating growth in capital, labor and energy flow (factors of production) to output growth. Therefore, highlighting that energy is a fundamental production factor as capital and labor (Kümmel et al., 1985; Kümmel, 1982; Ayres et al., 2013; Kümmel et al., 2002, 2010; Lindenberger and Kümmel, 2011; Stern and Kander, 2012; Stern, 2011).[5] This energy input increasingly takes the form of electricity, where electricity offers greater efficiency and adaptability with zero end-use pollution (Stern et al., 2019). As electrification expands across sectors, electricity consumption constitutes a more significant portion of overall energy use.

Understanding electricity consumption patterns is important for integrating renewable sources and ensuring grid stability.[6] High-income countries with high GDP per capita are strongly correlated with electricity consumption per capita and the ratio of electricity consumption to energy consumption. Thus, emphasizing the importance of using electricity ratio ($/kWh) instead of energy ratio ($ to toe) to signify a country's level of development (Ferguson et al., 2000). Additionally, electricity consumption and output growth are bi-directionally linked in richer countries, while in poorer countries electricity consumption drives growth only (Apergis and Payne, 2011).[7] Moreover, the relationship between growth and renewable and non-renewable energy consumption studied for OECD countries is examined by Aydin (2019), who show that both renewable and non-renewable energy consumption positively impact growth and vice-versa. Thus, their findings support policies that enhance the electricity supply security by promoting electricity consumption from renewable energy sources. Furthermore, numerous studies investigate the connection between electricity con-

[5] Multiple other studies focused on the connection between natural resources, capital, and labor (Humphrey and Moroney, 1975; Brown and Yuecal, 1999; Brown and Yücel, 2002; Yue, 2009).

[6] The relationship between electricity consumption and growth may vary across countries according to four possible hypotheses: growth, conservation, feedback, and neutrality hypotheses (Ozturk, 2010; Costa-Campi et al., 2018). The growth hypothesis proposes that energy consumption, along with capital and labor, directly and/or indirectly promotes growth. Thus, if there is evidence of causality from energy consumption to growth, then the growth hypothesis is confirmed. The second hypothesis is the conservation hypothesis, which states that causality runs from economic growth to energy consumption. Hence, it is reasonable to implement energy conservation policies without hindering growth. The feedback hypothesis is the third one and it suggests the existence of bidirectional causality between consumption and growth, where energy consumption promotes growth and growth promotes consumption. The last hypothesis is the neutrality hypothesis and which proposes the absence of any link between energy and economic growth. Therefore, making the implementation of energy conservation policies plausible as indicated by the conservation hypothesis.

[7] Apergis and Payne (2011) implement a panel vector error correction modelling approach showing that electricity consumption and output growth have a bi-directional relationship in richer countries, while in poorer countries electricity consumption drives growth only.

sumption and economic growth (Yoo, 2006; Jumbe, 2004; Narayan and Prasad, 2008; Costa-Campi et al., 2018; Soytas and Sari, 2007; Stern, 2011; Sarwar et al., 2017).[8]

Electricity prices and industrial development (Direct price channel). Electricity sector reforms and decarbonization policies have substantially reshaped electricity markets across many countries. Liberalization and restructuring efforts aimed to increase competition and improve efficiency, with the expectation that competitive markets would lower electricity prices (Robinson, 2007; Moreno et al., 2012). However, empirical evidence shows that reforms have produced heterogeneous price outcomes across countries and consumer groups. Some reforms, such as wholesale market creation, did not consistently reduce prices, while regulatory restructuring and competition-enhancing measures sometimes led to price declines (Steiner, 2001; Hattori and Tsutsui, 2004; Nagayama, 2007).
Since electricity constitutes an important production input, changes in industrial electricity prices directly influence production costs and industrial competitiveness. Consequently, a growing literature examines the relationship between electricity prices and economic growth, often finding that higher electricity prices reduce output or productivity, although effects differ across countries and sectors (Ai et al., 2020; Jamil and Ahmad, 2010; Kwon et al., 2016). These findings support the intuitive direct cost channel whereby higher industrial electricity prices weaken industrial development by increasing production costs.

Electricity price differentiation across consumer groups (Relative price channel). Electricity sector reforms have affected industrial and household electricity prices differently. Several studies document that reform packages can change the price relationship between consumer groups. For example, Hattori and Tsutsui (2004) find that reforms expanding retail access are associated with an increase in the household to industrial electricity price ratio, while establishing a wholesale spot market not

[8] Studying the connection between energy and economic growth served as a starting point for examining the more specific relationship between electricity consumption and growth. Various studies investigated the link between energy consumption and growth, where capital and labor are included as well as energy consumption and economic growth. Various inter-related methods are implemented to examine this connection as regression and (Granger) causality tests (Kraft and Kraft, 1978; Asafu-Adjaye, 2000; Payne, 2009), vector autoregression (VAR) (Stern, 1993, 2000; Huang et al., 2008), vector error-correction models (VECM) (Masih and Masih, 1998; Mahadevan and Asafu-Adjaye, 2007; Hondroyiannis et al., 2002; Mandal and Madheswaran, 2010; Lee and Chang, 2008), and auto-regressive distributed lags (ARDL) (Akinlo, 2008). By implementing different approaches such as Granger-causality tests and ARDL, these studies concluded mixed results of either finding a bi-directional causality or a uni-directional causality either running from electricity consumption to growth or vice-versa.

necessarily decrease prices. More broadly, Nagayama (2007) shows for a large cross-country sample that specific reform components (e.g., unbundling and the presence of an independent regulator) are associated with electricity price changes for different user groups, whereas other components such as wholesale spot markets do not consistently lower prices. Emphasizing heterogeneity, Erdogdu (2011) demonstrates that the same reform measure can have different effects across countries and can therefore alter cross-subsidy levels in different ways. Evidence on competition-enhancing reforms likewise suggests that their effects on prices depend on the specific reform design and context (Steiner, 2001). Consequently, as electricity price differences across consumer groups have persisted in many countries despite market reforms and liberalization. This raises the question of whether relative electricity price structures across consumer groups may still influence industrial outcomes.

Contribution. Taken together, existing literature indicates that electricity reforms and regulatory changes can influence not only price levels but also the relative pricing structure between households and industrial users. However, these studies primarily focus on explaining electricity price outcomes (or price ratios) as reform results. This motivates examining whether electricity price structures across consumer groups provide additional insight into industrial outcomes beyond these core factors. This paper addresses this gap, where the objective is to investigate the dynamic relationship between industrial development and the differentiation in electricity prices for households and industries. A panel vector autoregression (VAR) methodology is implemented to examine this connection for 17 OECD countries over a period of 25 years. The main question to answer is: Does the relative difference between household and industrial electricity prices matter for industrial development?

Three hypotheses are tested: (H1) The response of industrial development as a share of GDP to a higher household to industrial electricity price ratio is positive, (H2) The response of industrial development per capita to a higher household to industrial electricity price ratio is positive (in absolute terms), and (H3) The response of industrial development to a higher household to industrial electricity price ratio is positive given there is trade openness. These hypotheses focus on the connection between electricity cross-subsidies, industrial development, and trade openness.

The first hypothesis (H1) seeks to determine whether a larger difference between household and industrial electricity prices, leads to a positive impact on industrial development concerning a country's size of the economy (GDP). This provides insights into whether relative cross-subsidy price ratio stimulates industrial growth. The second hypothesis (H2) using per capita variables assesses whether cross-subsidization contributes to increased income and improved living standards for individuals, thus directly affecting welfare. The third hypothesis (H3) examines the relation between electricity cross-subsidy and industrial development, taking trade openness into account. This shows whether trade openness is associated with the positive effects of electricity cross-subsidization on industrial growth. Rising energy prices can reduce households' consumption as a result of increased spending on energy and thus demand for goods falls, leading to a decline in equilibrium output which in turn increases unemployment (Hamilton, 1988). This highlights the significant role of international trade in that case, which can mitigate the effect of diminished demand.[9]

Moreover, the analysis is aimed to inform electricity and industrial policy by highlighting the trade-offs between industrial competitiveness and household welfare. The central empirical measure is the cross-subsidy electricity ratio (CSE), which reflects the extent to which industrial users benefit from preferential pricing relative to households, providing a policy-relevant indicator.

3. Conceptual framework

To explain how cross-subsidized electricity pricing can influence industrial development, this section develops a conceptual framework capturing key economic mechanisms. The cross-subsidy electricity ratio (CSE) is defined as the ratio between household and industrial electricity prices and captures differences in electricity prices across consumer groups. When industrial electricity prices are lower than household prices, households effectively bear a relatively larger share of electricity costs, which is often interpreted as cross-subsidization (e.g. Erdogdu (2011)).[10] However, such price differences may also arise from regulatory, cost, or market structure factors rather than explicit subsidies, and this paper does not attempt to identify their underlying causes. Let EP^h and EP^{ind} denote the

[9] The role of trade in explaining the connection between capital and labor can be understood through importing labor-intensive intermediate goods that were previously produced domestically as capital-intensive intermediate goods (Knoblach and Stöckl, 2020).

[10] While the exact measurement of cross-subsidy differs across studies, the interpretation remains comparable.

electricity price for households and the industrial electricity price, respectively. The cross-subsidy electricity price ratio CSE is defined as:

$$CSE = \frac{EP^h}{EP^{ind}} \tag{1}$$

CSE may deviate from one when electricity prices differ across consumer groups due to institutional, regulatory, market, or policy factors. For example, Cassetta et al. (2022) argue that such differences may reflect public intervention in end-user price setting and differences in regulated price components. Therefore, the cross-subsidy electricity price ratio (CSE) should not be interpreted as evidence of explicit subsidies alone. Instead, it reflects the overall electricity pricing structure across consumer groups within a country's electricity system. A CSE greater than 1 indicates that households pay higher electricity prices than industrial users ($EP^h > EP^{ind}$). This structure reflects a pricing scheme arising from regulatory or market conditions that favor industry over households, allowing industrial users to access lower priced electricity and support production through lower input energy costs. [11] Two mechanisms link electricity prices and industrial development. The first channel is the well-established direct cost channel: higher industrial electricity prices reduce production competitiveness and industrial output. This mechanism is widely discussed in the literature and provides a benchmark expectation that EP^{ind} and industrial development should be negatively related (e.g. Ai et al. (2020); Kwon et al. (2016)). The second channel explored in this paper is an indirect, relative-price mechanism operating through the household to industrial price ratio (CSE). A higher CSE lowers EP^{ind} relative to EP^h. This indirect effect of CSE has received little empirical attention and represents the new mechanism examined in this study.

[11] Industrial production costs depend on energy (industrial electricity) prices, wages, and the cost of capital. A decrease in EP^{ind} (or, equivalently, a higher CSE) reduces production costs and improves firms' cost-competitiveness. Lower electricity prices for industries thus stimulate production and enhance industrial output.

Following Kümmel (1982); Kümmel et al. (1985); Cleveland et al. (1984) [12], energy is a key productive input. Industrial output (Q) is expressed as a Cobb-Douglas production function of industrial electricity consumption (EC^{ind}), capital (K), and labor (L):

$$Q = f(EC^{ind}, K, L) = A \ (EC^{ind})^{\eta} \ K^{\alpha} \ L^{\lambda} \tag{2}$$

Industrial electricity consumption EC^{ind} depends on its price, as well as other endogenous and exogenous variables (Madlener, 2011; Bohlmann and Inglesi-Lotz, 2021). Given that the industrial electricity price can be expressed relative to the household price through the cross-subsidy electricity price ratio, a higher CSE reflects lower industrial electricity prices. Consequently, electricity consumption depends positively on CSE such that:

$$EC^{ind} = h(EP^{ind}) = (EP^{ind})^{-\theta} = \left(\frac{EP^{h}}{CSE}\right)^{-\theta} = (EP^{h})^{-\theta} \cdot CSE^{\theta} \tag{3}$$

where $\theta > 0$, $EP^{ind} = \frac{EP^{h}}{CSE}$, and $\frac{\partial EC^{ind}}{\partial EP^{ind}} < 0$. A higher CSE (reflecting lower EP^{ind}) increases industrial electricity consumption (EC^{ind}), which raises industrial output (Q), or alternatively industrial development (IND). Although industrial electricity consumption primarily depends on its own price EP^{ind}, this study adopts the electricity price ratio $CSE = \frac{EP^{h}}{EP^{ind}}$ to capture the relative price structure between sectors. The ratio reflects the relative electricity price structure between households and industry, indicating the extent to which industrial users benefit from pricing relative to households. Using EC^{ind} as a function of CSE rather than EP^{ind} alone allows isolating policy-driven distortions from common price shocks and emphasizes the relative incentives shaping industrial behavior. Industrial electricity consumption (EC^{ind}) is not explicitly included in the empirical estimation (Section 5). It is introduced here to illustrate the link between electricity pricing, consumption, and industrial output.

Household electricity price (EP^{h}) also plays an important, though indirect, role in shaping industrial development. Higher EP^{h} discourages household electricity consumption. When household electricity becomes more expensive, household consumers may adopt energy-saving behaviors and

[12] Kümmel (1982); Kümmel et al. (1985) defined industrial output as a factor of capital, labor, and energy. Kümmel (1982) used energy flows instead of electricity consumption.

efficiency technologies, reducing household demand. This reduction can free up energy capacity for industrial use, particularly in systems with generation or grid constraints. Consequently, the energy saved by households can indirectly support industrial expansion and output growth. Moreover, higher EP^h can induce technological change and efficiency improvements that reduce overall energy demand pressures, enabling regulators to maintain lower industrial prices sustainably.

Combining the industrial and household mechanisms, industrial output can be written as a function of both CSE and standard production inputs. Substituting Eq. 3 into Eq. 2 and taking logs yields:

$$\ln Q = \ln A + \eta\theta \ln CSE - \eta\theta \ln EPh + \alpha \ln K + \lambda \ln L \tag{4}$$

In the empirical estimation in Section 5, the focus is on CSE as the relative price effect. The extended model includes EP^h to capture absolute price effects and test the indirect channel. This formulation in Eq. 4 implies that industrial output, and by extension industrial development (IND), rises with increases in CSE. While firms primarily respond to their own electricity prices EP^{ind}, differences between household and industrial electricity prices may reflect broader electricity pricing structures or conditions affecting the industrial sector. Electricity pricing structures are not static. As industries expand, energy demand rises, potentially prompting regulators to adjust tariffs. This bidirectional relationship justifies a dynamic empirical approach, such as the panel VAR model (in Section 5), to capture the feedback between CSE, industrial development, and the production factors. Overall, the conceptual framework highlights that lower industrial electricity prices reduce production costs and boost competitiveness, higher household prices encourage efficiency and can reallocate energy to production use, and the cross-subsidy ratio (CSE) captures the joint effect of these mechanisms. Hence, a higher CSE is expected to positively influence industrial development.

4. Data

This section provides an overview of the data used in the analysis, where a country-level dataset for 17 OECD countries is constructed. The 17 OECD countries are the Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Korea, New Zealand, Poland, Portugal, Slovakia, Spain, Switzerland, and the United Kingdom.[13]

Table 1: Variables Definition

Variable	**Definition**
IND	Industrial development, defined as industry including construction (as % of GDP). It consists of value added in mining, manufacturing, construction, electricity, water, and gas sectors. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.
IND^{pc}	IND (in absolute values) per capita corrected for inflation by using values in constant 2015 USD.
IND^{e}	IND weighted by the share of electricity in total electricity consumption of all OECD countries in a year, where industry (including construction) is measured as value added (as % of GDP).
EP^{h}	Electricity price paid by households
EP^{ind}	Electricity price paid by industry
CSE	Cross-subsidy electricity, which refers to the ratio of household electricity price to industry electricity price (EP^{h} / EP^{ind}).
CAP	Gross fixed capital formation (% of GDP). It comprises land improvements; plant, machinery, and equipment purchases, etc.
CAP^{pc}	CAP (in absolute values) per capita corrected for inflation using values in constant 2015 USD.
EMP	Employment to population ratio. It is the proportion of a country's population that is employed.
TRO	Trade openness, which is the sum of exports and imports of goods and services (% of GDP)

Notes: Data is available for 17 OECD countries from 1995 to 2019.

5. Empirical estimation

The methodology used in this study is panel-data vector autoregression (panel VAR), which merges the VAR method and the panel-data approach. Applying the VAR method involves endogenizing all variables in the system. This is combined with allowing for unobserved individual heterogeneity by using the panel-data approach. The VAR method tests whether a bidirectional causal relation exists among variables in the short-run. Thus, the first-order VAR model is defined for country i and year t as follows:

$$Y_{it} = B_0 + B_1 Y_{it-1} + \delta_i + \gamma_t + e_{it} \tag{5}$$

where Y_{it} is a vector of k-variables. The vector of [IND, CSE, CAP, EMP] is the benchmark specification as illustrated in Figure 1. The VAR model specification of the vector [IND^{pc}, CSE, CAP^{pc},

[13] Data are extracted from two sources, the first source is the International Energy Agency (IEA), which provides data for electricity prices for both industries and households. The IEA data is retrieved from the OECD library data source. Industrial and household electricity prices are provided in US dollars per MWh. The variable cross-subsidy electricity (CSE) is constructed as the ratio of household price to industrial price. The second data source is the World Bank Indicators database, which provides data on the remaining variables, such as industrial development, capital, employment, and trade openness.

EMP] is estimated to draw comparisons with the results from the primary benchmark specification [IND, CSE, CAP, EMP] (in shares of GDP). In addition, the VAR model specification for the vectors [IND, CSE, EP^{ind}, CAP], [IND, CSE, EP^{h}, CAP], and [IND, EP^{ind}, EP^{h}, CAP] is estimated. Since cross-subsidy electricity price ratio mechanically incorporates industrial electricity prices, including both variables in all VAR specifications would introduce strong dependence among regressors and complicate interpretation of dynamic responses. Therefore, the benchmark specification focuses on CSE as the relative price effect, while alternative specifications include industrial and household prices to distinguish absolute from relative price effects. The VAR model specifications for the vectors [IND, CSE, CAP, TRO] and [IND, CSE, CAP, EMP, TRO] are also estimated as an extension to the benchmark model by incorporating trade openness. Supplementary analysis is also provided by estimating the VAR model specifications for the vectors [IND^{e}, CSE, CAP, EMP] and [IND, EP^{ind}, CAP] (see Appendix B.3). Moreover, the various model specifications are estimated with respect to different sub-groups of the main sample of 17 OECD countries. These subsamples are used as a robustness check.

Figure 1: Model variations

Benchmark	**Electricity price dynamics**	**Benchmark extension:** including trade openness	**Supplementary**
IND CSE CAP EMP	IND CSE EP^{ind} CAP	IND CSE CAP EMP TRO	* IND EP^{ind} CAP
IND^{pc} CSE CAP^{pc} EMP	IND CSE EP^{h} CAP	* IND CSE CAP TRO	* IND^{e} CSE CAP TRO
	IND EP^{ind} EP^{h} CAP		

Notes: Results of * models are presented in the appendix.

The VAR model is estimated using the generalized method of moments (GMM). To overcome the concern that the underlying model structure has to be the same for each country in the panel, δ_i is included indicating country fixed effects. However, the δ_i is correlated with the predictor variables because of the dependent variable lags. A solution to this problem is provided by Arellano and Bover (1995) through implementing the 'Helmert transformation'. The 'Helmert transformation' requires using forward orthogonal deviation by removing the forward mean of all future observations available for each country-year. Thus, the transformation allows using lagged regressors as instruments and coefficients are estimated via GMM (see Appendix B). For instance, consider that r^*_{it} is the original untransformed variable. Whereas r_{it} is the transformed variable after applying forward orthogonal deviation such that $r_{it} = (r^*_{it} - \overline{r^*_{it}})\sqrt{T_{it}/(T_{it}+1)}$. The number of available future observations for country i and year t is denoted by T_{it} and the average of all available future observations is denoted by $\overline{r^*_{it}}$.

The γ_t controls for the common time effects by subtracting the cross-sectional mean from each variable. The idiosyncratic error is denoted by e_{it} and satisfies the following properties: $\mathbf{E}(e_{it}) = 0$, $\mathbf{E}(\boldsymbol{e}'_{it}\boldsymbol{e}_{it}) = \boldsymbol{\Omega}$, and for $t > s$, $\mathbf{E}(\boldsymbol{e}'_{it}\boldsymbol{e}_{is}) = \mathbf{0}$. Since it is not uncommon that economic variables are non-stationary, to estimate the panel VAR, all variables should be tested for stationarity or more precisely implement panel unitroot tests. To test for unitroot, $y_{it} = \rho_i y_{i,t-1} + \mathbf{z}'_{it}\gamma_i + \epsilon_{it}$ is considered, where y_{it} is the variable of interest, $t = 1, \ldots, T_i$ represents time, and the panels are indexed by $i = 1, \ldots, N$ (see Appendix B.1). The null hypothesis of all the unitroot tests implemented is that (all) panels contain unit roots. Variables are tested for unit roots at levels and at first-difference. If the variable is stationary at the level, then it is $I(0)$. A variable is $I(1)$ if it is stationary is at first-difference. In both cases, all variables should be either stationary at levels or at first-difference to estimate a panel VAR model. Various panel unit root tests are applied, including the Fisher-type Phillips-Perron (PP) test, Harris-Tsavalis (HT) test, and the Breitung test. Since the unit root tests differ in their testing procedures, multiple tests are applied to ensure a robust assessment of whether a variable is stationary. Cross-sectional dependence is also tested (Table B.8). If cross-sectional dependence is detected, the data is demeaned (subtract cross-sectional means).[14]

The k-variable VAR model is then estimated.[15] This is followed by checking the stability condition of the panel VAR (see Figures B.21, B.22, B.23, B.24). This is done by calculating the modulus of each eigenvalue of the fitted model, which indicates that the panel VAR is invertible and has an infinite-order vector moving-average (VMA) representation (Hamilton, 1994). Pre-estimation tests support the suitability of the panel VAR specification, confirming stationarity, model stability

[14] The next step is to test for cointegration if the variables are stationary at first-difference $I(1)$. A group of variables is said to be cointegrated when their $I(1)$ linear combination is stationary indicating equilibrium in the long-run. In other words, a group of $I(1)$ variables are cointegrated if they move together (Engle and Granger, 1987).

[15] To estimate a panel VAR there should be no cointegration between the group of variables that are $I(1)$, otherwise, one could implement a vector error-correction model VECM. Pedroni and Westerlund are used to test for cointegration. The null hypothesis for these tests is no cointegration, while the alternative hypothesis varies across tests. Results of the cointegration tests are provided in the Appendix B.2.

conditions, and the absence of cointegration required for estimation. Detailed results of these tests are reported in Appendix B.1 and Appendix B.2.

The subsequent step is to test whether past values of a variable help in predicting the values of another variable using Granger causality applying Wald test (Granger, 1969). Two or more variables can be correlated simply because they move in the same direction at the same time, however, these variables may still be unrelated. In that case, it is difficult to establish a causal connection between these variables using linear regression. Hence, Granger causality and cointegration tests are implemented to test for such causal connection (Granger, 1969; Stern and Kander, 2012). Granger causality tests support the dynamic relationships reported in the following section, with detailed results provided in Appendix B.4.

Furthermore, orthogonalized impulse-response functions are estimated based on the Cholesky decomposition, where impulse-responses refer to the reaction of a variable as a result of a shock in another given all other shocks are zero. This is accompanied by estimating the forecast-error variance decomposition also based on the Cholesky decomposition of the residual covariance matrix of the underlying panel VAR model. The forecast-error for p steps ahead can be written as

$$Y_{it+p} - \boldsymbol{E}(Y_{it+p}) = \sum_{i=0}^{p-1} \boldsymbol{e}_{i(t+p-i)} \boldsymbol{\Phi}_i \tag{6}$$

where the vector observed at $t+p$ is Y_{it+p} and the p-step ahead predicted vector at t is $\boldsymbol{E}(Y_{it+p})$. The $\boldsymbol{\Phi}_i$ is a vector of VMA parameters. In addition, Monte Carlo simulation is implemented to estimate standard errors and confidence intervals. The ability to capture more complex details is one of the main benefits of the panel VAR approach over alternative methods as time-series VAR models or panel data models. Panel VAR controls for unobserved heterogeneity across countries and treat all variables to be endogenous. This is in addition to allowing for better efficiency because of using a panel dataset (Nijman and Verbeek, 1990; Love and Zicchino, 2006; Atems and Jones, 2015; Abrigo and Love, 2016).

6. Results

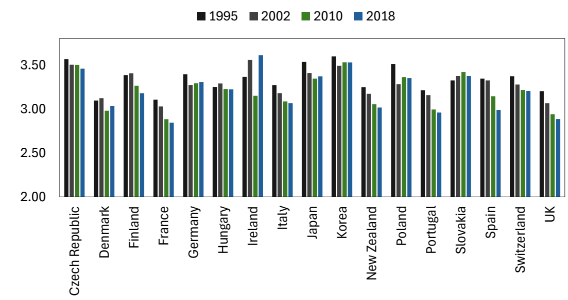
This section first summarizes the descriptive patterns between industrial development and cross-subsidy electricity price ratios (Section 6.1), followed by the VAR estimations for the model specifications (Section 6.2). Sections 6.3 and 6.4 present the impulse-response functions and variance decompositions, respectively.

6.1. Patterns in industrial development and cross-subsidy electricity price ratio

This section presents the descriptive statistics and patterns in industrial development and the cross-subsidy electricity price ratio. Figure 2 shows that countries with the highest levels of industrial development at the beginning of the study period are the Czech Republic, Korea, Japan, and Poland. In 2018, Ireland, Korea, Czech Republic, and Japan continue to exhibit the highest levels of industrial development. An overview of the variables is presented in Table A.6, including key summary statistics such as mean, median, and standard deviation.

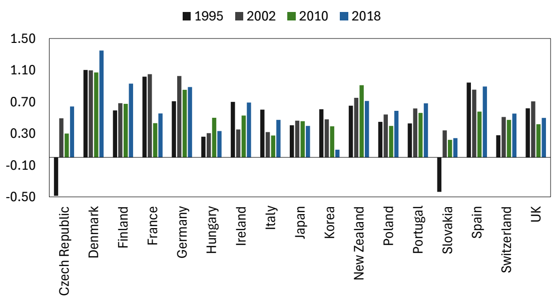
As illustrated in Figure 3, the cross-subsidy electricity (CSE) price ratio is usually greater than zero, indicating that the household price for electricity is greater than the industrial price. However, CSE is negative for the Czech Republic and Slovakia before the year 2000, indicating that during the period from 1995 to 1999 households paid less for electricity than industry. In addition, Denmark shows the highest level of CSE in the years 1995, 2002, 2010 and 2018.

Figure 2: Industrial Development (IND)



Notes: All variables are log-transformed.

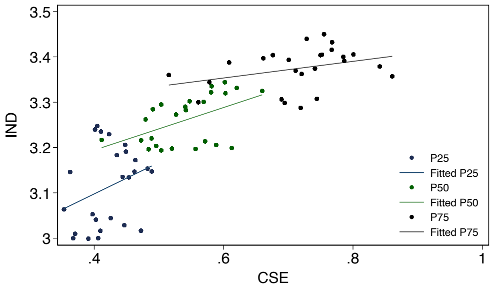
Figure 3: Electricity cross-subsidy (CSE)



Notes: All variables are log-transformed.

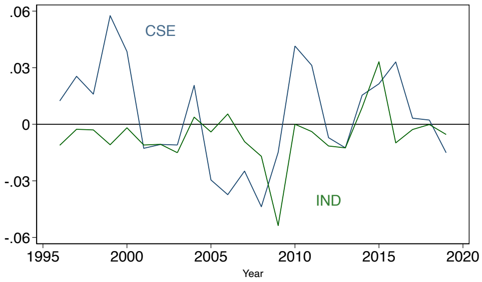
There are large discrepancies across OECD countries and over the years with respect to CSE. CSE also exhibits considerably higher volatility than industrial development. Industrial development across OECD countries appears more consistent over time and demonstrates much fewer discrepan-

Figure 4: Industrial Development (IND) vs. Electricity cross-subsidy (CSE)



Notes: All variables are log-transformed. P25 is the 25th percentile and Fitted P25 is the fitted line for the 25th percentile. P50 is the 50th percentile and Fitted P50 is the fitted line for the 50th percentile. P75 is the 75th percentile and Fitted P75 is the fitted line for the 75th percentile.

Figure 5: IND and CSE in first-difference (1995-2019)



Notes: All variables are log-transformed.

cies.[16] The relationship pattern between industrial development (IND) and cross-subsidy electricity (CSE) price ratio is illustrated in Figure 4, emphasizing that there can be a positive association between the two variables. Furthermore, the data is segmented into different groups, each displaying distinct fitted values for the 25th percentile, 50th percentile, and 75th percentile. This segmentation shows variations in the relationship across different levels of industrial development and cross-subsidy electricity price ratio.

6.2. VAR models estimation

In this section, VAR model estimations are presented and analyzed. The coefficients of the system in Eq. 5 are estimated for the different model specifications presented in Figure 1, where estimations are executed for the whole sample of 17 OECD countries and different sub-samples. Results of sub-samples estimations, such as using only European countries (14 countries) and countries with high CSE (CSE above the median), are presented in Appendix B.3.

Benchmark. The results of the benchmark specifications, which are the VAR estimations for variables as a share of GDP and per capita, are presented in Tables 2 and 3, respectively. Both versions of the benchmark specifications indicate a positive response of industrial development to electricity cross-subsidy (CSE) with respect to the estimated coefficients. Since electricity cross-subsidy is a

[16] Appendix A presents a detailed analysis of the changes in capital, employment levels, and trade across OECD countries throughout the years.

ratio, the positive response of industrial development may arise from two factors. First, lower industrial electricity prices (EP^{ind}) reduce production costs, thereby promoting industrial development. Second, higher household electricity prices may also indirectly support industrial development. As the variables used are in first-difference, this could also mean that as the increase in the CSE as a ratio increases, the increase in industrial development is higher. Thus, either EP^{ind} has decreased, EP^h has increased, or the increase in EP^{ind} is less than the increase in EP^h leading to an increase in CSE. I cannot confirm which factor is evident from this estimation so far. However, the main outcome is that the higher the CSE ratio, the higher the industrial development. It is also evident for the sub-sample of 14 EU OECD countries that industrial development responds positively to CSE (see Table B.13). As for the sub-sample of 9 OECD countries with CSE above the median, the coefficient of CSE is significantly positive (see Table B.13). Furthermore, the response of capital to the electricity price ratio (CSE) is positive and significant. Therefore, an increase in capital would need more energy and in that case more electricity consumption. To the extent that a higher CSE reflects relatively lower electricity costs for industrial users, such pricing structures may create a more favorable cost environment for capital accumulation. Hence, higher electricity consumption can facilitate capital accumulation. In addition, Granger causality is also tested in Appendix B.4.

Table 2: VAR estimations - Benchmark model (share of GDP)

	Response to IND(t-1)	CSE(t-1)	CAP(t-1)	EMP(t-1)
Response of				
IND(t)	-0.031	0.329***	0.518***	-0.428
	(0.137)	(0.102)	(0.191)	(0.489)
CSE(t)	-0.307	0.073	-0.372	0.558
	(0.258)	(0.174)	(0.229)	(0.827)
CAP(t)	0.323	0.408***	-0.257	0.034
	(0.217)	(0.144)	(0.212)	(0.751)
EMP(t)	0.099*	0.039	0.113**	-0.160
	(0.058)	(0.033)	(0.047)	(0.150)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10% . Main sample used (17 OECD).

A similar pattern is observed in the significant positive response of industrial development to capital. This outcome is also observed for the estimation using the sub-sample of 14 EU OECD countries (see Table B.13). Further, the response of employment to capital is significantly positive as shown in

Table 3: VAR estimations - Benchmark model (per capita)

	Response to IND^{pc}(t-1)	CSE(t-1)	CAP^{pc}(t-1)	EMP(t-1)
Response of				
IND^{pc}(t)	-0.134	0.159**	0.687***	-0.726
	(0.133)	(0.075)	(0.156)	(0.498)
CSE(t)	-0.290*	0.114	-0.006	-0.638
	(0.170)	(0.101)	(0.160)	(0.645)
CAP^{pc}(t)	0.325**	0.548***	0.555**	-1.353*
	(0.158)	(0.110)	(0.242)	(0.812)
EMP(t)	0.026	0.080***	0.144***	-0.074
	(0.030)	(0.024)	(0.044)	(0.155)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10% . Main sample used (17 OECD).

Tables 2 and 3. This is in line with the notion that an increase in capital leads to higher production, which increases the need for more labor to handle the increased capital (Doğrul and Soytas, 2010). The response of industrial development to employment is insignificant. However, a key distinction exists between employment levels and human capital; the latter being the true driver of industrial development. Due to the scarcity of data on human capital for all countries, I used employment levels. Moreover, employment can have an insignificant impact since the majority of countries in the sample predominantly rely on capital-intensive industries, rather than labor-intensive ones. On the other hand, it is not expected that industrial development has an impact on the cross-subsidy electricity price ratio. This is evident from the lack of a significant response of CSE to a shock in IND. This is also observed for estimations done using the different sub-samples of the dataset. Overall, across all specifications (see Tables 4 and 5), industrial development consistently responds positively to CSE, while capital remains a key transmission channel. Additional specifications confirm this pattern (see Appendix B.3).

Electricity price dynamics. Results reported in Table 4 show the different effects of CSE and electricity prices indicated by EP^{ind} and EP^{h}. Under this model specification, the CSE still has a positive impact on industrial development. However, the source of this effect needs further analysis to show whether it occurs from a decrease in industrial prices or an increase in household prices or both. Therefore, electricity prices along with the ratio of prices are included in the same model specification. The findings show that the response of industrial development to CSE is still positive

Table 4: VAR estimation - Electricity price dynamics

	Response to IND(t-1)	CSE(t-1)	EP^{ind}(t-1)	EP^{h}(t-1)	CAP(t-1)
Response of					
Panel A: CSE vs EP^{ind}					
IND(t)	-0.177	0.378***	0.002	X	0.346**
	(0.196)	(0.121)	(0.095)		(0.161)
CSE(t)	0.299	0.120	0.183	X	-0.343*
	(0.310)	(0.189)	(0.130)		(0.188)
EP^{ind}(t)	-0.168	0.409	0.168	X	0.558**
	(0.460)	(0.275)	(0.195)		(0.254)
CAP(t)	0.499*	0.193	-0.170	X	-0.420**
	(0.277)	(0.195)	(0.146)		(0.196)
Panel B: CSE vs EP^{h}					
IND(t)	-0.150	0.392***	X	-0.028	0.470***
	(0.183)	(0.107)		(0.089)	(0.175)
CSE(t)	0.225	0.012	X	0.208	-0.159
	(0.324)	(0.160)		(0.130)	(0.184)
EP^{h}(t)	0.080	0.155	X	0.483***	0.132
	(0.296)	(0.181)		(0.158)	(0.204)
CAP(t)	0.425	0.353**	X	-0.105	-0.278
	(0.325)	(0.152)		(0.145)	(0.194)
Panel C: EP^{h} vs EP^{ind}					
IND(t)	-0.096	X	-0.397***	0.320***	0.335**
	(0.174)		(0.102)	(0.117)	(0.157)
EP^{ind}(t)	-0.103	X	-0.267	0.367	0.196
	(0.335)		(0.229)	(0.2498)	(0.202)
EP^{h}(t)	0.245	X	-0.171	0.603***	-0.003
	(0.294)		(0.176)	(0.210)	(0.193)
CAP(t)	0.205	X	-0.438***	0.132	-0.239
	(0.323)		(0.144)	(0.192)	(0.200)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Main sample used (17 OECD).

and significant. However, industrial development does not respond to a shock in industrial electricity prices as indicated by the insignificant coefficient. Further, including household electricity prices as in panel B shows that the response of IND to CSE is also still significantly positive, but the coefficient for household prices is insignificant. In panel C, when CSE is excluded from the model and only household and industrial prices are left, it is observed that industrial prices have an expected significant negative coefficient and household prices have a significant positive coefficient. It is expected that industrial prices have a negative impact on industrial development.

However, a notable result is the significant positive impact of household prices on industrial development. The estimations in panels A, B, and C indicate that it is not the low industrial prices that can impact industrial development alone, but the ratio of what households pay compared to what industries pay that has a significant impact on industrial development. This raises the question of why household electricity prices matter for industrial development. This effect reflects the degree of cross-subsidization and differences in electricity price structures across consumer groups, indicating the extent to which industrial users benefit from preferential pricing relative to households. Higher household electricity prices can benefit the industrial sector in several ways. They can drive demand for energy-efficient products, stimulate innovation, and encourage investments in cost-effective renewable energy production. As a result, this can lead to increased production levels within the industrial sector leading to the positive response of industrial development to household prices. Another point to highlight is that the response of industrial development to capital is still positive and significant in all 3 panels (Table 4) implementing different model variations, which is in line with the previously discussed results.

Benchmark extension: including trade openness. The results in Table 5 show that the response of industrial development to CSE is positive and significant, which is in line with the previous model specifications results. This also applies to the significantly positive response of industrial development to capital. Moreover, the response of trade openness (TRO) to CSE is positive and significant. These findings emphasize that pricing structures in which industrial electricity prices are lower relative to household prices may reduce households' consumption, reflected in lower disposable income for households. However, an increase in CSE encourages more production and industrial development. Therefore, to continue producing more is to have trade openness, which mitigates the reduced local consumption.[17]

6.3. Impulse-response functions

Cumulative impulse response functions (IRFs) show the response of a variable to a one standard deviation shock in another variable with 5 percent error bands. These error bands are constructed using the Monte-Carlo simulations to establish the confidence intervals.

[17] Results in Table B.12 are provided as a robustness check and lead to similar inferences.

Table 5: VAR estimations - Benchmark extension: including trade openness

	Response to				
	IND(t-1)	CSE(t-1)	CAP(t-1)	EMP(t-1)	TRO(t-1)
Response of					
IND(t)	0.139	0.334***	0.397***	-0.305	-0.121
	(0.124)	(0.088)	(0.135)	(0.421)	(0.096)
CSE(t)	-0.151	0.038	-0.366**	0.665	0.076
	(0.192)	(0.136)	(0.171)	(0.636)	(0.129)
CAP(t)	0.582***	0.315***	-0.241	0.047	-0.281
	(0.216)	(0.118)	(0.212)	(0.673)	(0.183)
EMP(t)	0.132***	0.053**	0.097***	-0.167	-0.078**
	(0.048)	(0.027)	(0.034)	(0.127)	(0.032)
TRO(t)	0.134	0.204**	-0.359**	0.638	0.133
	(0.126)	(0.100)	(0.160)	(0.619)	(0.113)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10% . Main sample used (17 OECD).

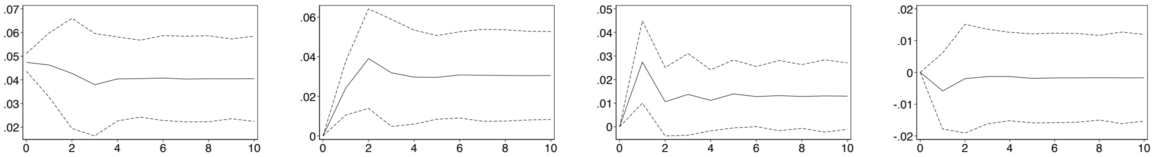
Benchmark. Cumulative IRFs for the benchmark model specifications are displayed in Figures 6 and B.27. Considering the response of industrial development to a one standard deviation shock of its own (in Figure 6), an insignificant response is observed. The response of industrial development to a one standard deviation shock in cross-subsidy electricity price ratio is positive and significant. This is confirmed by the confidence bands being above zero for 10 periods. As for the response of industrial development to capital, it is also positive, where industrial development moves up for the first 2 periods. Regarding the cumulative IRFs for both sub-samples, the response of industrial development to one standard deviation shock in cross-subsidy price electricity is positive and significant.[18] [19]

Electricity price dynamics. Cumulative IRFs for model specifications with cross-subsidy electricity ratio and industrial or household electricity prices are exhibited in Figures 7, 8, 9. The response of industrial development is positive to a shock in CSE. A shock in industrial prices does not change the response of industrial development (in Figure 7). A similar pattern is observed when using household electricity prices (in Figure 8).

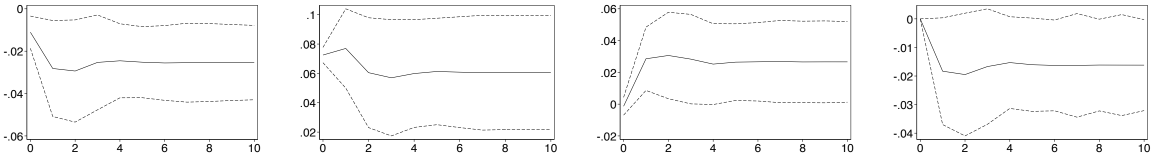
[18]Similar pattern is also observed for the response of industrial development to a shock in capital for the first two periods for both sub-samples in Figures B.25 and B.26.

[19]As for the benchmark model specification using per capita version of the variables, the response of industrial development to a one standard deviation shock in electricity cross-subsidy price is positive. The same applies to the response of IND^{pc} to a one standard deviation shock in CAP^{pc} (in Figure B.27).

Figure 6: Impulse responses - Benchmark model (share of GDP)



(a) IND : IND (b) CSE : IND (c) CAP : IND (d) EMP : IND

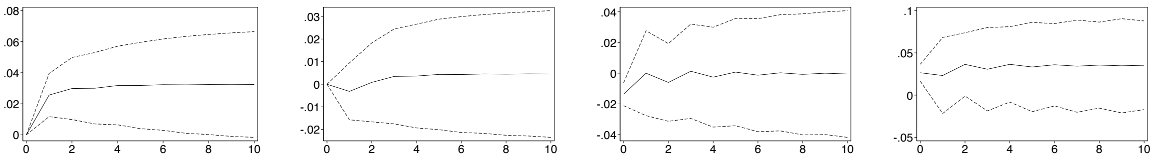


(e) IND : CSE (f) CSE : CSE (g) CSE : CAP (h) CAP : CSE

Notes: Impulse variable **:** response variable. $---$ indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

Benchmark extension: including trade openness. Cumulative IRFs for the VAR model specification with trade openness are presented in Figure 10, it is also evident that the response of IND to a one standard deviation shock in CSE is positive and significant. In addition, the response of IND to a one standard deviation shock in CAP is positive and significant during the first two periods. The response of trade openness to a one standard deviation shock in CSE is positive and significant during the first two periods.[20] [21]

Figure 7: Impulse responses - Electricity price dynamics (CSE vs EP^{ind})



(a) CSE : IND (b) EP^{ind} : IND (c) IND : CSE (d) IND : EP^{ind}

Notes: Impulse variable **:** response variable. $---$ indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

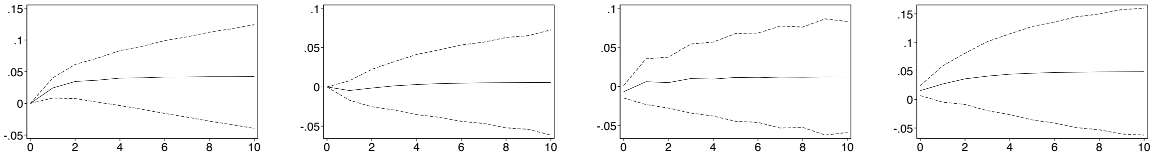
6.4. Variance decompositions

To isolate each variable's contribution to the forecast-error variance, shocks of the variables are orthogonalized. Hence, the contribution of a variable to the t periods ahead forecast-error variance

[20] Similar inferences can be made as displayed in Figure B.28.

[21] Cumulative IRFs for supplementary models (in Figure 1) as the VAR model with electricity consumption weighted industrial development is provided in Appendix B.5 (see Figures B.29 and B.30).

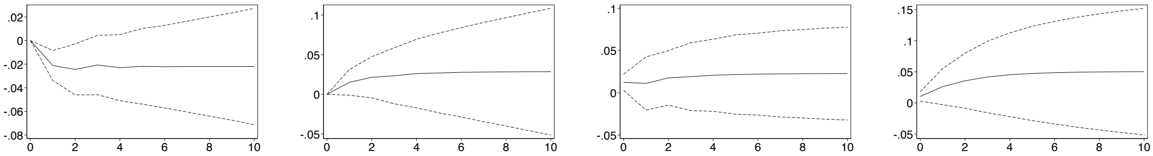
Figure 8: Impulse responses - Electricity price dynamics (CSE vs EP^h)



(a) CSE : IND　(b) EP^h : IND　(c) IND : CSE　(d) IND : EP^h

Notes: Impulse variable **:** response variable. $---$ indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

Figure 9: Impulse responses - Electricity price dynamics (EP^{ind} vs EP^h)



(a) EP^{ind} : IND　(b) EP^h : IND　(c) IND : EP^{ind}　(d) IND : EP^h

Notes: Impulse variable **:** response variable. $---$ indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

of another variable is calculated. The forecast-error variance decomposition is based on a Cholesky decomposition of the residual covariance matrix of the underlying panel VAR model as described in Section 5.

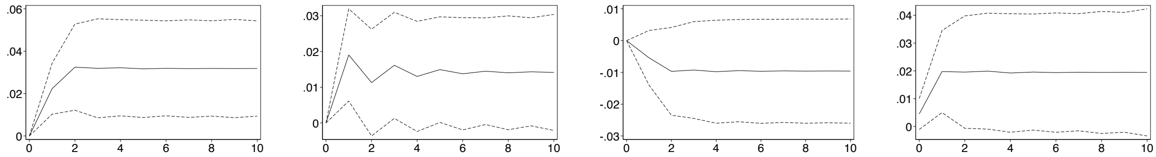
Benchmark. The variance decomposition for the benchmark model specification in Figure 11 and Table B.20 shows that cross-subsidy electricity price ratio explains around 20 percent of the variation in industrial development 10 periods ahead.[22] Moreover, CSE explains around 19 percent of the variation in CAP. Capital explains approximately 25 percent of the variation in industrial development 10 periods ahead.[23] Comparing the variation in industrial development over 1, 5, and 10 periods ahead (Figure 11), cross-subsidy electricity price ratio and capital together explain nearly 50 percent of the variation from the 5th to the 10th period.[24]

[22] This is also observed for both sub-samples used in the estimations (Table B.22).

[23] While capital explains around 18 percent of variations in industrial development 10 periods ahead for the sub-sample of EU OECD countries (Table B.22).

[24] As for the benchmark model using per capita variables presented in Figure B.31 and Table B.21, cross-subsidy electricity price ratio (CSE) explains around 11 percent of the variation in industrial development per capita (IND^{pc}) 10 periods ahead. Capital per capita approximately explains 25 percent of the variation in industrial development per capita 10 periods ahead.

Figure 10: Impulse responses - Benchmark extension: including trade openness



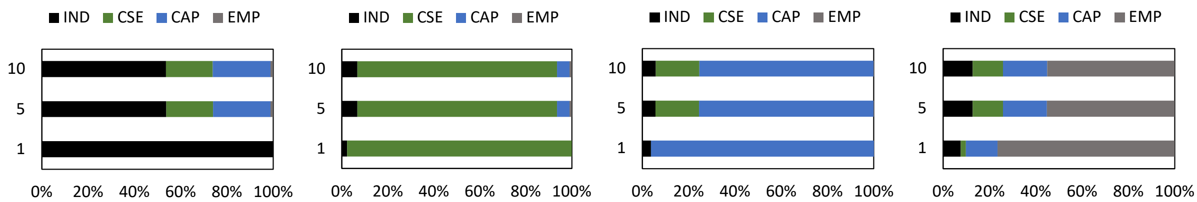
(a) CSE : IND (b) CAP : IND (c) TRO : IND (d) CSE : TRO

Notes: Impulse variable **:** response variable. $---$ indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

Electricity price dynamics. Figures 12, 13, 14 and Table B.23 show the variance decompositions for the electricity price dynamics models, where CSE explains approximately 16 percent of the variation in industrial development. While industrial electricity prices and household prices explain only 0.8 percent and 0.9 percent of the variation in industrial development 10 periods ahead respectively.

Benchmark extension: including trade openness. Variance decompositions for the VAR models that include trade openness are shown in Tables B.24, B.25, and Figure 15. The cross-subsidy electricity price ratio explains around 19 percent of the variation in industrial development. Capital explains around 14 percent of the variation in industrial development 10 periods ahead. Trade openness explains a small amount of the variation of industrial development for around 1 percent 10 periods ahead. Further, CSE explains approximately 11 percent and 9 percent of the variation in CAP and TRO respectively.[25]

Figure 11: Variance Decomposition - Benchmark model (shares of GDP)

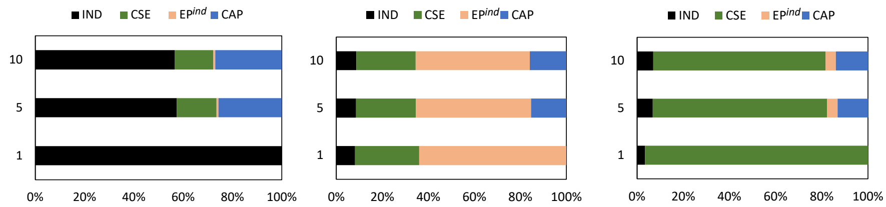


(a) Response of IND (b) Response of CSE (c) Response of CAP (d) Response of EMP

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD).

[25]Regarding the VAR model specification with industrial development weighted by electricity consumption similar patterns are observed, both CSE and capital explain a considerable amount of industrial development 10 periods ahead (see Table B.26).

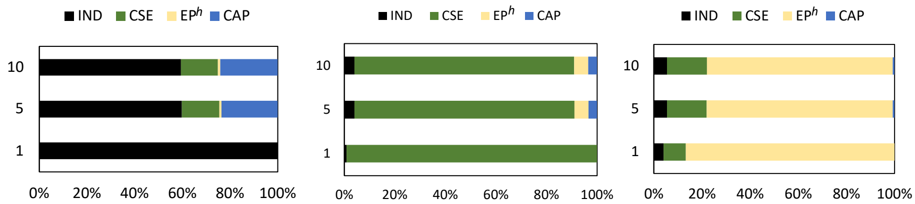
Figure 12: Variance Decomposition - Electricity price dynamics (CSE vs EP^{ind})



(a) Response of IND (b) Response of CSE (c) Response of EP^{ind}

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD)

Figure 13: Variance Decomposition - Electricity price dynamics (CSE vs EP^{h})



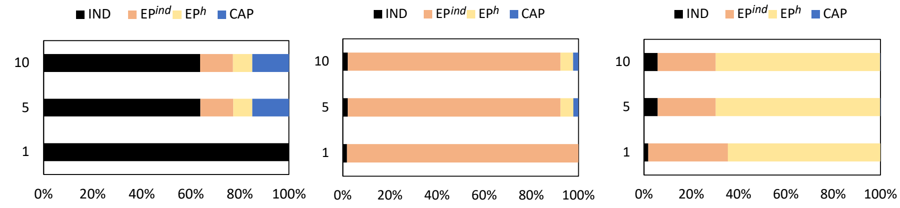
(a) Response of IND (b) Response of CSE (c) Response of EP^{h}

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD)

7. Discussion

This paper examines the relationship between the cross-subsidy electricity price ratio and industrial development. A panel VAR methodology is implemented using a comprehensive dataset of 17 OECD countries over a period of 25 years. Impulse-response functions are estimated, along with variance decompositions. The findings correspond closely to the two mechanisms outlined in Section 3. The expected direct cost channel is observed, where higher EP^{ind} reduces industrial development. However, the results also reveal a new indirect channel, whereby relative electricity pricing (CSE) affects industrial output. The results show a positive impact of the cross-subsidy electricity price ratio and capital on industrial development, supported by impulse-response estimates. Initially, the results may appear to be driven solely by a negative relationship between industrial development and industrial electricity prices. However, when both the cross-subsidy electricity price ratio and industrial electricity prices are included simultaneously in the model, the cross-subsidy ratio remains positive and statistically significant, confirming its independent effect on industrial development. Overall, the results provide evidence that the household to industrial electricity price ratio has a

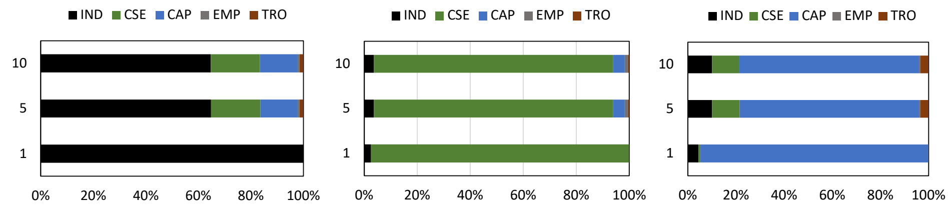
Figure 14: Variance Decomposition - Electricity price dynamics (EP^{ind} vs EP^h)



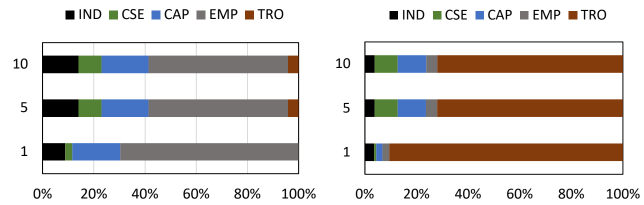
(a) Response of IND (b) Response of EP^{ind} (c) Response of EP^h

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD)

Figure 15: Variance Decomposition - Benchmark extension: including trade openness



(a) Response of IND (b) Response of CSE (c) Response of CAP



(d) Response of EMP (e) Response of TRO

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD)

separate effect on industrial development, beyond the role of industrial electricity prices alone.[26] [27] Estimations excluding absolute industrial prices allow for isolating the relative price mechanism captured by CSE, confirming that the observed effects are not solely driven by absolute electricity price levels. Thus, cross-subsidy ratio (CSE) captures the joint effect of these mechanisms and reflects an industry-friendly economic or regulatory environment.

The impact of electricity price ratio on industrial development operates through both direct and indirect channels. As for the direct effect, higher capital expenditure requires greater energy con-

[26] A similar outcome is observed when altering the sample to only European countries, as well, as when only using countries with very high ratio of electricity cross-subsidy price.

[27] Higher household electricity prices can benefit industrial development by driving demand for energy-efficient products, stimulating innovation, and creating new market opportunities. This can lead to increased production levels within the industrial sector, showcasing a positive response to household prices.

sumption, particularly electricity. For electricity consumption to increase, the industrial electricity price should decrease or remain relatively low, reflected in a higher electricity price ratio. Consequently, increases in capital are facilitated when electricity consumption rises, which occurs under higher cross-subsidization in favor of industry. The indirect effect operates through capital as a transmission channel. The electricity price ratio has a positive and statistically significant effect on capital, which in turn exerts a positive impact on industrial development. This indicates a pass-through effect from electricity pricing policies to industrial development via capital accumulation. In addition, industrial development responds positively to subsidizing electricity for industry relative to households in the presence trade openness. This mechanism is supported by the positive response of trade openness to increases in the electricity price ratio. Industrial development can be supported through two distinct channels. First, countries with structurally low electricity generation costs can maintain low absolute industrial electricity prices, directly reducing production costs. However, when achieving low absolute prices is not feasible countries may instead rely on relative price differentiation between households and industry. In this case, the cross-subsidy electricity price ratio (CSE) serves as an alternative mechanism through which industrial competitiveness can be preserved.

Four main implications are established from the evidence provided. First, lower industrial electricity prices act as a booster to more electricity-intensive production, which in turn promotes industrial development and indicates a price effect. Second, lower prices for industry relative to households provide support for production firms and manufacturers over private consumers. Electricity pricing structures in favor of industry reflect an industry-friendly economic or regulatory environment. Moreover, the electricity price ratio is straightforward to construct, providing a simple and transparent numerical measure of relative support for the industry. Fourth, higher cross-subsidy electricity price ratio is associated with higher levels of industrial development. This emphasizes the relevance of using the electricity cross-subsidy ratio ($\mathrm{EP}^{h}/\mathrm{EP}^{ind}$) as an indicator of a country's level of industrial development.

Expanding upon the outcomes, several important aspects should be discussed. First, measuring industrial development as a share of GDP provides an informative indicator of a country's level of industrialization and structural development.[28] This highlights that directing electricity subsidies toward industrial sectors rather than households positively affects industrial development relative to the size of the economy. This allows for meaningful cross-country comparisons and provides insights into the underlying economic structure. Countries in the early stages of industrialization typically experience an increase in industrial development as a share of GDP until a peak is reached, after which this share may stabilize, grow more slowly, or decline. [29] Accordingly, evidence that industrial development (as a share of GDP) responds positively to the cross-subsidy electricity price ratio helps explain why countries with relatively high cross-subsidy ratios, such as Denmark and Germany, can continue to experience increases in industrial development relative to GDP. In contrast, it is argued that beyond a certain stage of development, the share of energy-intensive secondary sectors should decline in favor of higher value-added manufacturing and tertiary activities, implying an inverse U-shaped relationship between industrial development and GDP per capita. From this perspective, a country like Germany, with high industrial development, GDP per capita, and a high cross-subsidy electricity ratio, may be interpreted as sustaining relatively uncompetitive industrial structures for an extended period, despite operating in an open economy.

Second, given that all countries in the sample belong to the OECD and are classified as developed, the discussion focuses on relative developmental levels. Therefore, it is necessary to construct a model employing per capita variables.[30] This enables absolute comparisons, complementing the share of GDP perspective. Estimating the benchmark model with both share of GDP and per capita variables yields consistent results, highlighting the positive response of industrial development to cross-subsidy electricity price ratio and emphasizing the importance of the interplay between industrial development and electricity price ratio.

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[28]This finding supports the first hypothesis, which predicts a positive response of industrial development (as a share of GDP) to subsidizing electricity for industry relative to households.

[29]Less developed countries or those at earlier stages of industrialization often exhibit higher industrial shares of GDP relative to more advanced economies.

[30]This supports the second hypothesis, which predicts a positive response of industrial development per capita to subsidizing electricity for industry relative to households. Assessing per capita outcomes allows evaluating whether such subsidies enhance income and living standards at the individual level.

Third, examining how industrial development responds to the household to industrial electricity price ratio highlights the role of trade openness.[31] The results also indicate that increases in CSE are associated with higher trade openness. This suggests that cross-subsidization may shift production toward export-oriented sectors when domestic consumption is weakens due to higher household electricity prices and reduced disposable income. Whether this outcome is desirable depends on broader policy objectives, as it may strengthen external competitiveness while simultaneously affecting domestic welfare. This mechanism is consistent with the experience of export-oriented economies. For example, Germany's postwar export growth; often described as an export "miracle", refers to the country's ability to match global economic growth despite severe postwar destruction (Giersch et al., 1992; Lang, 1990). A question to ask is whether such a connection, between industrial development and electricity price ratio, can be an alternative explanation for the German export 'miracle'? Prior to electricity market liberalization in the late 1990s, electricity pricing structures in Germany resulted in relatively high household to industrial price differences due to the way electricity costs were allocated across consumer groups. Despite an appreciating Deutsche Mark, the German industry remained competitive, supported in part by relatively low electricity costs. Electricity market liberalization introduced competition and market integration into the electricity sector. In principle, liberalization assumes that the law of one price holds, implying that competitive markets tend to reduce persistent price differences between industrial and household consumers that existed under regulated pricing regimes. Further, electricity pricing structures were also influenced by renewable energy support schemes largely financed through surcharges on electricity consumers (Pegels and Lutkenhorst, 2014) and by the allocation of free emission certificates to power producers during the early phases of the EU emissions trading system (EU ETS) (Sijm et al., 2006). Following the introduction of the euro, Germany could no longer adjust competitiveness through exchange rate movements, and industrial performance increasingly depended on domestic cost conditions, including labor costs and electricity price conditions faced by industrial producers, which directly affect industrial competitiveness, as analyzed in this study.

[31] This supports the third hypothesis, which predicts a positive response of industrial development to subsidizing electricity for industry relative to households in the presence of trade openness.

Fourth, investing in renewable energy sources for electricity generation is a central pathway toward achieving a low-emissions economy. However, such investments are often associated with significant costs and higher electricity prices, affecting both households and industries. Notably, if the burden of increased electricity prices falls more heavily on households than on industries, the electricity price structure can support industrial development, particularly in highly open trade environments. Therefore, electricity pricing policies that favor the industry by limiting increases in industrial electricity prices relative to household prices, can effectively promote decarbonization and transition to a greener economy while fostering industrial growth and maintaining competitiveness in global markets.

Finally, this study has some limitations. All countries in the sample are OECD members and represent developed economies in which the electricity sector accounts for only a relatively small share of overall economic activity. Consequently, the inclusion of the electricity sector within measures of industrial development should not be a major concern, as its contribution to industrial output in advanced economies is limited. While the analysis focuses on industrial development, broader welfare effects; such as impacts on household income and overall economic well-being, are not explicitly examined.[32] Moreover, the absence of key variables in earlier periods restricts the analysis to the current sample. This sample size constrains the extent to which subsamples can be formed or alternative groupings can be explored without a substantial loss of observations, potentially affecting the number of observations and statistical power. Despite these limitations, future research could explore the cross-subsidy ratio in developing countries, which often subsidize households more than industries, and its impact on household income and welfare.

8. Conclusion

This paper analyzes the relationship between industrial development and electricity price differentiation between industry and households using a panel VAR applied to 17 OECD countries from

[32] In principle, this could be addressed by analyzing the response of GDP per capita to changes in the electricity cross-subsidy ratio and comparing these results with those obtained for industrial development per capita. However, due to the presence of cointegration among the relevant variables, it is not possible to estimate a panel VAR model including GDP per capita. Additional analysis is conducted for the vectors [GDP^{PC}, CSE, CAP, EMP] and [GDP^{PC}, CSE, CAP, EMP], where GDP^{PC} denotes GDP per capita. In both cases, the variables were found to be cointegrated (results not reported), rendering panel VAR estimation inappropriate. An alternative approach, such as a panel vector error correction model (VECM), could be employed, but this lies beyond the scope of the current study.

1995 to 2019. Estimating several model specifications yields robust results. The findings indicate a positive effect of the cross-subsidy electricity price ratio on industrial development, along with a positive impact of capital. These results are further supported by impulse-response functions, which show that a shock in the cross-subsidy electricity price ratio results in a positive response of industrial development. Supporting industry can occur through maintaining low absolute industrial electricity prices and also through relative price structures favoring industrial users when low absolute prices cannot be achieved. Overall, the evidence suggests that the household to industrial electricity price ratio plays an independent role in shaping industrial development, beyond the effect of industrial electricity prices alone. The cross-subsidy electricity price ratio captures the joint effect of these mechanisms and reflects an industry-friendly economic or regulatory environment favoring industrial activity. In addition, the effect of the electricity price ratio on industrial development operates through both direct and indirect channels. Indirectly, higher capital expenditure requires greater energy (electricity) consumption, which is facilitated by relatively lower electricity prices for industry and thus a higher electricity price ratio. In the presence of trade openness, industrial development responds positively to subsidizing electricity for the industry relative to households, as foreign demand helps sustain higher production levels.

The analysis yields several important implications. First, lower industrial electricity prices act as a booster to more electricity-intensive production, thereby promoting industrial development and reflecting a direct price effect. Second, relatively lower electricity prices for industry compared to households have a positive impact on industrial development in OECD countries, reflecting an industry-friendly economic or regulatory environment to support production firms and manufacturers. Additionally, in the presence of trade openness, industrial development responds positively to the prioritization of electricity subsidization for industry over households. This relationship highlights the role of trade openness in amplifying the positive effects of electricity cross-subsidization on industrial development.

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Appendix A. Descriptive statistics

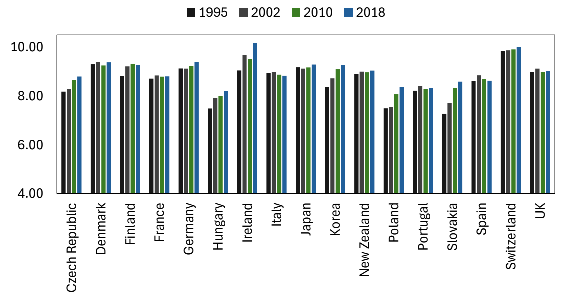
See Figures A.16, A.17, A.18, A.19 and Table A.6.

Table A.6: Summary statistics

	Mean	p50	SD	Min	Max
IND	3.252	3.270	0.188	2.844	3.649
IND^{pc}	8.855	8.944	0.583	7.272	10.178
IND^{e}	4.955	4.919	0.410	4.312	6.080
CSE	0.574	0.534	0.294	-0.554	1.389
EP^{ind}	4.511	4.552	0.456	3.325	5.473
EP^{h}	5.084	5.169	0.488	3.332	6.006
CAP	3.127	3.115	0.184	2.691	3.981
CAP^{pc}	8.709	8.833	0.630	6.648	10.578
EMP	3.999	4.011	0.117	3.656	4.217
TRO	4.334	4.266	0.482	2.797	5.531
Obs	**425**				

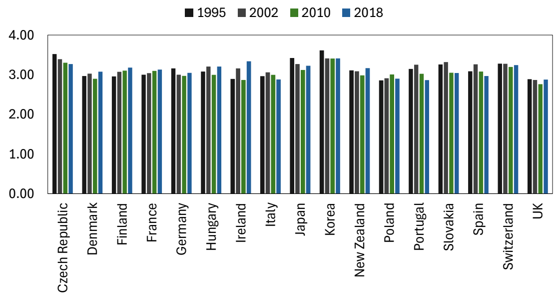
Notes: All variables are log-transformed.

Figure A.16: Industrial Development per capita (IND^{pc})



Notes: All variables are log-transformed.

Figure A.17: Capital (CAP) across countries



Notes: All variables are log-transformed.

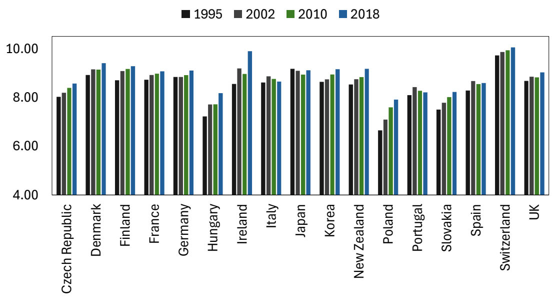
Appendix B. Supplementary Empirical Estimation Results

Appendix B.1. Pre-Estimation Analysis of VAR Model: Panel unit-root tests

The analysis starts with performing unit root tests. Unit root tests are implemented to test for nonstationarity in the data, where nonstationarity implies that the tendency of a variable to go back to a constant value is unclear or does not show a linear trend. In the context of panel data and first-order autoregressive element, I test for unit root for the variable y_{it}. The following equation is considered to test for unit root:

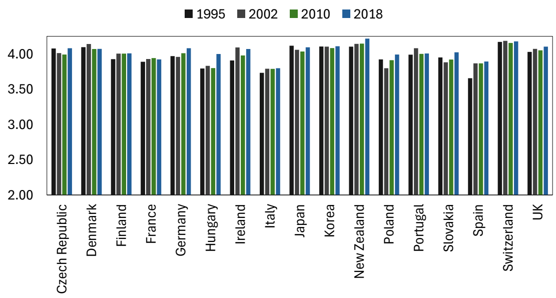
$$y_{it} = \rho_i y_{i,t-1} + \mathbf{z}'_{it}\gamma_i + \epsilon_{it} \tag{B.1}$$

Figure A.18: Capital per capita (CAP^{pc})



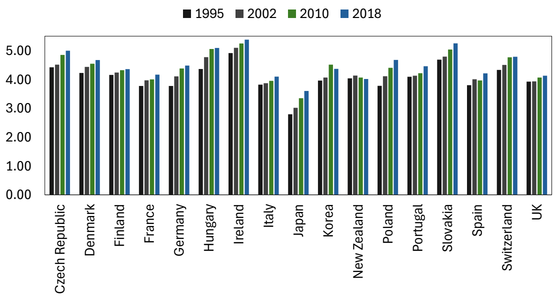
Notes: All variables are log-transformed.

Figure A.19: Employment (EMP)



Notes: All variables are log-transformed.

Figure A.20: Trade Openness (TRO)



Notes: All variables are log-transformed.

where $t = 1, \ldots, T_i$ represents time and the panels are indexed by $i = 1, \ldots, N$. Fixed effects or the panel-specific mean is indicated by the $\mathbf{z}'_{it}\gamma_i$. To check for nonstationarity of a variable, $\rho_i = 1$ is tested as the null-hypothesis. The alternative hypothesis differs according to the specific unit root test being implemented. I implement multiple unit root tests as the Breitung, Harris-Tsavalis (HT), and Fisher-type (Phillips-Perron) tests. These tests have numerous distinctions regarding their assumptions. One main important distinction to highlight is regarding the asymptotics theory of each test or how rates of T (periods) and N (panels) grow. Some tests either T or N or both are fixed, while others assume that T goes to infinity at a faster rate compared to N. This assumption relates to the sample size being used in the study. For the case of OECD sample countries, I can assume that N can be fixed while T can go to infinity or that T goes to infinity first then N using the sequential limit theory.

Three unit-root tests are performed for the variables in this panel dataset. The first test is the Fisher-type unit-root test which is the Phillips-Perron (PP) test and its null-hypothesis is that all panels contain unit roots. Furthermore, the Harris-Tsavalis (HT) and Breitung tests assume that panels contain unit roots for the null hypothesis. The main difference across these tests is regarding the alternative hypothesis, where Fisher-type tests have an alternative hypothesis of at least one panel is stationary. While HT and Breitung tests assume that panels are stationary for the alternative hypothesis. Due to the differences across the tests, I implement multiple unit root tests whose assumptions fit the data to be able to reach a concrete conclusion for the stationarity of each variable. Using the Akaike Information Criteria (AIC), optimal lags are selected for the tests. To mitigate the impact of cross-sectional dependence, unit root tests are performed on demeaned data.

Table B.7: Panel unit root tests

	PP	HT	Breitung
A: At levels			
IND	-0.350	0.956	-1.314
IND^{pc}	1.3511	0.9513	2.4134
IND^{e}	-1.353	0.997	0.023
CSE	-0.412	0.836**	-1.320
CAP	-0.754	0.879	-2.159**
CAP^{pc}	0.9028	0.9406	-0.2769
EMP	0.8173	0.9094	-2.154 **
EP^{ind}	-0.881	0.318***	-1.921**
EP^{h}	-2.241**	0.8655	-0.915
TRO	-2.1725**	0.8629	-0.6511
B: At first difference			
IND	-15.315***	-0.039***	-4.147***
IND^{pc}	-12.321***	0.1031 ***	-4.3563 ***
IND^{e}	-15.252***	0.034***	-4.328***
CSE	-12.823***	0.137***	-7.263***
CAP	-9.517***	0.108***	-4.058***
CAP^{pc}	-9.2317 ***	0.2218 ***	-4.4837 ***
EMP	-7.3176 ***	0.5036 ***	-4.6261 ***
EP^{ind}	-12.440***	0.144***	-5.537***
EP^{h}	-11.376***	0.209***	-4.415***
TRO	-11.5732***	0.1356 ***	-5.142 ***

Notes: All variables are log-transformed. *** indicates significance at the 1%, ** indicates significance at the 5%. Tests are performed on demeaned data to mitigate the effects of cross-sectional dependence (check appendix for cross-sectional independence test results). A lag of 1 is selected according to AIC.
PP: Phillips-Perron Test and its null-hypothesis is all panels contain unit roots.
HT: Harris–Tsavalis Test and its null-hypothesis is panels contain unit roots.
Breitung test has the null-hypothesis of panels contain unit roots.

Table B.7 reports the results of the different unit root tests. Panel A shows the unit root test results for all the variables used at levels. Almost all the tests for the variables indicate that they are nonstationary. Although for a few variables the results indicate stationarity, not all the tests confirm this stationarity for those variables. One might be tempted to conclude that these variables are stationary at levels. However, since the rest of the tests do not reject the null, it still implies that these variables can be nonstationary. Hence, the first difference of all variables is taken and unit roots are tested again. All the tests reject the null, thus indicating that all variables are stationary at first difference. Consequently, variables in differences are used to estimate the panel VAR models.

Appendix B.2. Pre-Estimation Analysis of VAR Model: Additional Findings

This section of the appendix provides supplementary information on the empirical estimation of the panel VAR, as well as a few extra tables from the results section that were excluded from the main text. First, a test for cross-sectional independence is given in Table B.8. Second, regarding the empirical methodology in Section 5, the framework for efficient instrumental variable estimators of random effects models was constructed by Arellano and Bover (1995), where they explained how transformations in panel data models are connected to existing estimators. Their work provided evidence that transformations to remove individual effects did not matter in case of having optimal estimators. In this paper, Arellano and Bover (1995) also provide a solution to the problem that the δ_i (in eq. 5) is correlated with the predictor variables because of the lags of the dependent variables. This is done through implementing the Helmert transformation. The Helmert transformation requires using forward orthogonal deviation by removing the forward mean of all future observations available for each country-year. Thus, the transformation allows using lagged regressors as instruments, where a small lag length is used rather than using all available lags as instruments. Then, coefficients are estimated via GMM.

Third, cointegration is also tested if the variables are stationary in first-difference $I(1)$. A group of variables is said to be cointegrated when their $I(1)$ linear combination is stationary indicating equilibrium in the long-run. In other words, a group of $I(1)$ variables is cointegrated if they move together (Engle and Granger, 1987). To estimate a panel VAR there should be no cointegration between the group of variables that are $I(1)$, otherwise, one could implement a vector error-correction model VECM. Pedroni and Westerlund tests are implemented to test for cointegration (see Table

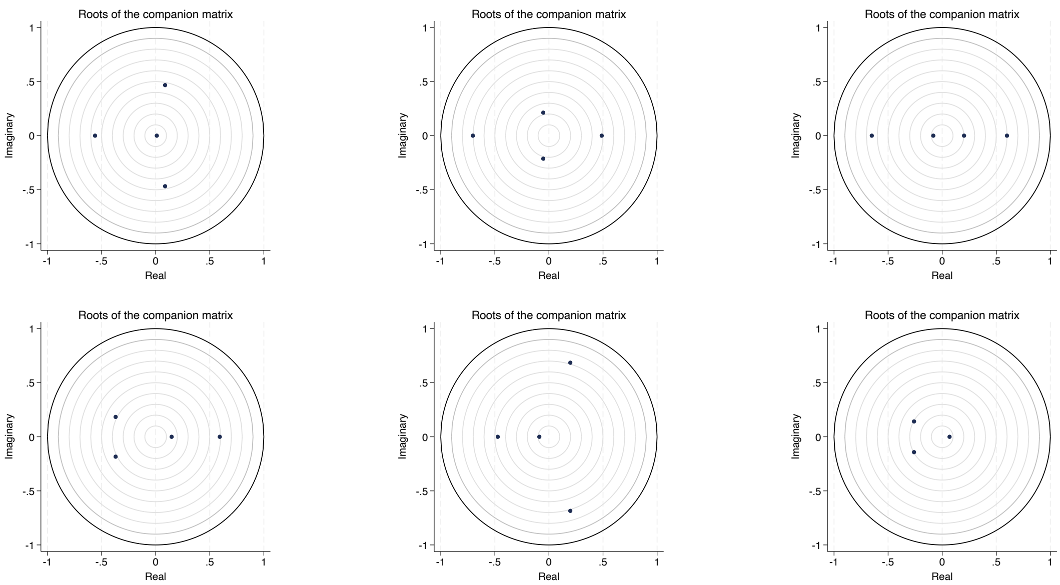
B.9). The null hypothesis for these tests is no cointegration, while the alternative hypothesis varies across tests. That is why all three tests are implemented to accurately decide if a cointegration exists or not (see Tables B.9, B.10, and B.11). Fourth, I also consider the test for overidentification, where the Hansen J test is implemented to test for over-identifying restrictions, where under the null hypothesis that the over-identifying restrictions are valid. All models do not reject the null hypothesis. In addition, VAR stability is being checked as shown in Figures B.21, B.22, B.23, and B.24. All models have 1 lag selected as the optimal, with a positive and high overall coefficient of determination (CD).

Table B.8: Testing for cross-sectional independence

	IND	IND^{pc}	CSE	CAP	CAP^{pc}
CD-test	27.83 ***	18.85 ***	3.47 ***	15.16 ***	26.42 ***
	EP^{ind}	EP^{h}	EMP	TRO	
CD-test	47.29 ***	47.98 ***	10.81 ***	41.03 ***	

Notes: All variables are at levels and log-transformed. *** indicates significance at the 1%, ** indicates significance at the 5%. Pesaran (2004) CD test is used to test for Cross-sectional independence. Null hypothesis: Cross-sectional independence.

Figure B.21: VAR model stability check - 17 OECD: Models A, B, C, D, E, F



Notes: Model versions refer to the following: (A) IND CSE CAP EMP , (B) IND CSE EP^{ind} CAP, (C) IND CSE EP^{h} CAP, (D) IND EP^{ind} EP^{h} CAP, (E) IND^{e} CSE CAP EMP, (F) IND EP^{ind} CAP

Table B.9: Cointegration tests

	Pedroni M PP-t	Westerlund VR
17 OECD Countries		
Model A	0.8858	-0.8166
Model B	1.2865 *	-0.3249
Model C	1.0213	-0.084
Model D	1.0213	-0.084
Model E	1.0213	-0.084
Model F	0.2192	-1.2227
Model G	0.3423	-1.3321 *
14 EU-OECD Countries		
Model A	0.6277	-0.8004
9 OECD Countries with CSE > p50		
Model A	-0.2785	-0.8032

Notes: All variables are log-transformed. *** indicates significance at the 1%, ** at the 5%, * at the 10%. M PP t is the Modified Phillips-Perron t-statistic. VR is the Variance Ratio. All tests include the demean option and the auto-regressive parameter is the same Null-hypothesis: No Cointegration Models: (A) IND, CSE, CAP, EMP (Benchmark model - share of GDP); (B) IND^{pc}, CSE, CAP^{pc}, EMP (Benchmark model - per capita) ; (C) IND, CSE, EP^{ind}, CAP (Electricity price dynamics); (D) IND, CSE, EP^{h}, CAP (Electricity price dynamics); (E) IND, EP^{ind}, EP^{h}, CAP (Electricity price dynamics); (F) IND, CSE, CAP, TRO (Benchmark extension - including trade openness); (G) IND, CSE, CAP, EMP, TRO (Benchmark extension - including trade openness)

Appendix B.3. VAR models estimation: Additional findings

Supplementary models. One may argue that for electricity prices to affect a country, electricity consumption should be sufficiently high.[33] This part of the analysis examines whether a country's industrial development that is heavily dependent on electricity-intensive industries exhibits such a pattern regarding the impact of electricity ratio on industrial development. Therefore, I construct a new variable from industrial development that adapts to changes in electricity consumption between countries and across periods. VAR estimations using industrial development weighted by electricity consumption IND^{e} are reported in Table B.14. The results indicate that electricity cross-subsidy has a positive and significant impact on IND^{e}. Furthermore, by estimating a similar model to that

[33] This is a robustness check that ensures the connection between the prices and electricity consumption, and then to industrial development.

Table B.10: Cointegration tests - Supplementary (IND weighted by electricity consumption)

	Pedroni M PP-t	Westerlund VR
17 OECD		
	1.3954*	1.1436

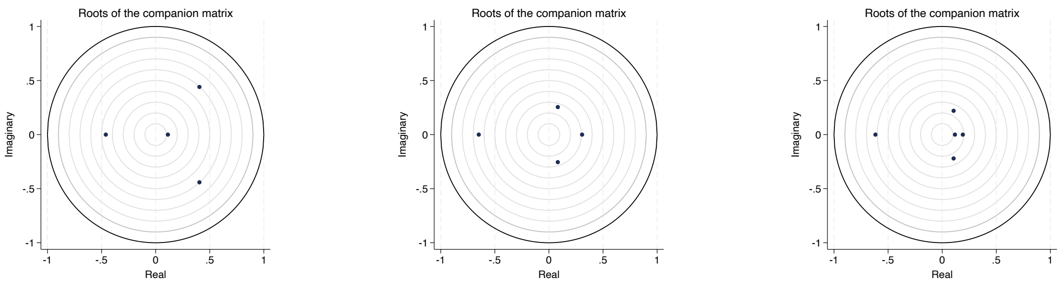
Notes: All variables are log-transformed. *** indicates significance at the 1%, ** at the 5%, * at the 10%.
M PP t is the Modified Phillips-Perron t-statistic. VR is the Variance Ratio. All tests include the demean option and the autoregressive parameter is the same
Null-hypothesis: No Cointegration
Model: IND^e CSE CAP EMP

Table B.11: Cointegration tests - Supplementary

	Pedroni M PP-t	Westerlund VR
17 OECD		
	0.8493	0.076

*Notes: All variables are log-transformed. *** indicates significance at the 1%, ** at the 5%, * at the 10%.*
M PP t is the Modified Phillips-Perron t-statistic. VR is the Variance Ratio. All tests include the demean option and the autoregressive parameter is the same
Null-hypothesis: No Cointegration
Model: IND EP^{ind} CAP

Figure B.22: VAR model stability check - 17 OECD: Models G, H, I



Notes: Model versions refer to the following: (G) IND^{pc} CSE CAP^{pc} EMP, (H) IND CSE CAP TRO, (I) IND CSE CAP EMP TRO

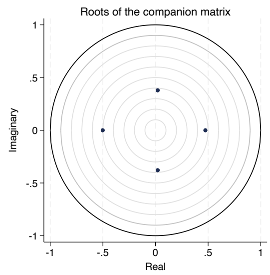
in Table 2, but using IND^e instead of IND, the same inferences can be made regarding the positive and significant impact of the variable CSE. Moreover, the response of IND^e to capital is evident from the positive and significant coefficient.

Appendix B.4. Granger Causality

In this section, I test for Granger causality. Granger causality tests if the joint lagged values of a variable x predict the values of another variable y conditional on past values of y (Granger, 1969). This is implemented as Wald tests with a null hypothesis that the x-variable "does not Granger cause" the y-variable. It also tests that the coefficients of all the lags of all x-variables are jointly zero (Abrigo and Love, 2016).

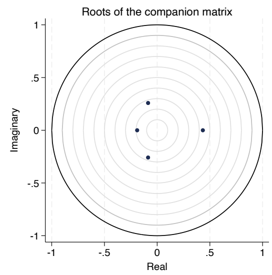
Performing Granger causality tests for coefficients of the benchmark models, where results of tests are reported in Tables B.16 and B.18. I find that the Wald test results also confirm the outcome of

Figure B.23: VAR model stability check - 14 EU OECD (Model A)



Notes: Model versions refer to the following: (A) IND CSE CAP EMP

Figure B.24: VAR model stability check - 9 OECD (Model A)



Notes: Model versions refer to the following: (A) IND CSE CAP EMP

Table B.12: Benchmark extension: including trade openness

	Response to IND(t-1)	CSE(t-1)	CAP(t-1)	TRO(t-1)
Response of 17 OECD				
IND(t)	-0.119	0.281 ***	0.449 ***	-0.023
	(0.155)	(0.103)	(0.124)	(0.120)
CSE(t)	0.125	0.004	-0.303 *	-0.191
	(0.269)	(0.185)	(0.156)	(0.196)
CAP(t)	0.520 **	0.226 *	-0.177	0.009
	(0.227)	(0.130)	(0.181)	(0.247)
TRO(t)	0.081	0.139	-0.199	0.114
	(0.141)	(0.103)	(0.124)	(0.128)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10% .

the panel VAR estimation in the previous section. This is indicated by rejecting the null hypothesis that $\Delta\ CSE$ does not granger-cause $\Delta\ IND$, where the coefficient of the chi-squared is significant at 1 percent. This is also true for the sub-sample of 14 EU OECD countries, as well as for the 9 OECD countries with CSE above the median. Moreover, the null hypothesis that $\Delta\ CAP$ does not granger-cause $\Delta\ IND$ is rejected, where the coefficient of the chi-squared is also significant at 1 percent. However, I cannot reject the null hypothesis that $\Delta\ EMP$ does not granger-cause $\Delta\ IND$, where the coefficient of the chi-squared is insignificant. Overall, the null hypothesis that $\Delta\ CSE$, $\Delta\ CAP$, and $\Delta\ EMP$ jointly do not granger-cause $\Delta\ IND$ is rejected at 1 percent, which means $\Delta\ CSE$, $\Delta\ CAP$, and $\Delta\ EMP$ jointly predict $\Delta\ IND$. As for whether $\Delta\ IND$ does not granger-cause $\Delta\ CSE$, the null hypothesis cannot be rejected for the main sample and for both sub-samples.

Table B.13: Benchmark model (shares of GDP) - sub-samples

	Response to			
	IND(t-1)	CSE(t-1)	CAP(t-1)	EMP(t-1)
Response of				
14 EU OECD				
IND(t)	0.154	0.330***	0.504**	-0.191
	(0.163)	(0.094)	(0.209)	(0.573)
CSE(t)	-0.230	0.072	-0.445*	1.341
	(0.236)	(0.152)	(0.228)	(0.810)
CAP(t)	0.423**	0.398***	-0.255	0.308
	(0.194)	(0.144)	(0.255)	(0.839)
EMP(t)	0.138***	0.070**	0.063	0.043
	(0.053)	(0.028)	(0.045)	(0.135)
9 OECD CSE $>$ P50				
IND(t)	0.130	0.446***	0.118	0.382
	(0.153)	(0.125)	(0.095)	(0.456)
CSE(t)	-0.118	-0.198	0.001	0.372
	(0.201)	(0.132)	(0.157)	(0.569)
CAP(t)	0.409**	0.387**	0.026	-0.111
	(0.204)	(0.166)	(0.188)	(0.722)
EMP(t)	0.002	0.096***	0.134***	0.115
	(0.034)	(0.031)	(0.039)	(0.134)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10% .

Similar inferences for panel VAR estimations can be made from the Granger causality tests for models in Table B.17. $\Delta\ CSE$ predicts $\Delta\ IND$ at 1 percent for models A and B. While $\Delta\ EP^{ind}$ and $\Delta\ EP^{h}$ also significantly predict $\Delta\ IND$ at 1 percent for model C. Additionally, the test results for models in Table B.19 reach the same conclusions provided by the panel VAR estimations discussed in the previous section.

Appendix B.5. Impulse-response functions and variance decompositions: Additional findings

Table B.14: Supplementary - IND weighted by electricity consumption

	Response to IND^e(t-1)	CSE(t-1)	CAP(t-1)	EMP(t-1)
Response of				
IND^e(t)	0.023	0.472***	0.724***	-0.022
	(0.177)	(0.123)	(0.242)	(0.822)
CSE(t)	-0.590**	0.187	-0.787*	1.748
	(0.286)	(0.235)	(0.439)	(1.266)
CAP(t)	0.240	0.479***	-0.123	0.317
	(0.194)	(0.151)	(0.221)	(0.782)
EMP(t)	0.045	0.027	0.202***	-0.254
	(0.046)	(0.036)	(0.057)	(0.181)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Main sample used (17 OECD).

Table B.15: Supplementary

	Response to IND(t-1)	EP^{ind}(t-1)	CAP(t-1)
Response of			
IND(t)	-0.059	-0.199**	0.187
	(0.187)	(0.079)	(0.154)
EP^{ind}(t)	-0.052	-0.235	0.058
	(0.402)	(0.222)	(0.311)
CAP(t)	0.121	-0.427***	-0.158
	(0.436)	(0.150)	(0.290)

Notes: Heteroskedasticity adjusted standard errors are in parentheses. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Main sample used (17 OECD).

Table B.16: Granger causality - Benchmark model

	17 OECD	14 EU OECD	9 OECD (CSE > P50)
	χ^2	χ^2	χ^2
ΔCSE $\rightarrow$ ΔIND	10.407***	12.3***	12.728 ***
ΔCAP $\rightarrow$ ΔIND	7.348 ***	5.841**	1.551
ΔEMP $\rightarrow$ ΔIND	0.766	0.111	0.701
All	19.453***	20.23***	14.009***
ΔIND$\rightarrow$ ΔCSE	1.418	0.954	0.35

Notes: Null-hypothesis: X $\rightarrow$ Y means that X does not granger cause Y. *** indicates significance at the 1%, ** at the 5%, * at the 10%.
Model: IND CSE CAP EMP

Table B.17: Granger causality - Electricity price dynamics

	17 OECD
	χ^2
Panel A	
ΔCSE $\rightarrow$ ΔIND	9.716***
ΔEP^{ind}$\rightarrow$ ΔIND	0.001
ΔCAP $\rightarrow$ ΔIND	4.613**
All	20.267***
ΔIND$\rightarrow$ ΔCSE	0.929
ΔIND$\rightarrow$ ΔEP^{ind}	0.134
Panel B	
ΔCSE $\rightarrow$ ΔIND	13.351***
ΔEP^{h}$\rightarrow$ ΔIND	0.097
ΔCAP $\rightarrow$ ΔIND	7.237***
All	22.578***
ΔIND$\rightarrow$ ΔCSE	0.482
ΔIND$\rightarrow$ ΔEP^{h}	0.072
Panel C	
ΔEP^{ind}$\rightarrow$ ΔIND	15.196***
ΔEP^{h}$\rightarrow$ ΔIND	7.476***
ΔCAP $\rightarrow$ ΔIND	4.553**
All	21.169***
ΔIND$\rightarrow$ ΔEP^{ind}	0.094
ΔIND$\rightarrow$ ΔEP^{h}	0.693

Notes: Null-hypothesis: X $\rightarrow$ Y means that X does not granger cause Y. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Panels refer to model versions: (A) IND, CSE, EP^{ind}, CAP; (B) IND, CSE, EP^{h}, CAP; (C) IND, EP^{ind} , EP^{h}, CAP

Table B.18: Granger causality - Benchmark model (per capita), Benchmark extension (including trade openness)

	17 OECD χ^2
Panel A	
Δ CSE $\rightarrow$ Δ IND^{pc}	4.481 **
Δ CAP^{pc} $\rightarrow$ Δ IND^{pc}	19.314 ***
Δ EMP $\rightarrow$ Δ IND^{pc}	2.123
All	36.297 ***
Δ IND^{pc} $\rightarrow$ Δ CSE	2.909 *
Panel B	
Δ CSE $\rightarrow$ Δ IND	7.379 ***
Δ CAP $\rightarrow$ Δ IND	13.180 ***
Δ TRO $\rightarrow$ Δ IND	0.037
All	19.989 ***
Δ IND $\rightarrow$ Δ CSE	0.216
Panel C	
Δ CSE $\rightarrow$ Δ IND	14.336 ***
Δ CAP $\rightarrow$ Δ IND	8.622 ***
Δ EMP $\rightarrow$ Δ IND	0.526
Δ TRO $\rightarrow$ Δ IND	1.580
All	27.422 ***
Δ IND $\rightarrow$ Δ CSE	0.622

Notes: Null-hypothesis: X $\rightarrow$ Y means that X does not granger cause Y. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Panels refer to model versions:
(A) IND^{pc} CSE CAP^{pc} EMP
(B) IND CSE CAP TRO
(C) IND CSE CAP EMP TRO

Table B.19: Granger causality - Supplementary models

	17 OECD χ^2
Panel A	
ΔCSE $\rightarrow$ ΔIND^e	14.816***
ΔCAP $\rightarrow$ ΔIND^e	8.941***
ΔEMP $\rightarrow$ ΔIND^e	0.001
All	30.545***
$\Delta IND^e \rightarrow$ ΔCSE	4.26**
Panel B	
$\Delta EP^{ind} \rightarrow$ ΔIND	6.239**
ΔCAP $\rightarrow$ ΔIND	1.46
All	7.817**
ΔIND$\rightarrow$ ΔEP^{ind}	0.017

Notes: Null-hypothesis: X $\rightarrow$ Y means that X does not granger cause Y. *** indicates significance at the 1%, ** at the 5%, * at the 10%. Panels refer to model versions:
(A) IND^e CSE CAP EMP
(B) IND EP^{ind} CAP

Table B.20: Variance Decomposition - Benchmark model (shares of GDP)

	Impulse			
	IND	CSE	CAP	EMP
Response				
IND	0.536	0.203	0.249	0.012
CSE	0.068	0.869	0.054	0.010
CAP	0.057	0.188	0.753	0.001
EMP	0.127	0.132	0.190	0.551

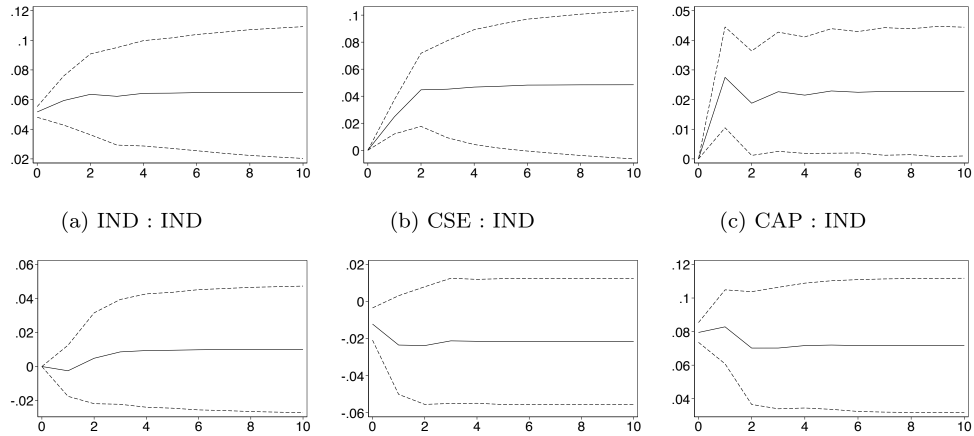
Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD).

Table B.21: Variance Decomposition - Benchmark model (per capita)

	Impulse			
	IND^{pc}	CSE	CAP^{pc}	EMP
Response				
IND^{pc}	0.598	0.114	0.248	0.040
CSE	0.098	0.829	0.056	0.017
CAP^{pc}	0.223	0.220	0.499	0.058
EMP	0.206	0.163	0.289	0.342

Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD).

Figure B.25: Impulse responses - Benchmark model (share of GDP) using sub-sample (14 EU OECD)

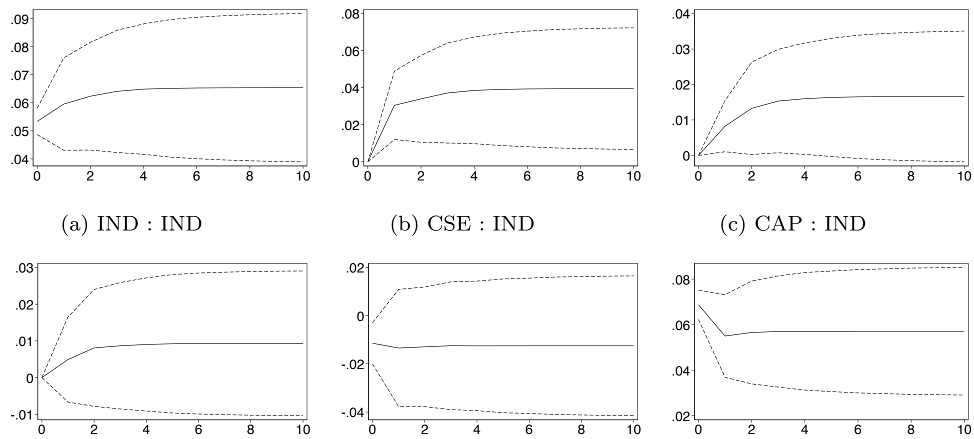


(a) IND : IND (b) CSE : IND (c) CAP : IND

(d) EMP : IND (e) IND : CSE (f) CSE : CSE

Notes: Impulse variable **:** response variable. − − −− indicates the 95% confidence interval using Monte-Carlo simulation.

Figure B.26: Impulse responses - Benchmark model (share of GDP) using sub-sample (9 OECD)

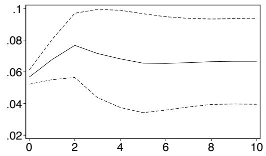


(a) IND : IND (b) CSE : IND (c) CAP : IND

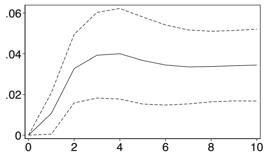
(d) EMP : IND (e) IND : CSE (f) CSE : CSE

Notes: Impulse variable **:** response variable. − − −− indicates the 95% confidence interval using Monte-Carlo simulation.

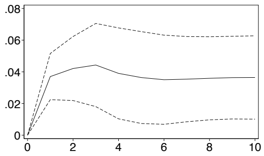
Figure B.27: Impulse responses - Benchmark model (per capita)



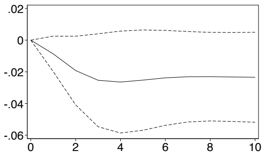
(a) IND^{pc} : IND^{pc}



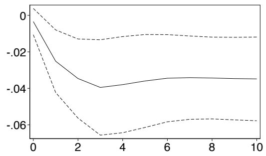
(b) CSE : IND^{pc}



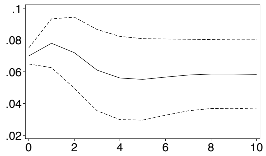
(c) CAP^{pc} : IND^{pc}



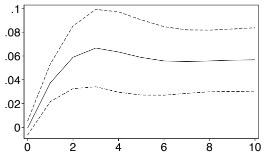
(d) EMP : IND^{pc}



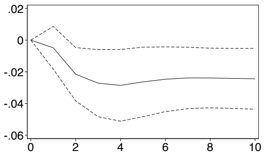
(e) IND^{pc}: CSE



(f) CSE : CSE



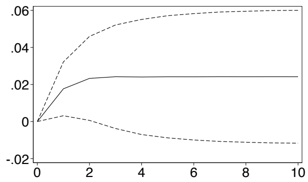
(g) CSE : CAP^{pc}



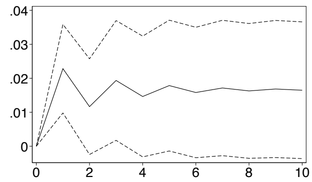
(h) CAP^{pc} : CSE

Notes: Impulse variable **:** response variable. − − − indicates the 95% confidence interval using Monte-Carlo simulation. Main sample used (17 OECD).

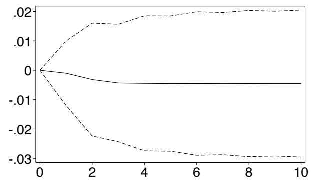
Figure B.28: Impulse responses - Benchmark extension - including trade openness (excluding employment)



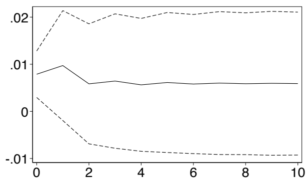
(a) CSE : IND



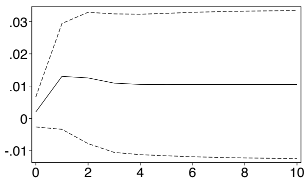
(b) CAP : IND



(c) TRO : IND



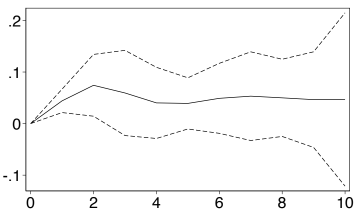
(d) IND : TRO



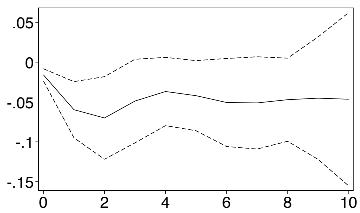
(e) CSE : TRO

Notes: Impulse variable **:** response variable. − − −− indicates the 95% confidence interval using Monte-Carlo simulation.

Figure B.29: Impulse responses - Supplementary model (IND^e CSE CAP EMP)



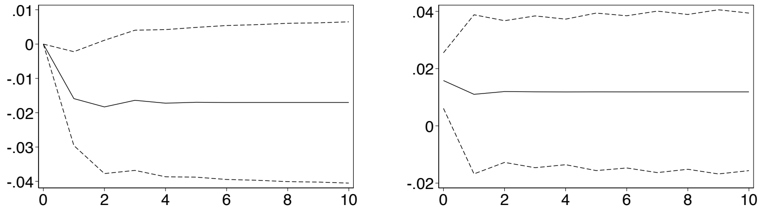
(a) CSE : IND^e



(b) IND^e : CSE

Notes: Impulse variable **:** response variable. − − −− indicates the 95% confidence interval using Monte-Carlo simulation.

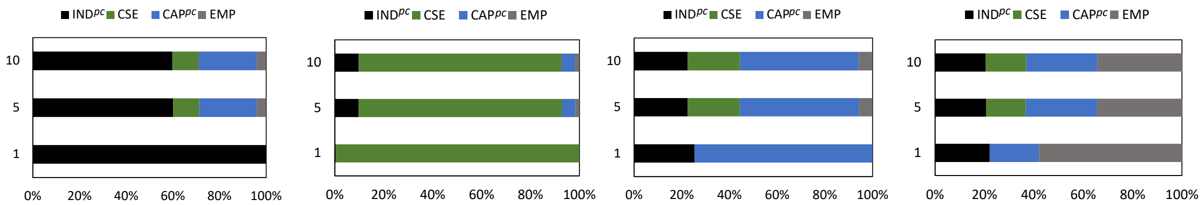
Figure B.30: Impulse responses - Supplementary model (IND EP^{ind} CAP)



(a) EP^{ind} : IND (b) IND : EP^{ind}

Notes: Impulse variable **:** response variable. − − −− indicates the 95% confidence interval using Monte-Carlo simulation.

Figure B.31: Variance Decomposition - Benchmark model (per capita)



(a) Response of IND^{pc} (b) Response of CSE (c) Response of CAP^{pc} (d) Response of EMP

Notes: Variance decomposition for the 1st, 5th, and 10th period. Main sample used (17 OECD)

Table B.22: Variance Decomposition - Benchmark model (share of GDP)

	Impulse IND	CSE	CAP	EMP
Response				
14 EU OECD				
IND	0.586	0.216	0.181	0.016
CSE	0.038	0.876	0.044	0.043
9 OECD CSE $>$ P50				
IND	0.727	0.240	0.025	0.009
CSE	0.027	0.967	0.002	0.005

Notes: Variation in the row variable (10 periods ahead) explained by column variable.
Model: IND CSE CAP EMP

Table B.23: Variance Decomposition - Electricity price dynamics

Panel A	**Impulse** IND	CSE	EP^{ind}	CAP
Response				
IND	0.566	0.157	0.008	0.269
CSE	0.070	0.747	0.044	0.139
EP^{ind}	0.086	0.258	0.496	0.160
Panel B	**Impulse** IND	CSE	EP^{h}	CAP
Response				
IND	0.594	0.156	0.009	0.241
CSE	0.040	0.869	0.055	0.036
EP^{h}	0.055	0.166	0.772	0.008
Panel C	**Impulse** IND	EP^{ind}	EP^{h}	CAP
Response				
IND	0.638	0.133	0.079	0.149
EP^{ind}	0.021	0.902	0.054	0.022
EP^{h}	0.058	0.245	0.696	0.001

Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD). Panel A is composed of the vector [IND, CSE, EP^{ind},CAP]. Panel B is composed of the vector [IND, CSE, EP^{h}, CAP]. Panel C is composed of the vector [IND, EP^{ind}, EP^{h}, CAP]

Table B.24: Variance Decomposition - Benchmark extension: including trade openness

	Impulse IND	CSE	CAP	EMP	TRO
Response					
IND	0.648	0.187	0.143	0.007	0.015
CSE	0.036	0.903	0.043	0.013	0.004
CAP	0.101	0.114	0.748	0.004	0.034
EMP	0.140	0.090	0.183	0.545	0.042
TRO	0.038	0.089	0.111	0.043	0.719

Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD).

Table B.25: Variance Decomposition - Benchmark extension (including trade openness and excluding employment)

	Impulse IND	CSE	CAP	TRO
Response				
17 OECD				
IND	0.665	0.105	0.227	0.002
CSE	0.034	0.889	0.064	0.013
CAP	0.135	0.095	0.768	0.002
TRO	0.036	0.056	0.056	0.852

Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD). Model: IND CSE CAP TRO

Table B.26: Variance Decomposition - Supplementary

	Impulse			
	IND^e	CSE	CAP	EMP
Response				
17 OECD				
IND^e	0.453	0.323	0.195	0.029
CSE	0.193	0.642	0.109	0.056

	Impulse		
	IND	EP^{ind}	CAP
Response			
17 OECD			
IND	0.817	0.121	0.062
EP^{ind}	0.032	0.967	0.003

Notes: Variation in the row variable (10 periods ahead) explained by column variable. Main sample used (17 OECD).