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Determinants of Sectoral Energy Efficiency in New EU Member States: Energy Prices, Energy Price Uncertainty, and Regulatory Quality

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Abstract:
Improving energy efficiency is a cornerstone of the EU Fit-for-55, competitiveness, and energy-security strategy, yet performance across the new member states remains uneven despite price convergence and common regulatory frameworks. This study examines how energy prices, energy price uncertainty, and regulatory quality jointly shape sectoral energy efficiency in transition economies. We estimate a Shephard energy distance frontier model for seven new EU member states across ten industrial sectors over 1995–2015, modelling energy inefficiency directly as a function of these determinants and discrete reform episodes. Methodologically, we employ a consistent true fixed effects stochastic frontier estimated via the pairwise-difference estimator of Belotti and Ilardi (2018), which resolves the incidental parameters problem and disentangles inefficiency from unobserved heterogeneity. To our knowledge, this is the first joint one-step frontier estimation of price, price uncertainty, and governance as direct drivers of inefficiency, closing a gap between energy-pricing theory and applied frontier econometrics. Average efficiency is relatively high, with scope for roughly 21% energy savings from eliminating existing inefficiencies. Higher real energy prices significantly reduce inefficiency, confirming the price-discipline hypothesis. Energy price uncertainty robustly raises inefficiency, with a markedly stronger effect during the pre-accession adjustment phase and a weaker effect in high energy-intensive sectors. Regulatory quality is, counterintuitively, associated with higher transient inefficiency, plausibly reflecting

adjustment costs. Results are robust to a balanced sub-sample and to Brent-based prices extending coverage to 2022 and eight countries. The findings imply that stabilising and credibly anchoring price signals matter more than raising average prices alone.

JEL: C23, O52, Q41, Q43, Q48
Keywords: Energy prices, energy price uncertainty, stochastic energy distance frontier, regulatory governance, energy efficiency.

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1. Introduction

Improving energy efficiency (EE) has become one of the most central pillars of contemporary climate mitigation, industrial competitiveness, and energy security strategies. Unlike supply-side decarbonization technologies, which often require large-scale infrastructure investment, EE delivers immediate economic and environmental benefits by reducing the energy required to generate a given level of output (Hausmann, 2023; UN, 2025). For this reason, international institutions like the International Energy Agency, the European Commission, and the World Bank have often referred to EE as the "first fuel" of the clean energy transition. Within the European Union, EE now anchors flagship policies ranging from the European Green Deal to the "Fit for 55" regulatory package. Yet, EE in the new EU member states remains uneven despite substantial convergence in energy prices and the adoption of common EU regulatory frameworks. Price uncertainties persist due to volatile market adjustments and interact with heterogeneous governance quality to shape firms' incentives to conserve energy and invest in EE (Yoon & Ratti, 2011; IEA, 2025). These countries underwent one of the most dramatic institutional and economic transformations of the modern era, transitioning from centrally planned systems toward gradually liberalized market economies (Urge-Vorsatz et al., 2006). Although subsequent energy market reforms, industrial restructuring, and EU accession induced substantial efficiency gains, persistent gaps relative to Western Europe remain, especially in energy-intensive manufacturing sectors (Mussini, 2020).

Among the factors shaping EE performance in new EU member states, energy prices play a central role. Standard microeconomic theory predicts that higher energy prices incentivise conservation, accelerate the turnover of inefficient capital, and induce energy-saving technological change. Empirical research across developed and developing economies consistently confirms that a higher energy price reduces energy demand, and stimulates efficiency improvements (Steinbuks & Neuhoff, 2014; Ajayi & Reiner, 2020; Ščasný et al., 2026). In the early phase of post-transition, the dismantling of socialist-era energy subsidies and the gradual introduction of cost-reflective tariffs produced some of the sharpest real energy price adjustments observed globally (World Bank, 2013).

However, prices alone rarely operate as a frictionless incentive signal. While energy markets in these countries have largely converged toward EU-level liberalized pricing, the recent European energy crisis spanning 2021 through 2023 showed that *market-based* does not mean *stable*. During the European energy crisis that peaked in 2022, energy prices, especially natural gas and electricity, rose sharply due mostly to post-pandemic demand recoveries, tight global LNG markets, and reduced Russian gas deliveries to Europe (IEA, 2025). While global natural gas markets have been rebalancing since the shock waves and market tensions have been easing, gas price volatility has remained persistently elevated, staying well above historical norms in both

European and Asian markets (Hudak et al., 2026; IAE, 2025). This matters for EE because most energy improvements require upfront investment in capital equipment, processes, or technologies, and therefore depend on expectations about future energy costs (Yoon & Ratti, 2011; Alberini et al., 2023). Studies such as Khuong et al. (2004) show that when energy prices are volatile or seen as politically reversible, firms may delay or reduce these largely irreversible investments even if current prices are high, which then weakens the long-term efficiency response that simple price-incentive arguments would predict.

Energy price uncertainty is more than just a cost shock problem. It is also a beliefs and incentives problem. Higher price uncertainty has been shown to make firms more guarded by reducing the elasticity of investment growth of sales (Yoon & Ratti, 2011). This is established in real options theory, which postulates that uncertainty increases the value of waiting when investments are partially irreversible (Dixit & Pindyck, 1994; Carruth et al., 2000). As a result, firms become more cautious and shift adjustment toward short-term operational responses rather than long-term capital growth. Recent European evidence aligns closely with this mechanism: firm-level research by Kalantzis et al. (2025), using data from the European Investment Bank Investment Survey, finds that while higher energy prices can trigger investment in EE and climate action, price uncertainty discourages firms from climate investment, making them give priority to short-term climate action over long-term investment. For new EU member states, this has clear policy implications. If price volatility and price uncertainty weaken firms' efficiency responses, then relying on temporary price spikes to push efficiency improvements is unreliable. Instead, policies that provide stable and predictable conditions, by reducing exposure to volatile fuels and limiting the risk of sudden policy reversals, are more likely to support sustained improvements in EE (Yoon & Ratti, 2011; Kalantziz et al., 2025).

At the same time, institutional and governance quality condition the effectiveness of price signals and policy instruments. The post-transition experience of new EU member states suggests that even under broadly similar energy price trends and EU market rules, countries have shown remarkably different behavioural responses in energy use and efficiency improvements. While CEE countries are often portrayed as a relatively homogenous group in their stance toward ambitious EU climate objectives, evidence (e.g., Heilmann et al., 2020) highlights substantial heterogeneity in their progress toward energy and climate transition goals, with some countries advancing more rapidly than others. Comparative studies attribute these heterogeneities to variations in factors such as regulatory quality, enforcement and market competition conditions (Cubbin & Stern, 2004; Buzarovski et al., 2016; Nosko & Misik, 2016; Heilmann et al., 2020; Kopečná et al., 2026; Ščasný et al., 2026). Where regulatory quality is high, independent regulators enforce tariff discipline, competition restrains rent-seeking, and procurement rules foster technological diffusion. Weak governance, on the other hand, dilutes the incentives of market reforms. Theoretical and empirical work increasingly recognizes that institutions operate

as multipliers of EE policies (Nosko & Misik, 2016; Heilmann et al., 2020), yet the direct incorporation of governance indicators into frontier-based efficiency analysis is limited.

Despite the importance of energy prices, price uncertainty, and governance to the analysis of EE, the empirical literature remains limited along three major dimensions. First, a large of share of applied studies, including those focusing on new EU states and other transition economies, continues to rely on energy intensity indicators like energy use per unit of output or gross value added, as proxies for EE (e.g., Miskinis et al., 2006; Apostu et al., 2022). While convenient, such proxies do not distinguish whether energy intensity declines arise from technological improvements, factor substitution, or demand shifts. Previous studies, such as Filippini & Hunt (2011), show that energy intensity measures are not good proxies for EE. Second, even within the rapidly expanding frontier-based efficiency literature using stochastic frontier analysis (SFA), most studies either treat prices as a shift variable in the frontier itself or exclude them altogether. Moreover, very few studies explicitly model how prices and price uncertainty affect inefficiency directly (e.g., Lin & Long, 2015 for the case of China's chemical industry), despite that inefficiency is precisely the object policymakers seek to influence through pricing reform. Third, systematic sector-level frontier studies for post-transition countries remain remarkably scarce, particularly those modelling the joint effects of energy pricing and governance quality. Most existing work either focuses on single countries, highly aggregated national data, or short time windows that cannot capture the full dynamics of reform and EU accession.

This study directly addresses these limitations by developing a sector-level stochastic energy distance frontier model for seven new EU member states spanning 1995-2015, explicitly modelling energy inefficiency as a function of energy prices, energy price volatility, the quality of regulatory governance and some discrete and policy reform effects. Robustness checks using an alternative energy price measure allow sample extension up to 2022 and include two additional countries. Methodologically, we adopt a consistent true fixed effects SFA estimated using the pairwise difference estimator following Belotti & Ilardi (2018), which ensures consistent inference in short and moderate panels and resolves the incidental parameters problem in fixed effects SFA. This empirical strategy allows us to isolate the three channels through which policy shapes EE: (i) price incentives (ii) price uncertainty/volatility and (iii) institutional moderation via regulatory quality. In meeting these objectives, this study makes several central contributions. First, it provides one of the few multi-country, sector-level SFA studies of EE in new EU member states, grounded explicitly in production theory, rather than intensity accounting. Second, it delivers to our knowledge, the first joint one-step frontier estimation of price, price uncertainty, and governance as direct determinants of inefficiency, thereby closing a major gap between energy-pricing theory and applied frontier econometrics. Third, it employs modern consistent true fixed estimation into the EE literature, focusing on the new EU states, enabling credible policy inference in the presence of unobserved heterogeneity inherited from the centrally-

planned socialist era. Lastly, from a policy perspective, the results are directly relevant to ongoing EU-level debates about the inadequacy of energy price signals alone in incentivizing EE improvements.

The rest of the study is organized as follows: the next section, Section 2 reviews the related literature on energy efficiency and its drivers. Section 3 provides discussion of the model, data and methods. Section 4 presents and discusses the study's findings, while section 5 concludes and provides policy recommendations.

2. Review of related literature

2.1 Energy efficiency proxies versus frontier-based approaches

At the economy-wide level, two broad approaches to measuring EE are prevalent in literature. The first approach uses aggregate proxies like energy use per unit of GDP or industrial output commonly called energy intensity (e.g., Antonietti & Fontini, 2019; Ajayi & Reiner, 2020; Matthess et al., 2023). The second approach applies frontier methods from production economics to derive EE scores, most commonly using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Instead of relying on ad hoc energy intensity measures, DEA as well as SFA treat EE as a relative concept, defined by the distance between observed energy use and a best practice frontier, conditional on output and other inputs (e.g., Zhou et al., 2008; Coelli et al. 2005).

The DEA is a non-parametric linear programming method that constructs an empirical production frontier from data on decision-making units, which could be countries, firms, households, or sectors. In EE applications, DEA can be used to calculate total-factor EE scores (e.g., Wang & Zhang, 2013). A limitation of the DEA is its sensitivity to data noise and outliers. Since it attributes all deviations from the frontier to inefficiency, differences in data quality or random shocks are not accounted for. Additionally, DEA provides no statistical inferences on the estimates.

SFA on the other hand is a parametric approach that estimates a frontier and a two-part error term: one part representing inefficiency and the other part, statistical noise (Aigner et al., 1977). It has been widely used to measure EE at various levels. One strand of literature, following Filippini & Hunt's work, estimates an energy demand frontier, which includes energy prices, output, climate and demographic conditions, economic structure and technological change (e.g., Filippini & Hunt, 2011; Lundgren et al., 2016; Alatas et al., 2024). The frontier represents the minimum energy needed for a given level of output and other conditions. Filippini & Hunt (2011) applied this to OECD countries, coining the term *underlying energy efficiency* for the efficiency measure derived from this procedure. Their results show that raw energy intensity is a poor proxy for true EE. Subsequent studies have used similar SFA models for various samples; Filippini & Hunt (2015) for the United States, Filippini et al. (2014) for the EU countries, Otsuka (2023) for

Japanese regions, and others, consistently finding that this approach influences EE rankings and indicates significant "efficiency gaps" even in the advanced economies. An advantage of the SFA energy demand approach is that it captures both technical and allocative efficiency (Filippini & Hunt, 2015). Because price is included in the energy demand function, the resulting EE scores reflect excess usage of energy beyond cost-minimization. The downside is the need to specify a functional form (often a long-linear or translog demand function) and distribution of inefficiency, as results can be sensitive to these choices.

Another SFA approach is to embed energy in a distance function. Here, one can use an input distance function focusing on energy. Zhou et al. (2012) propose an approach for measuring EE using the Shephard Energy Distance Function (SEDF), which measures the maximum proportional reduction in energy input feasible for a given level of output and other inputs. As discussed in Filippini & Hunt (2015), this formulation is theoretically equivalent to the input requirement function proposed by Boyd (2008). This modelling approach has been employed in several studies to capture technical efficiency (e.g., Hsiao et al., 2018; Okwoche et al., 2025). The advantage is consistency with production theory and the ability to include multiple outputs. A limitation of the SEDF is that it captures only technical EE, leaving out allocative efficiency, since observed energy use is not evaluated relative to cost-minimizing input choices.

2.2 Determinants of energy efficiency

Understanding what drives energy efficiency has attracted extensive research globally. Here, we review three key factors in line with our research objectives: energy prices, energy price uncertainties (subsidies/taxes) and regulatory quality. We employ a broad approach to the analysis of previous studies, with an eye to their relevance to new EU states. Beginning with price as a disincentive for inefficiency, economic theory and empirical evidence conceptualize price as a fundamental determinant of energy use and EE (e.g., Antonietti & Fontini, 2019; Csereklyei, 2020; Eshun et al., 2025). Higher energy prices (e.g., due to market forces or taxation) create pressure on firms and consumers to conserve energy or invest in energy-saving technology, thereby improving EE over time. In cross-country panels, a short price elasticity of energy demand is around -0.3, while the long-run counterpart is -0.4 (Ščasný et al., 2026). Standard econometric models of energy demand or intensity, therefore, routinely include energy price (or its inverse, energy cost share) as a regressor. In industrial contexts, if fuel or electricity becomes more expensive, firms may retrofit equipment, adopt more EE processes, or shift to less energy-intensive input mixes to save costs. Over time, industries with persistently high energy prices tend to have lower energy intensities (Newell et al., 1999). Broad international evidence supports this: countries with historically higher energy taxes (such as in Western Europe) often achieved faster improvements in energy productivity than those with cheap energy (Sorell et al., 2009).

In stochastic energy demand frontier models, energy use is specified as an input-demand function that includes the real energy prices alongside output and other determinants, in line with standard demand theory (Filippini & Hunt, 2011; Lundgren et al., 2016; Alatas et al., 2024). The estimated price elasticities are expected to be negative, so that higher prices lower the conditional frontier level of energy demand, on average, other factors held constant.

Recent work emphasizes that the relevant price signal is not only the level of energy prices but also their stability and predictability (Kalantzis et al., 2025; Alberini et al., 2023). For EE investments, which are often capital embodied and partially irreversible, uncertainty about future energy prices can reduce incentives to invest even when current prices are high. Real options theory provides a mechanism: when investment cannot be easily reversed, greater uncertainty raises the value of waiting, leading firms to postpone or scale down investment and rely more on short-term operational adjustments (Dixit & Pindyck, 1994). Empirical studies such as Yoon & Ratti (2011) confirm that energy price uncertainty weakens investment responses and is especially relevant for energyintensive activities. Contemporary European evidence from Kalantzis et al. (2025) reinforces this view, showing that energy price uncertainty significantly discourages longer-horizon climate and energy-efficiency investments, even when energy costs rise.

This distinction between price levels and price uncertainty is particularly relevant for the new EU member states. While EU market liberalization has largely reduced persistent, administratively set industrial price distortions, the post-2021 environment featured sharp energy price volatility and repeated policy interventions that altered effective energy costs. The IEA notes that even after the 2022 supply shock began to ease, gas price volatility remained well above historical norms (IEA, 2025). EU reporting similarly documents the scale of the crisis shock and the diversity of national policy responses affecting end-user prices and incentives (European Commission, 2025). Given the variations in institutional capacity and exposure to external shocks, this suggests that the efficiency implications of prices may operate less through sustained high price discipline and more through the credibility and predictability of the price environment. This highlights the need to explicitly separate price level effects from price uncertainty effects, while allowing governance to condition these effects.

Apart from price effects, the institutional and regulatory environment in which energy is produced and consumed has a significant influence on efficiency outcomes. High-quality regulation can promote competition, encourage best practices, and reduce inefficiency, whereas poor governance can allow waste inertia (Apergis & Garcia, 2019; Akorli & Adom, 2023; Abdelkawy & Alzuwaidi, 2025). The literature on this topic often intersects with studies on market liberalization and economic reforms. In the context of transition economies, research by Nepal et al. (2014) is particularly notable. Using a panel of transition countries, they found that market-

oriented reforms (including liberalization of energy markets, privatization, and improved financial sector governance) have significantly driven EE improvements. Their econometric analysis shows that countries which scored higher on indices of market liberalization and institutional reforms saw greater reductions in energy intensity over the period 1990-2010. Similarly, in Central Europe and the Baltics, where regulatory quality frameworks (e.g., independent energy regulators, competition laws) advanced rapidly under EU accession, EE gains were stronger compared to the former Soviet republics, where reforms lagged (Urge-Vorsatz et al., 2006).

Several mechanisms explain this link. One is competition and liberalization. When energy supply industries (electricity, gas) are liberalized and monopolies broken, producers have incentives to reduce costs, including improving thermal efficiency of power plants and reducing network losses. Empirical studies on electricity market reform, such as Jamasb et al. (2005), document efficiency gains in generation after liberalization in the UK and Eastern Europe. Likewise, allowing energy service companies and competitive energy supply can spur industrial users to adopt efficiency measures. Another factor is that of regulatory enforcement. Strong regulators can enforce building codes, appliance standards, and industrial efficiency regulations. For example, OECD countries with stringent efficiency standards and well-resourced enforcement agencies often report better improvements in sectors like buildings and automobiles (Geller et al., 2006).

3. Model, methods, and data

3.1 Shephard energy distance frontier

SFA provides the economic framework necessary to separate inefficiency from random shocks and measurement error. It also provides the ability to incorporate an explicit inefficiency effects model linking inefficiency to policy, institutional and price-related determinants. Debreu (1951) and Farell (1957) introduced output- and input-measures of technical efficiency, jointly known as Debreu-Farell efficiency (Kumbhakar, 2000), which Lovell et al. (1994) show to be reciprocal to the input and output distance functions proposed by Shephard (1970). Following Shephard's input-oriented efficiency concept, Zhou et al. (2012) proposed the sub-vector input distance function for energy known as the Shephard energy distance function (SEDF). This study measures EE following Zhou et a. (2012). The key idea is to evaluate the extent to which observed energy use exceeds the minimum feasible level required to produce a given level of output, conditional on non-energy inputs. Energy inefficiency is therefore interpreted as excess energy use, rather than as inefficiency in the use of all production inputs.

It presents a neo-classical production framework where country-sector unit i employs capital K, labour L, and energy E to produce a single output Y at time t, with T denoting the feasible production technology as follows:

$$T = \{(K_{it}, L_{it}, E_{it}, Y_{it}) : (K_{it}, L_{it}, E_{it} \text{ can produce } Y_{it}\} \quad (1)$$

The SEDF is then defined as

$$D_E(K_{it}, L_{it}, Y_{it}, E_{it}) = \sup\{\alpha: (K_{it}, L_{it}, \frac{E_{it}}{\alpha}, Y_{it}) \in T\}\,, \quad (2)$$

Equation (2) defines how much a unit can proportionally shrink energy use and remain feasible in the technology set T, holding K, L and Y fixed. The scalar α is a feasible shrinkage factor, while D_E gives the maximum feasible shrinkage factor. The implication of $eq.2$ is that $D_E \geq 1$, with equality ($D_E = 1$) specifying location on the efficiency frontier, meaning that no further shrinkage of energy is possible. Values greater than one, therefore, indicate energy inefficiency, meaning that energy input can be proportionally reduced while maintaining the same level of output. The corresponding frontier energy input (i.e., the minimum required energy use given K, L, and Y), is given as:

$$E^* = \frac{E}{D_E(K_{it}, L_{it}, E_{it}, Y_{it})} \quad (3)$$

The energy efficiency index (EEI) is then defined as the ratio of frontier energy input E^* to observed energy input E:

$$EEI = \frac{E^*}{E} = \frac{E/D_E}{E} = \frac{1}{D_E} = \frac{1}{D_E(K_{it}, L_{it}, E_{it}, Y_{it})} \quad (4)$$

where EEI lies between 0 and 1, with higher values indicating greater energy efficiency.

A defining property of the SEDF of linear homogeneity in energy input implies that:

$$D_E(K_{it}, L_{it}, Y_{it}, E_{it}) = E_{it} D_E(K_{it}, L_{it}, 1, Y_{it}) \quad (5)$$

Taking logarithms and rearranging *eq. 5* yields an estimable stochastic frontier econometric representation as follows:

$$-e_{it} = f(k_{it}, l_{it}, y_{it}) + v_{it} - u_{it} \quad (6)$$

where lower cases of variables indicate logarithmic transformation; v_{it} is a two-sided statistical noise, and $u_{it} \geq 0$ captures energy inefficiency, following an exponential-normal distribution. Capital and labour are treated as fully efficient inputs, while inefficiency is attributed solely to energy use.

It is important to resolve four functional-form choices for $eq\ (6)$: how to present the underlying technology (translog or Cobb-Douglas), how to specify the stochastic frontier (cost or production frontier), whether to model technological change (using time trend), and how to account for unobserved heterogeneity (fixed or random effects). First, likelihood ratio tests strongly reject Cobb-Douglas restrictions in favour of a translog functional form. Tables 3-9 report these tests for each specification estimated. Regarding the choice between cost- *versus* production-type

SEDF, we follow Schmidt and Lin (1984), who demonstrate that residual skewness from OLS estimation indicates frontier orientation. The result of the procedure, reported in Table A3 in Appendix, points to a cost-type SEDF. Third, likelihood-ratio tests strongly reject the restricted model without time controls in favour of an extended specification with time controls (see Table A4 in Appendix), indicating the presence of statistically significant technological change in energy use over the sample period.

Fourth, traditional pooled SFA models impose a common intercept across all units. This assumption conflates unobserved heterogeneity with inefficiency, resulting in biased estimates of inefficiency. In macro-sectoral applications, where persistent characteristics such as industrial composition and technological capacity differ systematically across units, ignoring such heterogeneity is untenable. Greene's (2005) true fixed effects (TFE) and true random effects models address this issue by explicitly disentangling time-invariant heterogeneity from inefficiency. However, the TFE model suffers from the incidental parameters problem. The true random effects model avoids this bias but relies on strong assumptions regarding the independence between heterogeneity and regressors, a condition commonly violated in practice. In our case, Hausman tests support the use of fixed effects (Appendix Table A2). To address the limitation of standard true fixed effects, we employ the consistent true fixed effects (CTFE) method using the pairwise difference estimator proposed by Belotti & Illardi (2018). This approach transforms the pairwise differences across time for each unit, where the difference removes time-invariant heterogeneity without introducing additional nuisance parameters. Crucially, this estimator avoids the incidental parameters problem because it does not require estimating individual effects. It is consistent under standard regularity conditions, even for relatively long panels of moderate cross-sectional size typical in macro-sectoral studies. The estimator is suited to our aim to estimate energy inefficiency and examine its drivers in a one-step estimation design.

While Zhou et al. (2012) implement a Cobb-Douglas specification for parsimony, they show in Appendix A that the same framework naturally extends to a translog approximation of the SEDF. Consistent with their emphasis on parsimony and on modelling energy inefficiency rather than the full curvature of the production technology, no squared terms in inputs or output are introduced. Moreover, given statistical support for modelling exogenous technological change (see Table A4 in Appendix), we extend the model to include a deterministic time trend. Furthermore, we allow biased technical change (i.e., input/output augmenting). Specifically, this implies that the time trend is interacted with inputs and output, allowing the rate of technological progress to vary across sectors. With these extensions, we specify the SEDF with lower-case letters denoting variables in logs, as follows:

$$-e_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_y y_{it} + \beta_t t + \beta_{kl}(k_{it} \times l_{it}) + \beta_{ky}(k_{it} \times y_{it}) + \beta_{ly}(l_{it} \times y_{it}) + \beta_{kt}(k_{it} \times t) + \beta_{lt}(l_{it} \times t) + \beta_{yt}(y_{it} \times t) + v_{it} - u_{it} \quad (7)$$

To explain systematic variation in energy inefficiency u_{it} across country-sector units and over time, the inefficiency term is modelled as:

$$u_{it} = Z_{it}\delta + \varepsilon_{it} \quad (8)$$

where Z_{it} includes energy prices following Lin & Long (2015), who examine China's chemical industry, as well as price uncertainty (e.g., Deng & Hao, 2024; Iheonu et al., 2025), regulatory quality, and policy-related time dummies capturing major institutional changes. Specifically, a 2004 dummy accounts for EU accession for most countries in the sample, while the 2007 dummy captures Romania's accession. The 2008-2009 dummies account for the peak years of the global financial crisis.

3.2 Data

Using sectoral national accounts and industry energy balances, we construct an unbalanced panel dataset for seven new EU member states (Czechia, Hungary, Lithuania, Poland, Romania, Slovakia, and Slovenia) spanning 1995-2015.

Due to limited sectoral coverage of official capital stocks for some countries, we construct capital stocks series using the perpetual inventory method (PIM) based on data for real gross fixed capital formation. The PIM constructs capital stocks recursively as

$$K_{it} = (1 - \delta)K_{it-1} + I_{it} \quad (9)$$

where I_{it} denotes real sectoral investment and δ is the depreciation rate assumed to be 7% following Dombi (2013). A single $\delta = 7\%$ for aggregate capital in new EU states over 1995-2015 is well supported by the literature. Asset-level evidence implies δ well above the conventional 5% rule: international datasets like EUKLEMS, and Penn World Table use rates ranging from ≈2 to 3% for structures to 25-30% for ICT, yielding economy-wide averages above 6% even in advanced economies (Inklaar & Timmer, 2013; Feenstra et al., 2015). For new EU states, δ is likely higher due to rapid obsolescence and scrappage during transition (Pula, 2003; Dombi, 2013), reinforced by the post-accession shift toward short-lived ICT and intangible assets (Berlemann & Jam-Eerik, 2014).

Research emphasised that CEE capital stocks are unusually sensitive to the choice of initial capital K_0 because reliable pre-transition investment data are limited and the transformation period involved a one-off disruption to the inherited stock (Dombi, 2013). Choosing K_0 is thus a first-order issue for CEE panels starting in the mid-1990s. We adopt the approach of Young (1995), known as the Quasi-Herberger approach, to initialise K_{1995}. The approach assumes that real

investment grows at an approximately constant rate g_I and yields a closed-form initial stock expression based only on observable real investment and δ.

In addition to capital input, measured by capital stocks in billions of 2015 euros, labour input is total employment, defined as the number of persons employed in millions, while output is measured using gross value added in billions of 2015 euros. Table 1 provides summary statistics of variables along with definitions and sources of data.

Turning to the variables in the inefficiency determinants equation, real energy prices are measured using the fixed-weight energy price index (FEPI) developed by Sato et al. (2019), which provides internationally comparable industrial energy prices by country, sector, and year. FEPI is constructed as the log of the weighted geometric mean of fuel-specific prices, where fuel weights are fixed over time using pre-sample sectoral fuel composition shares, thereby isolating variation in underlying fuel prices. The fixed-weight design mitigates simultaneity between energy prices and energy use, which makes the FEPI suitable for reduced-form estimation in panel settings and robust to endogeneity arising from firms' technological responses. Because prices enter in logs prior to aggregation, time-invariant fuel-specific measurement errors are absorbed by country-sector fixed effects, ensuring consistency in multi-country sectoral analyses. FEPI series are expressed in constant (2010) prices.

Energy price uncertainty is measured using daily international crude oil prices following the approach of Deng and Hao (2024). Daily data on West Texas intermediate (WTI) spot price are obtained from the U.S. Energy Information Administration and converted to daily log returns. Two alternative indicators of energy price uncertainty are constructed. First, uncertainty is proxied by the standard deviation of daily oil price returns within each year, capturing short-term price volatility. Second, we estimate a GARCH (1, 1) model with an autoregressive mean specification for daily returns and use the conditional variance as a measure of time-varying oil price volatility. The GARCH-based uncertainty index is obtained by averaging the daily conditional variance over each period. Since daily oil prices contain missing observations due to weekends and market holidays, returns are computed using available observations, and days with undefined returns are excluded.

Regulatory quality summarises perceptions of government's capacity to formulate and implement sound regulations that promote private sector development. It is a world governance indicator constructed from multiple surveys and expert-based data sources (Kaufmann et al., 2011) normalised to a continuous scale ranging from approximately -2.5 (weak governance) to +2.5 (strong governance). A higher score reflects more effective regulatory environments that can enhance EE through improved enforcement, reduced uncertainty, and more credible investment incentives.

3.3 Model extensions: balanced panel and Brent crude oil prices

The unbalanced structure of the data is caused mainly by the presence of gaps in sectoral series for capital stocks that cannot be reconciled without either imputing missing observations or aggregating data across sectors. Both approaches would materially alter the object of estimation. Imputation risks introducing unobserved measurement error correlated with sectoral structure, while aggregation implicitly imposes a common aggregate technology that conflates heterogeneous sectoral production processes and can bias substitution and efficiency estimates. To address this trade-off between coverage and internal consistency, the empirical strategy distinguishes between a baseline estimation using unbalanced data and a robustness check using a balanced sample. The balanced-sample estimations are conducted on a restricted sample comprising Czechia, Hungary, Romania, and Slovakia, for which data for capital are consistently available for all sectors over the full sample period.

To address concerns regarding the temporal coverage of energy prices, the robustness of our findings to alternative price proxies, and sample representativeness, we extend the analysis by replacing sectoral FEPI prices with the Brent crude oil price. This allows extending the sample period from 2015 to 2022, covering both EU accession and market integration as well as the recent European energy crisis. Importantly, this also allows the inclusion of Latvia, which was excluded from the baseline analysis due to limited data for energy prices. As a result, the extended specification improves both the temporal depth and cross-country coverage of the sample.

4. Results and discussion

4.1 Energy efficiency scores

Beginning with the estimates of energy efficiency performance (Table 2A-2B), we find that overall, the estimated EE scores indicate relatively high average performance. It is encouraging to see that measured EE scores are roughly similar across the unbalanced and balanced samples, indicating robustness of findings across these samples (compare rows 1 and 2 of Table 2A). On average, we find that efficiency improvements of up to 21% are possible if new EU states eliminate existing inefficiencies. Furthermore, the results show that average measured EE is higher during the pre-accession period (0.82) relative to the post-accession period (0.78), due perhaps to strong reform pressure and investment incentives created by preparation for EU accession (row 3 Table 2A). This pressure may have weakened slightly after accession, which filters through to a slightly lower EE score during this latter period (row 3 Table 2A). Energy intensive sectors also presented higher shares in the CEE transition economies. Indeed, at the sectoral level, we find that more energy- and capital-intensive industries such as wood and wood

products (0.84) and iron and steel (0.83) show higher average EE, while construction (0.76) and textile and leather (0.77) seem to lag and display greater dispersion, perhaps reflecting more heterogeneous technologies and practices (see Table 2B).

[Table 2A-2B]

4.2 Determinants of energy inefficiency

The CTFE estimations (Tables 3-9) provide the following five key conclusions. First, energy prices are associated with significant improvements in EE. Second, price uncertainty robustly undermines EE. Third, the uncertainty effect is stronger in the pre-accession phase compared to post-accession, and it is weaker in high energy-intensive sectors relative to low energy-intensive sectors. Fourth, regulatory quality conditions these effects, albeit going against expectations. Lastly, year dummies corresponding to EU accession and the global financial crisis appear important in reducing EE in the model.

Before turning to the detailed analysis of these findings, it is useful to briefly summarise the frontier results. Across Tables 3-7, the estimated frontier parameters are remarkably stable in sign, magnitude and significance, despite changes in sample composition, time coverage and inefficiency specifications. This supports the interpretation that differences in results across specifications are driven by inefficiency determinants, rather than instability in the estimated frontier model.

Labour input consistently presents a negative and significant coefficient in most specifications, implying that increases in labour input are associated with lower values of -lnE, i.e., higher minimum feasible energy requirements, conditional on output and capital. This applies to the output, although the results are not robust to variations in sample composition and other specifications (Tables 4-9).

Capital typically presents a small and generally insignificant effect in its linear form, though its interactions with output and time trend are consistently significant. The positive capital-output interaction highlights improved energy efficiency at higher production scales, while the negative capital-time interaction suggests that technological change reduces the energy-saving role of capital over time, possibly showing the diminishing efficiency gains from additional capital accumulation as economies mature.

Lastly, the time trend presents a positive and significant estimate value, consistent with energy-saving technological change. That is, apart from factor substitution, efficiency gains over time are driven by exogenous improvements in production technology.

Turning to the core of our analysis, while Table 3 presents several different estimations, varying according to how the inefficiency term is modelled, we consider column [4] as our benchmark specification for three reasons. First, it provides a more comprehensive specification of economic mechanisms. It jointly captures the effects of energy prices, price uncertainty, regulatory governance, and policy and crisis dummies, according to the framework laid out in section 3. Second, it has the strongest policy relevance. That is, since policymakers in new EU states do not face isolated pricing and governance quality, a specification that conditions on all of them provides the most informative marginal effects. Lastly, econometrically, this model performs well: coefficients are precisely estimated, signs are stable relative to the nested specifications, and the criterion function improves relative to the simpler models. Given these reasons, the results reported in Table 3, col. [1]–[3] and in tables 4-9 are used for robustness and comparison. It is important to note that while the two measures of price uncertainty produce similar and stable estimates, the baseline specification (col. [4]) employs the simpler return-based standard deviation.

[Table 3]

Beginning with the price effect, energy prices present a consistently negative coefficient estimate across specifications, suggesting that higher prices are associated with improved EE. In the preferred specification (col [4]), the coefficient of -0.45 suggests a sizeable efficiency-enhancing response to price signals. When the sample is restricted to a balanced panel of 4 countries, the Czech Republic, Hungary, Romania, and Slovakia (Table 4), the effect remains economically meaningful and statistically significant at the 10% level, with a coefficient of -0.35 in the preferred specification (col 4). Focusing on the pre-accession period (1995-2003) yields a larger estimate of around 0.55 (Table 5), suggesting stronger price responsiveness when markets were adjusting, and efficiency gains were less exhausted, although the estimates are only weakly significant. In Table 6, which focuses on the post-accession period (2004-2015), the results return to baseline magnitudes (-0.43) in the preferred specification, col (3), again with weak statistical significance. This affirms that the stronger pre-accession response was influenced by the adjustment process.

Given that inefficiency measures excess energy use relative to the best practice frontier, this result is fully consistent with standard microeconomic theory: higher prices strengthen incentives to economise on energy, retrofit equipment, and adopt energy-saving practices (Newell et al., 1999; Filippini & Hunt, 2011). The result aligns with Zhang (2013), who observed large declines in energy intensity in Eastern Europe and Central Asia during 1998-2008, attributing them mainly to energy price increases. Ščasný et al. (2026) also find that energy prices have a statistically significant effect in reducing energy demand in CEE economies, with a negative long-run energy price elasticity of 0.42. Unlike standard demand elasticities, we examine the effect of price on inefficiency rather than on energy use itself. Nonetheless, the size and significance of the

estimate (0.45 in our preferred specification) suggest that price reforms in transition economies improve EE, even if only gradually and unevenly (Cornillie & Fankhauser, 2004; Urge-Vorsatz et al., 2006).

Price uncertainty also presents a robust and economically meaningful effect across specifications and samples. Table 3 reports a positive estimate of 0.09 in the baseline (col [4]) with comparable estimates of 0.1 and 0.05 in the simpler estimations, see col. [2] and [3]. The larger effect of price uncertainty in the baseline model is associated with higher energy inefficiency, holding other factors constant. When the analysis is restricted to the balanced sample (Table 4), the magnitude and significance of the coefficients remain close to the baseline, ranging from 0.07 to 0.12. At the same time, the price uncertainty effect exhibits some important heterogeneities that need to be highlighted. First, it seems to vary with the stages of development: the pre-accession sub-sample presents a strongly significant and relatively more sizeable estimate of 0.29 in the preferred regression (Table 5, col 3), while the post-accession sample reports smaller estimates that are, albeit not significant in any of the regressions (Table 6). The comparison suggests that uncertainty played a stronger role during earlier stages of market adjustment, with its influence diminishing as economies became more integrated into EU markets. Second, the uncertainty effect appears to vary with the level of sector energy intensity; we discuss this further in section (4.3).

[Table 4]

[Table 5]

[Table 6]

Regulatory quality seems strongly associated with increased inefficiency, which, albeit appears counterintuitive and requires further examination, particularly as this finding remains consistent across specifications and sample compositions. Nevertheless, when contemplated in the context of accession and market building phases in CEE, it may point to the potential of high adjustment costs in worsening measured inefficiency, even if temporarily, especially in sectors characterised by legacy capital (Zhang, 2013). The results appear to be consistent with the true fixed effects approach employed here, which measures time-varying (transient) inefficiency rather than persistent (long-run) inefficiency (Kumbhakar et al., 2014).

Reform dummies also exhibit significant effects in the inefficiency equations of Table 3-5. The accession dummies 2004-2007 are negative and significant in both the baseline estimations displayed in Table 3 and continue to be significant in the sub-samples. This points to the presence of discrete reductions in inefficiency associated with EU accession. It may reflect institutional harmonisation, market opening, and accelerated capital upgrades around accession dates. Additionally, the coefficient for the 2008 dummy is consistently negative, which lines up with the

sharp reductions in energy use relative to output during the global financial crisis. While part of this may reflect cyclical contraction rather than genuine efficiency gains, controlling for output in the frontier suggests that crisis-induced restructuring also played a role. In contrast, the 2009 dummy often yields a positive and significant effect. The peak of the global financial crisis accords with sharp output contractions combined with slow input adjustment, which temporarily increased inefficiency through capacity underutilization.

4.3 Low versus high energy-intensive sectors

Earlier, we highlighted the presence of heterogeneous effects of price uncertainty, showing that they also vary by the level of sectoral energy intensity. Table 2C presents summary statistics for energy intensity measured as total final energy use (TJ) divided by gross value added (million euros). Five sectors exhibit average energy intensity well above 10 TJ per million euros – Chemicals and petrochemicals (50.35), iron and steel (20.95), machinery (24.09), non-metallic minerals (24.26), and wood, paper and paper products (17.43) – and are classified as high energy-intensive. The remaining sectors having average intensity below 10 – construction (1.10), food and tobacco (8.78), mining and quarrying (3.30), textile and leather (5.14), and transport equipment (5.11) – form the low energy-intensive group. Given the data limitation issues discussed earlier, we do not carry out separate estimations for each group. Instead, for each of the energy prices and uncertainty effects, we examine whether the marginal effect is statistically different between high- and low-intensive sectors. In a nutshell, we find that it is.

[Table 7]

Using the classification discussed above, we create a dummy variable that takes the value 1 if a sector is classified as high energy-intensive. We then interact this individually with price and price uncertainty and examine their effects in separate regressions, using both the baseline unbalanced sample and the restricted (balanced) sample. Table 7 reports the results. While energy prices themselves are not significant, the interaction between price and the high-energy-intensity dummy is negative and only weakly significant in the balanced sample regression (col [2]). This highlights limited sample-sensitive heterogeneity in the price channel. In contrast, price uncertainty is positive and strongly significant across samples (cols [3] and [4]), while its interaction with the high-intensity dummy is statistically negative. The ensuing conclusion is that price uncertainty consistently increases inefficiency, but this effect is weaker in high energy-intensive sectors. This result is not easily justifiable, given that energy is a binding input in this group. Energy intensive sectors, which are naturally heavy energy users, usually benefit from long-term contracts, avoiding huge energy price fluctuations as well as from a stronger bargaining power to get a better contract. Yet, while uncertainty raises inefficiency, improved adaptation to energy market risk and tighter operational discipline can attenuate the effect of uncertainty on inefficiency. Deng and Hao (2024) similarly find that environmental policy stringency (akin to

adaptation to market risk and tighter operational discipline) weakens the impact of energy price uncertainty in pollution-intensive industries.

4.4 Alternative energy price measure: Brent oil prices (1995-2022)

Here, we employ the real Brent oil price as an alternative measure of energy prices, while continuing to use the daily returns-based standard deviation of the international oil price as our measure of price uncertainty. Also, using oil price measures allows an extension of the sample beyond 2015, now spanning 1995-2022. Additionally, it allows the inclusion of an additional CEE country, namely Latvia, that was excluded from the baseline analysis due to data limitations. The analysis is carried out in three incremental steps. The results are displayed in Table 8. First, we re-estimate the baseline model using the alternative energy price measure while maintaining the original sample of seven countries over the period 1995-2015. This allows isolating the effect of the price proxy without altering the cross-sectional or temporal dimensions of the data (col. [1]–[2]). Second, we retain the same set of seven countries and expand the period to 1995-2022 to exploit the longer time coverage enabled by the Brent price series. This allows us to examine whether the estimated relationships are stable when incorporating more recent developments in energy markets and policy environments (cols [3]–[4]). Third and lastly, we extend the sample to 8 countries, with the inclusion of Latvia, while preserving the extended period 1995-2022 (cols [5]–[6]). It should be noted that in this robustness analysis, the price and uncertainty variables are related because both are based on oil prices. To avoid collinearity concerns, we do not include both variables in one regression as in our preferred baseline estimation in Table 3, col [4]. Rather, we include price and price uncertainty in separate regressions to allow for a clean interpretation of the respective channels through which oil price dynamics influence energy efficiency. Accordingly, the estimated price coefficients here should be compared to the baseline price effect in Table 3, col. [1], while the uncertainty coefficients are comparable to the baseline results shown in Table 3, col [2]–[3].

Beginning with the price effect, Table 8 shows a consistently negative and significant estimate across all specifications. Using the alternative price proxy while retaining the baseline sample period (1995-2015) yields an estimated coefficient of -0.428 (col. (1)), similar to the estimated reported in Table 3 (col. [1]). This affirms that the price effect is not sensitive to the choice of price measure. Extending the sample period to 1995-2022 leads to a slightly smaller, though still highly significant coefficient of -0.295 (col [3]). Further expanding the cross-section by an additional country leaves the estimate virtually unchanged at -0.299 (col [5]). This robustness of the price effect applies similarly to the price uncertainty effect. For the baseline sample and period, the estimated coefficient in column [2] is positive and significant at the 1% level (0.22), exceeding the magnitude (0.10) reported in the baseline (Table 3, col [2]). When the sample period is extended to 1995-2022, the coefficient declines slightly to 0.146 but remains strongly

significant. A similar estimate of 0.164 is obtained when an additional country is included while maintaining the extended time span. Lastly, regulatory quality remains strongly similar to the baseline until we extend the cross-section in columns [5] and [6], where the coefficient rises from around 0.5 to around 0.8. The combination of greater cross-country and time coverage seems to reinforce the importance of governance for energy efficiency.

[Table 8]

5. Conclusion and policy recommendations

This study examines the key factors shaping sectoral energy efficiency outcomes in new EU member states. Methodologically, it provides one of the first multi-country, sector-level applications of an SEDF model for new EU states, focusing on the effects of energy prices, energy price uncertainty, and governance on EE, while controlling for discrete reform episodes. Empirical analysis employs sector-level panel data for seven new EU countries over the period 1995-2015, with extensions to 2022 and an expanded sample of eight countries in the robustness analysis. A consistent true fixed effects approach, which allows disentangling inefficiency from random noise and heterogeneity, presents several robust findings. First, although heterogeneities exist, frontier analysis presents relatively high average efficiency performance, showing that efficiency improvements of up to 21% are possible if existing inefficiencies are eliminated. Energy efficiency score was a bit larger during the pre-accession period (1995-2004) compared to the period coming afterwards and low energy-intensive sectors in CEE region were performing slightly better (with the score at 76-77%) than their high energy-intensive counterparts (83-84%).

Second, from the inefficiency component of the model, we find first that real energy prices are associated with lower technical energy efficiency, in line with the price-discipline hypothesis emphasised in the theoretical and empirical literature. It aligns with frontier-based evidence from both the advanced and transition economies and reinforces the central role of energy prices in driving efficiency improvements.

Third, energy price uncertainty presents a robust and economically meaningful effect, being positively associated with energy inefficiency: industrial sectors in new EU member states facing unstable prices exhibit poorer EE performance, other factors held constant. Findings further show that this result varies with the stages of development and the levels of energy intensity. Price uncertainty appears to be more dominant in the pre-accession phase compared to the post-accession phase. We attribute this stronger response to market adjustment effects that diminished in influence as countries integrated more into the EU market system. Furthermore, while price uncertainty has an inefficiency-increasing effect across sector categories, this effect is weaker in high energy-intensive sectors.

Fourth, regulatory quality is consistently associated with increased inefficiency against expectation. While we believe that this finding requires further examination, it may reflect the transient increases in inefficiency associated with higher adjustment costs that coincide with more stringent regulatory governance.

Lastly, EU accession, measured using accession dummies for 2004 and 2007, and the financial crisis dummy for 2008, coincides with significant efficiency improvements, while the peak financial crisis year shows increased inefficiency, consistent with deeper contractions and capacity underutilization.

The policy lessons for new transition economies emerge from this study's findings. First, in line with other related studies we conclude that increases in energy prices are associated with improvements in energy use through the efficiency-increasing price effect even in the transition economies. From a policy perspective, it implies that market-based instruments like energy taxes or carbon pricing can be powerful tools to improve efficiency. Even without explicit technology policy, price signals alone encourage private agents to reduce energy and hence environmental burden. However, energy efficiency policy should not rely on raising average energy prices alone since stable long-term energy prices that minimise uncertainty are even more critical. Policies aimed at improving EE should therefore focus more on stabilising and strengthening the credibility of price signals faced by industry. For example, policymakers can support long-term energy contracts, such as fixed-price supply contracts or power purchase agreements, by reducing regulatory barriers. When firms can secure stable energy costs over the life of an investment, energy prices become a credible signal for improving efficiency rather than a short-term shock to be endured. This distinction between price levels and price uncertainty is particularly relevant for the new EU member states. While EU market liberalization has largely reduced persistent, administratively set industrial price distortions, the post-2021 environment featured sharp energy price volatility and repeated policy interventions that altered effective energy costs. The IEA notes that even after the 2022 supply shock began to ease, gas price volatility remained well above historical norms (IEA, 2025). EU reporting similarly documents the scale of the crisis shock and the diversity of national policy responses affecting end-user prices and incentives (European Commission, 2025). Given the variations in institutional capacity and exposure to external shocks, this suggests that the efficiency implications of prices may operate less through sustained high price discipline and more through the credibility and predictability of the price environment. This highlights the need to explicitly separate price level effects from price uncertainty effects, while allowing governance to condition these effects.

Second, given that uncertainty varies with reform phases, policy should focus on managing adjustment costs during major reforms. Clear policy timelines, simple implementation, and supportive measures can help limit exposure to price uncertainty when firms are most vulnerable

to unstable price signals. Furthermore, the stronger uncertainty effect in low energy-intensive sectors suggests that firms with limited exposures to energy costs are less prepared to manage energy price risks, which makes uncertainty more disruptive for their efficiency. Policy should focus on reducing exposure and improving risk management, not lowering prices. Third, given that EU accession and market integration are associated with EE gains, continued efforts to deepen market integration, strengthen cross-border interconnections, and enhance regulatory coordination remain central.

This study has limitations that point to avenues for future research. First, data constraints, especially for capital, affect the quality of the sample. Future work could exploit fuller micro-level datasets to better examine the drivers of inefficiency in new EU countries. Second, SEDF allows multiple inputs and outputs. This study focuses on only one output following Zhou et al. (2012). Extending the framework to jointly model environmental outputs like emissions would increase the scope for assessing the trade-offs between EE and decarbonization. Despite these limitations, the evidence presented here underscores the central role of coherent energy pricing and institutional quality in shaping EE outcomes in transition economies.

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TABLES

Table 1. Descriptive Statistics

Variable	Full name of variable	Obs.	Mean	SD	Min	Max
E	Industry final energy consumption in PJ - Eurostat	1470	23.79	33.32	.0072	217.6
K	Capital stocks in billions of (2015) euros - Eurostat	966	6.789	6.561	0.201	40.9
L	Employed (in millions) - Eurostat	1470	0.135	0.168	0.002	1.281
Y	Gross value added in billions of (2015) euros - Eurostat	1470	2.466	3.516	0.026	33.85
P	Energy price index as in Sato et al. (2019)	1388	7.577	2.550	5.450	14.21
P (Brent)	Energy prices using real Brent oil prices in 2010 USD (WB Pink Sheet)	2520	57.62	26.84	15.47	101.6
Uncertainty	Measure of price uncertainty (1) using daily returns SD of intl. oil price	1470	2.260	.653	1.200	3.681
,,	Measure of price uncertainty (2) using a GARCH (1,1) model	1470	6.143	1.035	4.777	8.418
,,	Measure of price uncertainty (3) using SD of Sato's energy price index	1383	2.647	0.223	2.104	3.001
RQ	Regulatory quality – World Governance Indicator	1400	0.846	0.290	-0.105	1.309

Note: The Brent oil price is used in the robustness analysis using an extended sample spanning 1995-2022. The first two uncertainty measures are also used in the robustness checks because the data are also available for the extended period. However, the descriptive statistics are here reported for the baseline estimations, where the sample covers 1995-2015; Daily data on West Texas intermediate (WTI) spot price are obtained from the U.S. Energy Information Administration and

Table 2A. Energy efficiency across specifications and sample

Specification/sample	Mean	Std. Dev.	Min	Max
Full sample (unbalanced)	.789	.145	.152	.997
Sub-sample (balanced)	.790	.145	.160	.996
Sub-sample (pre-accession)	.820	.160	.139	.996
Sub-sample (post-accession)	.775	.128	.280	.997

Table 2B. Energy efficiency scores – sector level comparison

Sectors	mean	SD	Min	Max
Chemical and petrochemical	.781	.148	.415	.992
Construction	.761	.163	.151	.997
Food and tobacco	.780	.108	.537	.978
Iron and steel	.829	.120	.509	.987
Machinery	.784	.107	.563	.987
Mining and quarrying	.794	.194	.242	.994
Non-metallic minerals	.773	.131	.492	.985
Textile and leather	.772	.126	.513	.990
Transport equipment	.784	.126	.497	.989
Wood and wood products	.843	.139	.479	.984

Table 2C. Energy intensity - sector level comparison

Sectors	mean	SD	Min	Max
Chemical and petrochemical**	50.35	47.32	4.219	286.4
Construction	1.097	0.780	0.144	3.638
Food and tobacco	8.788	4.471	3.046	27.64
Iron and steel**	20.95	16.94	0.283	69.22
Machinery**	24.09	24.23	3.735	139.5
Mining and quarrying	3.266	2.534	0.483	14.55
Non-metallic minerals**	24.26	20.21	5.297	116.0
Textile and leather	5.146	3.240	1.288	22.14
Transport equipment	5.116	7.569	0.034	62.93
Wood and wood products**	17.43	7.076	4.629	40.73

Note: ** denotes sectors with energy-intensity above 10 TJ per million euros. We use this to categorize sectors as high energy-intensive and low energy-intensive sectors.

Table 3. Consistent TFE – Baseline results: full sample (unbalanced panel), 1995-2015

	Energy prices	Energy price uncertainty		Energy prices & uncertainty
		Returns SD	GARCH (1, 1)	
	[1]	[2]	[3]	[4]
β_k	.036	.045	.046	.035
	(.073)	(.069)	(.069)	(.071)
β_l	-.743***	-.738***	-.741***	-.738***
	(.096)	(.092)	(.092)	(.095)
β_y	-.164**	-.153**	-.152**	-.166**
	(.066)	(.064)	(.063)	(.066)
β_t	.014***	.016***	.015***	.014***
	(.005)	(.005)	(.005)	(.005)
β_{kl}	-.071	-.078	-.078	-.069
	(.065)	(.062)	(.063)	(.064)
β_{ky}	.158***	.163***	.163***	.156***
	(.043)	(.041)	(.041)	(.042)
β_{ly}	-.105***	-.106***	-.107***	-.103***
	(.03)	(.029)	(.029)	(.03)
β_{kt}	-.016***	-.016***	-.016***	-.016***
	(.004)	(.004)	(.004)	(.004)
β_{lt}	.01*	.01**	.01**	.009*
	(.005)	(.005)	(.005)	(.005)
β_{yt}	.004	.002	.002	.003
	(.005)	(.005)	(.005)	(.005)
σ_{eprice}	-.462**			-.449**
	(.219)			(.22)
σ_{p_uncert}		.101**	.052*	.091**
		(.044)	(.027)	(.045)
σ_{rq}	.533***	.534***	.531***	.558***
	(.151)	(.155)	(.156)	(.156)
σ_{2004}	-.221***	-.22***	-.212***	-.228***
	(.076)	(.07)	(.071)	(.075)
σ_{2007}	-.217**	-.197**	-.205**	-.193*
	(.099)	(.098)	(.098)	(.103)
σ_{2008}	-.21**	-.397***	-.37***	-.353***
	(.099)	(.096)	(.096)	(.108)
σ_{2009}	.255**	.101	.111	.15
	(.124)	(.135)	(.137)	(.149)
$\sigma_{constant}$	-.895**	-2.001***	-2.089***	-1.143**
	(.435)	(.209)	(.266)	(.471)
STN	.050**	.044**	.045**	.050**
	(.020)	(.021)	(.021)	(.021)
Criterion function	-2938	-3143	-3147.8	-2927
LR test	1735.3***	2113***	2371.8***	1718***
LR (*p*-value)	<.001	<.001	<.001	<.001
Observations	897	914	914	897

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio; Year dummies corresponding to EU accession (2004, 2007) and the global financial crisis (2008, 2009) are included; LR test is a likelihood ratio test, which employs a null hypothesis of a Cobb-Douglas model against the alternative hypothesis of a translog model. Column 4 employs the simpler uncertainty measure using the daily returns standard deviation of international oil price. Full sample includes Czechia, Hungary, Lithuania, Poland, Romania, Slovakia, and Slovenia.

Table 4. Consistent TFE – Robustness analysis using a restricted balanced sample, 1995-2015

	Energy prices	Energy price uncertainty		Both incl.
		Returns STD	GARCH	
β_k	-.003	.009	.01	-.005
	(.077)	(.071)	(.072)	(.075)
β_l	-.789***	-.795***	-.799***	-.779***
	(.105)	(.1)	(.1)	(.102)
β_y	-.113	-.097	-.095	-.118
	(.073)	(.069)	(.069)	(.073)
β_t	.01*	.011**	.01*	.011**
	(.006)	(.005)	(.005)	(.005)
β_{kl}	-.005	-.009	-.01	-.001
	(.069)	(.065)	(.066)	(.068)
β_{ky}	.141***	.146***	.147***	.139***
	(.047)	(.045)	(.045)	(.047)
β_{ly}	-.126***	-.126***	-.127***	-.123***
	(.031)	(.031)	(.031)	(.031)
β_{kt}	-.01***	-.009**	-.01**	-.01**
	(.004)	(.004)	(.004)	(.004)
β_{lt}	.006	.006	.006	.005
	(.005)	(.005)	(.005)	(.005)
β_{yt}	.000	-.002	-.002	.000
	(.006)	(.005)	(.005)	(.006)
σ_{eprice}	-.366*			-.349*
	(.200)			(.200)
σ_{p_uncert}		.121**	.071**	.11**
		(.048)	(.029)	(.047)
σ_{rq}	.537***	.553***	.553***	.564***
	(.155)	(.16)	(.159)	(.16)
σ_{2004}	-.21***	-.212***	-.203***	-.219***
	(.079)	(.076)	(.076)	(.078)
σ_{2007}	-.197**	-.168*	-.174*	-.167*
	(.092)	(.094)	(.093)	(.096)
σ_{2008}	-.199**	-.408***	-.398***	-.371***
	(.093)	(.103)	(.103)	(.111)
σ_{2009}	.25*	.093	.087	.124
	(.128)	(.145)	(.146)	(.155)
$\sigma_{constant}$	-1.12**	-2.122***	-2.284***	-1.418***
	(.455)	(.224)	(.282)	(.489)
STN	.057***	.054**	.055**	.056**
	(.021)	(.020)	(.020)	(.021)
Criterion function	-2388	-2403.9	-2406.1	-2374.5
LR test	2868***	2673.8***	2229***	1921.5***
LR (*p*-value)	<.001	<.001	<.001	<.001
Observations	797	797	797	797

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio. The balanced sample comprises 4 countries, namely the Czech Republic, Hungary, Romania, and Slovakia. The LR test is a likelihood-ratio test that compares a null hypothesis of a Cobb-Douglas model against an alternative hypothesis of a translog model.

Table 5. CFE estimation: Robustness analysis using pre-accession sample (1995-2003)

Variables	Energy prices	Price uncertainty	Both incl.
β_k	-.268**	-.252**	-.262**
	(.11)	(.106)	(.109)
β_l	-.461***	-.505***	-.475***
	(.148)	(.146)	(.149)
β_y	-.079	-.056	-.074
	(.064)	(.063)	(.066)
β_t	.024***	.021**	.022**
	(.009)	(.009)	(.009)
β_{kl}	.171**	.164**	.164**
	(.076)	(.077)	(.077)
β_{ky}	.153***	.15***	.152***
	(.049)	(.047)	(.049)
β_{ly}	-.273***	-.273***	-.272***
	(.045)	(.043)	(.044)
β_{kt}	-.026***	-.025***	-.027***
	(.007)	(.007)	(.007)
β_{lt}	.021**	.023***	.022***
	(.008)	(.008)	(.008)
β_{yt}	-.003	-.004	-.003
	(.008)	(.008)	(.008)
σ_{eprice}	-.551*		-.549*
	(.316)		(.318)
σ_{p_uncert}		.299***	.289***
		(.097)	(.087)
σ_{rq}	.304	.339	.314
	(.205)	(.206)	(.204)
σ_{2000}	-.239**	-.437***	-.392***
	(.096)	(.121)	(.105)
σ_{2001}	-.301***	-.449***	-.423***
	(.111)	(.1)	(.109)
σ_{2002}	-.433***	-.286***	-.275***
	(.101)	(.099)	(.102)
σ_{2003}	-.407***	-.529***	-.531***
	(.155)	(.151)	(.168)
$\sigma_{constant}$	-.633	-2.406***	-1.336**
	(.6)	(.312)	(.616)
STN	.044*	.046**	.046*
	(.024)	(.023)	(.024)
Criterion function	-102	-134.6	-96.2
LR test	2725***	1827.2***	2537
LR test (*p*-value)	<.001	<.001	<.001
Observations	357	362	357

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio; LR test is a likelihood ratio test, which employs a null hypothesis of a Cobb-Douglas model against the alternative hypothesis of a translog model. Data from 7 countries (full).

Table 6. CFE estimation: Robustness analysis using post-accession sample (2004-2015)

Variables	Energy prices	Price uncertainty	Both incl.
β_k	.025	.022	.021
	(.095)	(.091)	(.094)
β_l	-.917***	-.954***	-.918***
	(.147)	(.145)	(.147)
β_y	-.088	-.069	-.081
	(.148)	(.145)	(.148)
β_t	.015***	.017***	.015***
	(.006)	(.006)	(.006)
β_{kl}	-.179**	-.201***	-.177**
	(.071)	(.066)	(.071)
β_{ky}	.142***	.154***	.143***
	(.054)	(.052)	(.054)
β_{ly}	.025	.016	.023
	(.035)	(.035)	(.036)
β_{kt}	-.006	-.007	-.005
	(.005)	(.005)	(.005)
β_{lt}	.016*	.018**	.016*
	(.009)	(.008)	(.009)
β_{yt}	-.006	-.007	-.006
	(.009)	(.009)	(.009)
σ_{eprice}	-.437*		-.434*
	(.256)		(.240)
σ_{p_uncert}		.031	.035
		(.029)	(.031)
σ_{rq}	.501**	.456**	.499**
	(.223)	(.218)	(.224)
σ_{2004}	-.329	-.262	-.269
	(.363)	(.354)	(.450)
σ_{2007}	-.018	-.004	-.029
	(.354)	(.348)	(.348)
σ_{2008}	-.075	-.055	-.092
	(.361)	(.350)	(.353)
σ_{2009}	.428***	.367***	.39***
	(.096)	(.096)	(.101)
$\sigma_{constant}$	-1.16**	-2.034***	-3.664**
	(.56)	(.228)	(1.606)
STN	.033**	.030*	.035**
	(.016)	(.017)	(.016)
Criterion function	-460.6	-545.9	-459.6
LR test	1273***	1557 ***	1122***
LR test (*p*-value)	<.001	<.001	<.001
Observations	540	552	540

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio; Year dummies corresponding to EU accession (2004, 2007) and the global financial crisis (2008, 2009) are included; LR test is a likelihood ratio test, which employs a null hypothesis of a Cobb-Douglas model against the alternative hypothesis of a translog model. Data from 7 countries (full).

Table 7. Consistent TFE – Robustness analysis: interaction terms with energy-intensive sectors

	Price effect		Uncertainty effect	
	Full sample	Balanced sample	Full sample	Balanced sample
β_k	.035	-.001	.039	.004
	(.07)	(.073)	(.069)	(.072)
β_l	-.746***	-.782***	-.751***	-.794***
	(.104)	(.11)	(.103)	(.108)
β_y	-.14**	-.099	-.135**	-.091
	(.066)	(.071)	(.063)	(.068)
β_t	.013**	.01*	.014***	.01*
	(.005)	(.006)	(.005)	(.006)
β_{kl}	-.052	.011	-.058	.004
	(.066)	(.07)	(.066)	(.069)
β_{ky}	.153***	.137***	.158***	.141***
	(.044)	(.048)	(.044)	(.047)
β_{ly}	-.11***	-.129***	-.111***	-.128***
	(.032)	(.034)	(.033)	(.034)
β_{kt}	-.014***	-.008*	-.014***	-.008**
	(.004)	(.004)	(.004)	(.004)
β_{lt}	.01*	.006	.011**	.006
	(.005)	(.005)	(.005)	(.005)
β_{yt}	.001	-.002	.000	-.003
	(.005)	(.005)	(.005)	(.005)
σ_{eprice}	.022	.162		
	(.353)	(.347)		
σ_{p_uncert}			.072**	.115***
			(.037)	(.04)
$\sigma_{eprice \times intensity}$	-.162	-.184*		
	(.099)	(.102)		
$\sigma_{p_{uncert} \times intensity}$			-.152***	-.151**
			(.054)	(.06)
σ_{rq}	.495***	.493***	.498***	.516***
	(.16)	(.168)	(.157)	(.166)
$\sigma_{constant}$	-1.695***	-1.976***	-1.795***	-1.952***
	(.592)	(.595)	(.158)	(.167)
STN	.057***	.065***	.058***	.067***
	(.020)	(.020)	(.019)	(.019)
Criterion Function	-2898.9	-2333.6	-3037.7	-2310.7
LR test	781	3644	2284.3	1474
LR (*p*-value)	<.001	<.001	<.001	<.001
Observations	897	797	897	797

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio. As in previous estimations, year dummies corresponding to EU accession (2004, 2007) and the global financial crisis (2008, 2009) are included but not reported for brevity. Data from 7 countries (full).

Table 8. Robustness check using Brent prices, baseline model

Variables	Full sample (1995-2015)		Full sample (1995-2022)		Full + Latvia (1995-2022)	
	[1]	[2]	[3]	[4]	[5]	[6]
β_k	.047	.057	.107*	.087	.184***	.168***
	(.066)	(.069)	(.059)	(.059)	(.052)	(.052)
β_l	-.669***	-.64***	-.803***	-.771***	-.784***	-.745***
	(.078)	(.08)	(.068)	(.068)	(.068)	(.071)
β_y	-.209***	-.216***	-.167***	-.181***	-.22***	-.244***
	(.063)	(.062)	(.061)	(.06)	(.062)	(.063)
β_t	.024***	.019***	.006*	.004	.011***	.009***
	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)
β_{kl}	-.101	-.112*	-.136**	-.122**	-.152***	-.145***
	(.061)	(.061)	(.055)	(.053)	(.046)	(.046)
β_{ky}	.162***	.167***	.166***	.158***	.127***	.126***
	(.041)	(.04)	(.046)	(.044)	(.035)	(.035)
β_{ly}	-.058**	-.07***	-.062**	-.067**	.006	.002
	(.026)	(.026)	(.03)	(.029)	(.026)	(.026)
β_{kt}	-.012***	-.013***	-.013***	-.013***	-.02***	-.02***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
β_{lt}	.01**	.01**	.012***	.011***	.016***	.014***
	(.005)	(.005)	(.004)	(.004)	(.004)	(.004)
β_{yt}	-.001	.001	.004	.005	.004	.006
	(.005)	(.005)	(.004)	(.004)	(.004)	(.004)
σ_{eprice}	-.428***		-.295***		-.299***	
	(.072)		(.083)		(.080)	
σ_{p_uncert}		.222***		.146***		.160***
		(.048)		(.048)		(.037)
σ_{rq}	.529***	.5***	.532***	.509**	.824***	.813***
	(.16)	(.163)	(.2)	(.199)	(.175)	(.177)
σ_{2004}	-.135**	-.161**	-.083	-.077	-.144**	-.139*
	(.062)	(.064)	(.065)	(.066)	(.071)	(.075)
σ_{2007}	.004	-.113	.037	-.032	-.064	-.126
	(.091)	(.092)	(.091)	(.084)	(.105)	(.095)
σ_{2008}	.045	-.537***	.08	-.307***	-.019	-.425***
	(.088)	(.112)	(.097)	(.107)	(.109)	(.091)
σ_{2009}	.295***	-.008	.332***	.132	.187*	-.023
	(.099)	(.137)	(.087)	(.128)	(.106)	(.123)
σ_{2020}			-.326***	-.904***	-.071	-.724***
			(.103)	(.216)	(.065)	(.199)
σ_{2021}			-.422***	-.381***	-.122**	-.098**
			(.099)	(.104)	(.048)	(.049)
σ_{2022}			-.055	-.275**	.179***	-.064
			(.131)	(.114)	(.059)	(.071)
$\sigma_{constant}$	-.125	-2.25***	-.547*	-2.019***	-.648**	-2.18***
	(.291)	(.21)	(.312)	(.245)	(.322)	(.206)
STN	.246***	.279***	.123***	.123***	.125***	.131**
	(.006)	(.008)	(.023)	(.025)	(.035))	(.056)
Criterion function	-2033.9	-3133.2	-4981.7	-5079.9	-9158	-9146.8
LR test	1154.2	1823.7	1237.9	1804.4	1637.9	1397.6
LR (p-value)	<.001	<.001	<.001	<.001	<.001	<.001

Observations	779	779	1101	1101	1341	1341

Note: Robust standard errors in parentheses; *, **, *** denote significance at 10%, 5%, and 1%, respectively. STN denotes the signal-to-noise ratio; The extended sample (cols 5 and 6) includes an additional country (Latvia), which for data limitations, were excluded from the baseline sample. In addition to including year dummies corresponding to EU accession and the global financial crisis, the estimations in columns 3-6 include crisis dummies capturing the covid-19 and European energy crisis years (years 2020-2022).

Appendix

Appendix Table A1. Country and sectors

Countries	Sectors
Czech Republic	Chemical and petrochemical
Hungary	Construction
Lithuania	Food and tobacco
Poland	Iron and steel
Romania	Machinery
Slovakia	Mining and quarrying
Slovenia	Non-metallic minerals
(Latvia)*	Textile and leather
	Transport equipment
	Wood and wood products

* Latvia is included in the robustness check, with Brent prices for energy (Table 8, col [5]–[6]).

Appendix Table A2. Hausman test for the choice between fixed and random effects estimation

Statistic [Chi-square (10)]	23.3
Prob>Chi-square	.001

Note: Rejection of null hypothesis of random effects gives support for fixed effects

Appendix Table A3. Skewness test

Model	Skewness	Pr(Skewness)	Pr(Kurtosis)	Joint Chi-Square test
Baseline sample (Table 3)	0.172	0.029	0.489	5.23*
Balanced sub-sample (Table 4)	0.217	0.006	0.017	13***

Note: *, **, & *** denote significance at 10%, 5%, and 10%, respectively.

Appendix Table A4. Likelihood ratio test for technical change

Statistic [Chi-square (2)]	37.4

Prob>Chi-square	.000

Note: Rejection of null hypothesis of no technical change gives support for including time controls.

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