

Energy Efficiency and Energy Savings Potentials in the Austrian Manufacturing and Construction sectors - Firm-level Evidence from a Stochastic Frontier Analysis *

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Abstract This paper investigates the drivers of changes in energy intensity and explores energy-saving potentials at the firm level within Austria's manufacturing and construction sectors from 2008 to 2022. The analysis focuses on the role of energy efficiency. Using firm-level data and applying stochastic frontier analysis, the study reveals that reductions in energy intensity were primarily attributable to scale efficiency gains and technological progress rather than improvements in energy efficiency alone. Despite considerable heterogeneity among firms, counterfactual scenarios with varying ambition levels suggest that raising low-efficiency firms to the median efficiency could yield one-off energy savings of 11.7–13.2%. However, rebound effects would reduce net savings to 8.4–9.7%, corresponding to 12.3–14.2% of the final energy consumption reduction mandated by the Austrian Energy Efficiency Act (EEffG). While these savings are significant, they fall short of offsetting recent energy price shocks and their contribution to the achievement of long-term national and EU policy targets is limited. The findings underscore the need for policy approaches that extend beyond energy-specific measures to also foster productivity, innovation, and structural transformation.

Keywords: Energy intensity, energy efficiency, firm behaviour, stochastic frontier analysis, energy savings, rebound effects

JEL Classification: Q40 Q55 D24 L60 D22 D61

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Non Technical Summary

Aim

This paper investigates how energy efficiency in Austria's manufacturing and construction sectors has evolved over the period 2008–2022, with a particular focus on identifying the drivers of changes in energy intensity at the firm level. The study aims to distinguish genuine improvements in energy efficiency from changes resulting from scale effects, technical progress, or structural shifts within firms. It also quantifies the potential for energy savings based on observed firm-level heterogeneity and assesses the magnitude of rebound effects that may offset these savings. Understanding these mechanisms is critical for the design of effective energy and climate policy, particularly in the context of the EU's net-zero emissions goals and the need to shield firms from volatile energy prices.

The analysis is especially relevant in light of recent geopolitical developments and the corresponding energy price shocks experienced in 2021 and 2022. These events have underlined the vulnerability of industrial energy users and the importance of energy efficiency as a tool for both long-term decarbonization and short-term economic resilience. From a policy standpoint, the results can help identify where support measures, incentives, or regulatory efforts could be most effectively targeted to enhance energy efficiency and reduce carbon emissions in the business sector.

Main Results

The study draws on detailed firm-level data from Austria's official business statistics, covering over a decade of operations across manufacturing and construction sectors. Using stochastic frontier analysis (SFA), the paper estimates the partial elasticities of energy costs with respect to prices, output, and quasi-fixed inputs such as capital and labor. These results are used to derive firm-level energy efficiency scores, which are further analyzed to estimate potential energy savings and decompose the drivers of changes in energy intensity over time.

The findings reveal three major insights:

- **Limited Role of Energy Efficiency in Past Improvements in Energy Intensity:** The main drivers of reductions in firm-level energy intensity over the last decade were improvements in scale efficiency and technical change – not direct energy efficiency gains. In fact, average energy efficiency has slightly deteriorated, particularly in recent years and among smaller or non-ETS firms. This suggests that while firms have become more energy productive through economies of scale and technological upgrading, there is still significant unrealized potential in actual energy-saving behavior or technology adoption.
- **Substantial Heterogeneity and Savings Potential:** Based on counterfactual scenarios with varying degrees of ambition bringing the least efficient firms to match the practices of median-efficiency peers, could deliver a one-off energy saving ranging between 11.7 and 13.2%. After adjusting for rebound effects – which occur when improved efficiency leads to increased output and energy demand – the net potential savings would amount to between 25 and 29 PJ. This corresponds to between 12.3 or 14.2% respectively of the reduction of final energy consumption mandated by the Austrian Energy Efficiency Act (EEffG). If implemented quickly this reduction could lead to an important contribution towards the 650PJ cumulative energy savings goal established in the act. The largest opportunities are concentrated in energy-intensive sectors, though even less energy-intensive and construction firms show a meaningful potential for gains.

- **Rebound Effects Are Non-Trivial but Do Not Eliminate Gains:** The paper estimates rebound effects ranging from 14.8% in construction to over 43.1% in industries with medium energy intensity. For energy-intensive sectors, the rebound effect ranges between 23.8% and 37.7% depending on the sector definition. While these effects reduce the net energy savings from efficiency improvements, they do not outweigh them. While not explicitly estimating rebound effects for firms participating in the EU ETS we find that they tend to be more efficient and show lower energy saving potentials, lending further empirical support to the hypothesis that carbon pricing and emissions trading schemes create incentives for sustained efficiency improvements.

Policy Implications

The findings of this study carry several key implications for energy and industrial policy in Austria and the broader EU context. First, the results suggest that current efficiency improvements are insufficient to drive the energy transition in manufacturing and construction. Since energy use is expected to increase significantly in energy-intensive industries as part of the net-zero transition – potentially doubling in some sectors – energy efficiency alone cannot offset future demand. Therefore, more ambitious and targeted efficiency policies are needed.

Second, since the main contributors to past energy intensity gains were scale efficiencies and technical change, policymakers should consider instruments that enhance firm competitiveness, innovation, and investment in new technologies. While measures focusing on energy-saving behavior may yield some results, policy should consider focusing more on broader drivers of productivity that also reduce energy use per unit of output.

Third, the observed heterogeneity in energy efficiency performance indicates the need for targeted interventions, especially to support lagging firms. These could include better access to information on available technologies, support for financing energy efficiency investments (especially under liquidity constraints), and addressing behavioral or organizational barriers to adoption. Stable carbon pricing through the EU ETS and consistent energy price signals can reinforce these incentives.

Lastly, while industry plays a central role in achieving climate goals, the limited energy savings potential within energy-intensive sectors implies that other sectors such as transport, residential buildings, and services must make proportionally greater contributions to overall energy conservation. Energy efficiency policy must therefore be embedded in a wider economic strategy, addressing system-wide energy use and promoting structural shifts toward low-carbon activity while at the same time also strengthening the competitiveness of the Austrian manufacturing sector.

1 Introduction

This paper uses Austrian firm-level data for the period 2008–2022 to examine the extent to which the business sector can support the achievement of energy-saving targets set by European policy and mitigate the negative impact of energy-price shocks by improving firm-level energy efficiency. Within European climate policy, energy efficiency is considered a key pillar of the transition to net zero by 2050 because it reduces overall energy consumption and alleviates the need for major investments in grid infrastructure to integrate the growing share of renewable energy. The European Union has therefore adopted more stringent targets, mandating an average annual energy-savings rate of 1.49% between 2024 and 2030 - nearly twice the 0.8% required from 2021 to 2023.

Central to this framework is the Energy Efficiency Directive (European Commission, 2023), which sets the objective of reducing final energy consumption in the EU by 11.7% by 2030 relative to projected 2030 use under the 2020 reference scenario. The Directive also institutionalises the “energy-efficiency-first” principle, ensuring that efficiency measures remain a priority across sustainability, climate-neutrality, and green-growth initiatives. Although it spans multiple sectors (transport, housing, and industry), it places particular emphasis on energy-intensive industries, recognising their pivotal role in reducing consumption and emissions. Austria implements the Directive through its Energy Efficiency Act (EEffG), which aims to reduce final energy consumption from 1,124 PJ in 2021 to 920 PJ by 2030, requiring cumulative savings of at least 650 PJ. While the Act does not assign sector-specific targets, large enterprises are obliged to conduct energy audits or implement recognised energy-management systems.

Despite these ambitious EU and national goals, there is limited systematic and up-to-date evidence for EU countries on the drivers of energy intensity and the scope for firm-level energy savings through efficiency improvements. Designing well-targeted policies requires a clear understanding of the determinants of energy intensity, as well as the substantial heterogeneity of energy use across firms. A key contribution of this paper is to provide an up-to-date assessment of the determinants of firm-level energy intensity in Austria, based on a decomposition of energy-intensity changes across sectors with different energy intensities and energy mixes.

Beyond regulatory compliance, energy efficiency is also critical for firms’ economic performance. It is considered to offer immediate benefits such as reduced energy demand, enhanced security of supply, and greater resilience as well as long-term advantages by permanently lowering costs and supporting competitiveness (e.g. International Energy Agency, 2022a,b). Energy costs are a key determinant of international competitiveness, particularly for energy-intensive firms exposed to price volatility. This vulnerability became sharply evident during the 2022 European energy crisis, when energy-intensive industries experienced substantial output declines, with Austrian firms among the hardest hit (cf. Reinstaller and Sellner, 2025). Policymakers incorporated efficiency measures into crisis-mitigation strategies (cf. European Commission, 2022), although these were often overshadowed by fiscal interventions. The extent to which efficiency-induced energy savings can cushion the impact of high energy prices at the firm level remains uncertain. The present analysis sheds light on this question by estimating potential energy savings from improvements in firm-level energy efficiency.

Methodologically, the paper applies stochastic frontier analysis to firm-level energy cost functions and uses the resulting efficiency estimates to decompose changes in energy intensity across firms. This approach identifies the determinants of energy use and clarifies the relationship between energy consumption, economic activity, and efficiency across sectors. Estimated firm-level efficiencies are then used to evaluate potential energy savings in two counterfactual scenarios in which low-efficiency firms are brought up to sectoral

average levels. To ensure realistic estimates, rebound effects are calculated and savings adjusted accordingly.

The findings indicate that reductions in energy intensity are driven primarily by scale-related efficiency gains and technological progress rather than by improvements in energy efficiency alone. This underscores the complex interplay between economic activity, energy consumption, and costs. Although energy-efficiency improvements have played a limited role in overall intensity reductions in Austria, targeted improvements raising low-efficiency firms to average performance can yield substantial savings even after accounting for rebound effects. Nevertheless, these gains remain insufficient to offset short-term energy-price shocks of the magnitude experienced during the 2021–2022 crisis or to fully achieve policy-driven energy-savings targets.

The paper is organised as follows. Section 2 reviews the relevant literature. Section 3 outlines the empirical approach, and Section 4 describes the firm-level data. Section 5 presents the results. Section 6 concludes with a summary and a discussion of implications for energy-efficiency policy.

2 Related literature

Understanding the drivers of energy intensity and the scope for firm-level efficiency improvements is central to the design of effective energy and climate policies. While firms operating under cost-minimisation principles have an incentive to use energy efficiently, real-world frictions such as imperfect information, externalities, behavioural biases or misestimated savings can prevent them from adopting cost-effective technologies. These frictions give rise to an “energy efficiency gap”, an empirically observed deviation from optimal energy use that can justify targeted policy intervention (Jaffe and Stavins, 1994; Filippini and Hunt, 2015). As emphasised by Gillingham et al. (2018), accurate measurement of this gap is crucial for well-designed policies.

When monitoring the development of energy efficiency policy makers and environmental agencies typically rely on energy intensity as a key indicator to track the development of energy efficiency and energy savings at the aggregate level (cf. International Energy Agency, 2023; European Commission, 2024; Umweltbundesamt, 2024). Energy intensity quantifies energy consumption per unit of output (e.g., MWh per ton of steel), with higher intensity indicating greater energy use. However, this concept differs from energy efficiency, which reflects improvements in energy services per unit of input, leading to lower marginal energy costs.

While energy intensity can decline through energy conservation, i.e. the reduction in total energy consumption, such conservation may or may not result from efficiency gains (e.g. Metcalf, 2019; Gillingham et al., 2009). Energy conservation without efficiency improvements implies reduced energy services, whereas conservation driven by efficiency achieves the same service level with lower energy inputs. Notably, energy consumption may rise alongside efficiency gains due to the rebound effect, where declining marginal costs stimulate higher energy demand. It is also crucial to distinguish between energy and economic efficiency, as maximizing economic efficiency does not necessarily optimize energy efficiency. Using energy intensity as a proxy for energy efficiency especially in policy targets can thus be misleading because it is influenced by structural, behavioral, and economic factors not directly related to technical efficiency (cf. Filippini and Hunt, 2015).

To disentangle the energy intensity from energy efficiency earlier research has either tried to control for various firm- or sector-specific factors and isolate inefficiency from structural characteristics (cf. Filipovic et al., 2015), or engage into various decomposition exercises that allow to draw an explicit distinction between economic activity, structural factors and energy efficiency (cf. Ang and Xu, 2013; Gorus and Karagol, 2022; Román-Collado and Economidou, 2021). These studies generally conclude that true energy efficiency improvements often contribute less to observed energy intensity reductions than technological change or substitution ef-

facts.

With the increasing availability of firm-level microdata, a growing body of research turns to Stochastic Frontier Analysis (SFA) to identify efficiency differentials across firms and sectors. SFA decomposes deviations from an optimal energy frontier into random noise and inefficiency, allowing direct estimation of firm-level energy efficiency. For example, Lundgren et al. (2016) analyse 14 Swedish manufacturing sectors for the period 2000-2008 and find substantial inefficiencies in electricity and fuel use, with little evidence that the EU ETS improved energy efficiency. Lutz et al. (2017), using German firm-level data for 14 two-digit manufacturing sectors in Germany over the period 2003-2012, similarly identify significant heterogeneity and find that exporting, innovating, and environmentally active firms are more efficient, while EU ETS-regulated firms are less so. Finally, Adetutu et al. (2020) combine SFA with a decomposition of energy intensity gains (EIG) in the UK and show that carbon taxation reduced energy intensity primarily via technological progress and factor substitution; energy efficiency itself was the least responsive component. In this paper, we will apply and extend this approach to study the development of energy intensity at the firm level in Austria. Together, these studies underscore that energy intensity trends cannot be interpreted without accounting for structural drivers and heterogeneity in firm-level efficiency performance.

Beyond explaining past developments, policy design in the realm of climate and energy policy also requires an understanding of the potential energy savings that could be realised if inefficient firms improved their performance. This potential represents the “untapped” capacity for reducing energy use and emissions under current technologies.

A key reference in this area is Boyd and Lee (2019), who estimate plant-level energy efficiency in the U.S. metal-based durable goods sector using SFA. The metal-based durable goods manufacturing sector in this study comprises inter alia the production of fabricated metal products, machinery or transportation equipment. They simulate a counterfactual scenario in which all plants in the least efficient quartile improve to the sector median. Their results indicate possible energy savings of 21.4%, based on existing best practice within the sector. However, the authors note that their estimates do not account for rebound effects, which may significantly offset these theoretical savings.

Rebound effects arise when efficiency improvements reduce the effective cost of energy services, thereby increasing energy use. The empirical literature finds substantial heterogeneity in rebound magnitudes. For example, Amjadi et al. (2018) estimate large rebound effects—58–65% for fuel and 76–86% for electricity in Swedish heavy industries, meaning that only a fraction of expected savings is actually realised. Amjadi et al. (2022) confirm these findings for a slightly longer firm panel using a two-stage DEA and dynamic panel regression approach across 14 Swedish manufacturing sectors. They show that rebound effects are stronger in the short run.¹ In contrast, Berner et al. (2022) report relatively modest rebound effects (4.5–5.3%) in German manufacturing, where rebounds stem largely from growth following efficiency gains. Larger rebounds are observed for firms that are more capital-intensive, invest heavily, or are highly exposed to international markets.

One reason rebound effects arise is that energy efficiency often improves economic performance. Studies such as Caragliu (2021), Montalbano et al. (2022), and a recent World Bank analysis (Aterido et al., 2025) find positive associations between energy efficiency and productivity, sales, employment, or resilience to energy price shocks. These performance improvements may, in turn, stimulate output expansion and additional energy demand. Berner et al. (2022) highlight that such growth-induced rebounds are particularly relevant in competitive and capital-intensive sectors.

¹The authors classify rebound effects (RE) also along five scenarios which they call 1) backfire (RE>100%), 2) Full rebound (RE=100%), 3) Partial rebound (RE<100%), 4) zero rebound (RE=0%), 5) super-conservation (RE<0%).

Energy efficiency policies therefore have to deal with an important trade-off. Gillingham et al 2013; 2014 argue that energy efficiency policies need to account for rebound effects without overestimating them. They argue that while rebound effects do reduce the net energy savings from efficiency improvements, most empirical evidence suggests that rebound effects are typically moderate, often well below 100%. Thus, these effects do not negate the value of energy efficiency policies. Rebound effects should therefore be included in cost–benefit analyses and energy modeling to yield more realistic expectations.

The analysis in the following sections will draw on these contributions to assess the drivers of energy intensity at the firm level in Austria between 2009 and 2022. More specifically it uses the decomposition exercise proposed by Adetutu et al. (2020) to identify the drivers of energy intensity at the firm level and assess the importance of genuine energy efficiency improvements in its development over time. The analysis then proceeds to assess potential energy savings in line with the approach outlined by Boyd and Lee (2019). However, these estimates are corrected by estimates for sector specific rebound effects. The combination of these analytical approaches should provide a solid empirical base for the assessment of energy saving and efficiency policies at the national and EU levels. As our data cover also the years 2021 and 2022 we expect to observe some adjustments related to the increase in energy prices and their volatility.

3 Empirical Strategy

3.1 Estimating firm-level efficiencies

The firm-level efficiency levels are estimated via a stochastic energy cost frontier model. The short-run energy cost frontier function c^e is given by the minimum energy costs for a given output y , costs for materials and services, other quasi-fixed inputs capital K and labour L and exogenous technological change (as a function of time):

$$c^e(p^e, p^m, y, K, L, t) = \min_e \{p^e e : y \leq f(e, K, L, M, t)\}. \quad (1)$$

Following from basic production set and technology assumptions, Equation (1) should be homogeneous of degree 1, monotonically increasing and concave in prices p^e and p^m and monotonically increasing in output (see Kumbhakar and Lovell, 2000, page 34). To ensure linear homogeneity we normalise energy costs c^e and prices p^e with costs for intermediate inputs p^m .

A stochastic version, introducing output-oriented cost inefficiency u_{it} and measurement error v_{it} , can be estimated using observations on firm i in year t :

$$\tilde{C}_{it}^e = \tilde{p}_{it}^e e_{it} = \tilde{c}^e(\tilde{p}_{it}^e, y_{it}, K_{it}, L_{it}, t) \exp(u_{it} + v_{it}). \quad (2)$$

To estimate Equation (2), we need to specify the functional form of \tilde{c}^e and make distributional assumptions about the stochastic terms u_{it} and v_{it} . Our preferred specification is a translog energy cost function of the form

$$\begin{aligned}
\ln \tilde{C}_{it}^e &= \alpha_i + \alpha_1 \ln \tilde{p}_{it}^e + \beta_1 \ln y_{it} + \phi_K \ln K_{it} + \phi_L \ln L_{it} + \theta t + \frac{1}{2} \zeta t^2 \\
&+ \frac{1}{2} \alpha_{11} (\ln \tilde{p}_{it}^e)^2 + \alpha_y \ln \tilde{p}_{it}^e \ln y + \frac{1}{2} \beta_{11} (\ln y_{it})^2 \\
&+ \alpha_K \ln \tilde{p}_{it}^e \ln K_{it} + \alpha_L \ln \tilde{p}_{it}^e \ln L_{it} + \beta_K \ln y_{it} \ln K_{it} + \beta_L \ln y_{it} \ln L_{it} \\
&+ \frac{1}{2} \phi_{K1} (\ln K_{it})^2 + \frac{1}{2} \phi_{L1} (\ln L_{it})^2 + \phi_{KL} \ln K_{it} \ln L_{it} \\
&+ \theta_K \ln K_{it} \cdot t + \theta_L \ln L_{it} \cdot t + \sum_{\{e \in \{ec, ng, o\}\}} s_{e,i,t} + u_{it} + v_{it}
\end{aligned} \tag{3}$$

with $\ln \tilde{C}_{it}^e$ being the natural logarithm of normalised total energy expenditures of firm i in year t , \tilde{p}^e denotes the normalised energy price, y the real output, $\ln K_{it}$ and $\ln L_{i,t}$ are the quasi-fixed other inputs of labor, capital in real terms and a quadratic time trend. To account for differences in the energy mix and related adjustment we also include the shares $s_e \in [0, 1]$ of electricity (ec), natural gas (ng) and oil products (o) in total energy consumption as additional control variables. These do not necessarily sum to one as we have omitted other energy carries such as coal or biofuels which are however not used by only a subset of firms.

Pindyck and Rotemberg (1983) were among the first to use this specification to estimate the impact of energy price changes on firm level energy costs which is frequently used in energy cost estimations (cf. Amjadi et al., 2018; Adetutu et al., 2020). Assuming that capital is fixed in the short-term as a common assumption and needs no further discussion. That labour may also be considered as a quasi-fixed factor in the short-run is equally an accepted assumption ever since Oi (1962). Employment protection legislation (cf. Lundgren et al., 2016) among other factors influences its slow adjustment compared to energy cost changes. Material and energy inputs can be well argued to be variable also in the short-run. This does not pose any problems for energy, as we have data on firm-specific energy unit values available. For non-energy intermediate goods and services (what we called in short 'material' above), we only have 2-digit industry-level price deflators available. This makes them however suitable as factor to normalise energy costs and prices.

While imposing less restrictions on the functional form, than a standard Cobb-Douglas cost function the Translog specification is much more demanding in terms of parameters. The resulting energy cost elasticities of price, output, quasi-fixed inputs and time must be evaluated for each observation (see Thompson, 2006; Adetutu et al., 2020, and the technical appendix (B)). Thus the assumptions that energy costs should be monotonically increasing in energy price and output may be violated for some observations (cf. Ogawa, 2011). As a cross-check we also report the estimates of a simple Cobb-Douglas energy cost of the form:

$$\ln \tilde{C}_{it}^e = \beta_i + \beta_p \ln \tilde{p}_{it}^e + \beta_y \ln y_{it} + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \delta_1 \cdot t + \frac{1}{2} \delta_2 \cdot t^2 + \sum_{\{e \in \{ec, ng, o\}\}} s_{eit} + u_{it} + v_{it} \tag{4}$$

Note that unlike in the Translog function technical change is not factor dependent but Hicks-neutral in this specification.

To identify energy cost inefficiencies we follow the literature by assuming that the measurement errors v_{it} are i.i.d. and normal distributed with zero mean and variance σ_v whereas the cost inefficiencies follow an exponential distribution:

$$v_{it} \sim \mathcal{N}(0, \sigma_v^2), \tag{5}$$

$$u_{it} \sim \mathcal{E}(\sigma_u). \tag{6}$$

SFA allows to accomodate different distributions for the cost inefficiency terms. Alternatives are either

the truncated-normal, half-normal or gamma distributions. There is no guideline in the literature as to which distribution should be most appropriately used under specific analytical settings.² The use of the exponential distribution is viewed critically by some authors because of its implicit underlying assumption that most firms are efficient and that few are highly inefficient. Greene (2008, p.90ff) argues that what matters most is the functional form assumed for the cost function. The estimates for u_{it} show a strong agreement between cost inefficiency estimates obtained from different distributions. He concludes that estimated inefficiencies seem therefore to be quite robust to variations in this assumption.

As our dataset covers a panel between 2008-2022, we can utilize panel data methods to control for unobserved time-invariant heterogeneity that would otherwise confound with technical inefficiency. We do this by estimating a “true fixed effect model (TFE)” (Greene, 2005a,b) of Equations (3) and (4). The firm fixed effects are given by the parameters β_i and α_i in these models respectively. The TFE model relies on a within-transformation to remove fixed effects before the maximum likelihood estimation of the stochastic frontier model. This specification allows to disentangle time-varying inefficiency from unit-specific time-invariant heterogeneity. With the use of the TFE model, the incidental parameters problem may arise. This is the case when the number of units n is large relative to the panel T with the consequence that unit-specific intercepts may be inconsistently estimated. (Belotti and Ilardi, 2018) show that a time dimension of $T \geq 10$ is appropriate for the use of Greene’s TFE approach. Our panel has dimensions $T \approx 13.7$ and $n = 1576$ (Section 4) which should permit consistent estimation of unit specific intercepts.

In applied stochastic frontier analysis it is important to consider the inclusion of potential exogenous variables in the model that are supposed to affect the distribution of inefficiency. In this case inefficiency terms may be biased (see Kumbhakar and Lovell, 2000, page 115ff). In the case of energy cost functions observable exogenous variables that vary over time and may affect the distribution of inefficiency may be changes in technology, energy prices, regulation or specific subsidies. By using a careful modelling approach it is possible to account for a large number of potential transmission channels of exogenous variables affecting the inefficiency distribution.

In our modelling we jointly address a wide range of potential sources of heteroskedasticity in inefficiency. The Translog cost function accommodates input substitution and scale effects. The inclusion of time trend and its interactions allows modelling heterogeneous technical change across inputs and to control for technical change affecting energy efficiency related to changes in capital or the quality of labor. The time-varying covariates for the energy mix allow to capture observed dynamic influences on inefficiency in the presence of variations in adjustment capacity or substitution across energy carriers across firms, e.g. in the face of energy price shocks related to a single energy carrier or changes in energy carrier specific subsidies. By using the TFE estimator we control for unobserved, time-invariant heterogeneity (e.g. managerial ability, location, firm size). Finally, as argued in Section 3.5 we reduce heterogeneity in our firm-level estimations by running the model for groups of industries with similar energy use intensity. In more energy intense industries there may be systematic differences in incentives to improve energy efficiency as compared to industries in which energy costs typically represent only a minor cost position. Carrying out the SFA at the level of these subgroups of firms allows to account for systematic differences in behavior across firm types.

As heteroskedasticity in the inefficiency term may still persist due to unobserved time-varying shocks, firm-specific volatility, or a misspecified variance structure we report a sensitivity analysis of the stochastic frontier analysis using models allowing for heteroscedasticity in the inefficiency term. Given the overall ro-

²The estimates for the firm-level cost-efficiencies are derived via $CE_{it} = E[\exp(-u_{it})|\tau_{it}]$ with $\tau_{it} = \nu_{it} + u_{it}$ using the estimator of Battese and Coelli (1988). We use this exponential distribution for u_{it} , since it has the desirable scaling property (see Alvarez et al., 2006), i.e. the covariates \mathbf{z} only change the scale, and not the shape of the distribution, and it allows the parameters κ to be interpreted as semi-elasticities.

bustness of the results of the baseline model outlined in this section with regard to the alternatives where we have modelled the heteroskedasticity in the inefficiency term with a number of potential co-variates (results available from the authors) our preferred specification is the former. Results reported in the main part of the paper refer to this specification.

3.2 Decomposition of energy intensity at the firm level

Following the approach proposed by Adetutu et al. (2020) it is possible to disentangle the relationship between the development of energy intensity, i.e. the energy consumption per unit of output, and the energy efficiency estimates obtained from the analysis described in the previous section. Taking the logarithmic derivative of Equation (2) gives the factors influencing the change of energy costs over time. Considering that energy intensity gains (EIG) at the firm level result from the output growing faster than energy use and that energy use equals energy costs divided by energy prices, the decomposition of EIG at the firm level into its different behavioural components results from combining Equations 8) and (7) (see Appendix C for technical details):

$$\Delta \ln \tilde{C}_{it}^e = \tilde{\varepsilon}_{it}^e \cdot \Delta \ln \tilde{p}_{it}^e + \varepsilon_{it}^y \cdot \Delta \ln y_{it} + \varepsilon_{it}^K \cdot \Delta \ln K_{it} + \varepsilon_{it}^L \cdot \Delta \ln L_{it} + \epsilon_{it} + \Delta u_{it} \quad \text{and} \quad (7)$$

$$\text{EIG}_{it} \equiv \Delta \ln y_{it} - \Delta \ln e_{it}, \quad (8)$$

to obtain

$$\text{EIG}_{it} = (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e + (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it} - \varepsilon_{it}^K \cdot \Delta \ln K_{it} - \varepsilon_{it}^L \cdot \Delta \ln L_{it} - \epsilon_{it} - \Delta u_{it},$$

From this follows the decomposition of the (expected) energy intensity gain (EIG) simply as:

$$\text{EIG}_{it} = \text{AEC}_{it} + \text{SEC}_{it} + \text{OIC}_{it} + \text{TC}_{it} + \text{EEFC}_{it}. \quad (9)$$

Equation (9) represents the (expected) energy intensity gain (EIG) at the firm level over time as a sum of changes in allocative efficiency (AEC), scale effects (SEC), changes in other input factors (OIC), technical change (TC) and energy efficiency improvements (EEFC). The latter reflect pure improvements in energy efficiency as identified by means of the stochastic frontier analysis. We omit changes in the random error term Δv_{it} and use a difference notation to express changes between discrete points in time. Table 1 summarises the definition and interpretation of each component:

Table 1: Components of the normalized energy efficiency gain decomposition

Term	Interpretation
$\text{AEC}_{it} = (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e$	Allocative Efficiency Change
$\text{SEC}_{it} = (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it}$	Scale Effect Component
$\text{OIC}_{it} = -(\varepsilon_{it}^K \cdot \Delta \ln K_{it} + \varepsilon_{it}^L \cdot \Delta \ln L_{it})$	Other Inputs Contribution
$\text{TC}_{it} = -\epsilon_{it}$	Technical Change
$\text{EEFC}_{it} = -\Delta u_{it}$	Energy Efficiency Frontier Change

The elasticities needed to compute the single components are the estimated parameters of either the Translog or Cobb-Douglas model and are defined as (see Appendix C for definitions):

$$\tilde{\varepsilon}_{it}^e = \frac{\Delta \ln \tilde{c}}{\Delta \ln \tilde{p}_{it}^e}, \quad \varepsilon_{it}^y = \frac{\Delta \ln \tilde{c}}{\Delta \ln y_{it}}, \quad \varepsilon_{it}^K = \frac{\Delta \ln \tilde{c}}{\Delta \ln K_{it}}, \quad \varepsilon_{it}^L = \frac{\Delta \ln \tilde{c}}{\Delta \ln L_{it}}, \quad \epsilon_{it} = \frac{\Delta \ln \tilde{c}}{\Delta t}.$$

It is then possible to obtain the contributions of these components at different levels of aggregation using the Tornqvist approximations:

$$AEC_t = \sum_i (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e \approx \frac{1}{2} \sum_i [(1 - \tilde{\varepsilon}_{it}^e) + (1 - \tilde{\varepsilon}_{it-1}^e)] \cdot [\ln \tilde{p}_{it}^e - \ln \tilde{p}_{it-1}^e] \quad (10)$$

$$SEC_t = \sum_i (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it} \approx \frac{1}{2} \sum_i [(1 - \varepsilon_{yit}) + (1 - \varepsilon_{yit-1})] \cdot [\ln y_{it} - \ln y_{it-1}] \quad (11)$$

$$OIC_t = - \sum_i \sum_{k \in K, L} (\varepsilon_{it}^k) \Delta x_{it}^k \approx - \frac{1}{2} \sum_i \sum_k [(\varepsilon_{kit}) + (\varepsilon_{kit-1})] [\ln x_{ikt} - \ln x_{ikt-1}] \quad (12)$$

$$TC_t = - \sum_i (\epsilon_{it}) \approx - \frac{1}{2} \sum_i (\epsilon_{it} + \epsilon_{it-1}) \quad (13)$$

$$EEFC_t = - \sum_i (\Delta u_{it}) \approx \sum_i \ln (CE_{it}/CE_{it-1}) \quad (14)$$

Equations (10) - (14) underscore that at the aggregate level changes of energy intensity in the business sector are not only determined by changes in energy efficiency, but also by allocative choices, technical change and the overall scale of production. This distinction and especially the relative importance of each of these factors in determining energy intensity is important to understand the aggregate dynamics of energy intensity. We will assess the relative importance of each of these factors in changes in energy efficiency at aggregate levels.

3.3 Counterfactual energy savings scenario

Having computed the relative importance of energy efficiency in changes in (inverse) energy intensity, it is possible to utilize the estimates on the firm-level inefficiencies \hat{u}_{it} to simulate counterfactual energy savings scenarios. We follow the scenario of Boyd and Lee (2019) and compute the energy savings assuming that for each year the energy efficiency level of the least efficient quartile (i.e. the 4th quartile of inefficiencies) moves to the median of the sample. The percentage increase of actual costs (C_{it}^e) compared to cost when fully economically efficient ($C_{it}^{e,eff}$) is given by (see Kumbhakar et al., 2015, Chapter 4):

$$\frac{C_{it}^e}{C_{it}^{e,eff}} - 1 = \exp(\hat{u}_{it}) - 1, \quad (15)$$

which yields counterfactual energy costs of moving from \hat{u}_{it} to \hat{u}_t^{median} of

$$C_{it}^{e,cf} = \frac{C_{it}^e}{(1 + \exp(\hat{u}_{it} - \hat{u}_t^{median}) - 1)}. \quad (16)$$

Assuming exogenous energy prices, counterfactual energy demand is given by $e_{it}^{cf} = C_{it}^{e,cf}/p_{it}^e$. Other scenarios are clearly possible but we stick to the scenario proposed by Boyd and Lee (2019) for better comparability of the results and because its underlying assumption that such a target is attainable being based on current, real-world performance of the median plant.

3.4 Estimating the rebound effect

In general, energy efficiency improvements are recognized as cost-effective measures for reducing energy use (see Amjadi et al., 2022). However, a decreased real unit price of energy service for a firm may lead to a re-optimization response of firms, substituting other factors for relatively cheaper energy services. The

lower costs reduces output prices, which increases demand and thus output and demand for energy inputs. Saunders (2008) termed these the 'intensity' and 'output' part of the energy rebound effect that describes the phenomenon of increasing energy demand following energy efficiency improvements (see also Khazzoom, 1980). The size of these two effects will depend on the shape of the production function and price elasticity of demand respectively (see Berkhout et al., 2000).

Following Berkhout et al. (2000); Zhang et al. (2017), the rebound effect RE can be defined as

$$RE = \frac{AE}{ES} \times 100\% = -\frac{\epsilon_{y,e} * \epsilon_{CE,y}}{\epsilon_{CE,e}} \times 100\%, \quad (17)$$

with AE the additional energy consumption as difference between expected and actual energy savings (ES). As in Berner et al. (2022) we approximate the expected energy savings by the elasticity of energy demand with respect to efficiency $\epsilon_{CE,e}$ and the additional energy consumption from the output effect by the product between the elasticity of energy demand with respect to output $\epsilon_{y,e}$ and the elasticity of output with respect to energy efficiency $\epsilon_{CE,y}$. We estimate these elasticities via the regressions:

$$\ln e_{it} = \epsilon_{CE,e} \ln CE_{it} + \epsilon_{y,e} \ln y_{it} + \beta_{epe} \ln p_{it}^e + \alpha_{1i} + \eta_{1t} + \tau_{1it}, \quad (18)$$

$$\ln y_{it} = \epsilon_{CE,y} \ln CE_{it} + \beta_{ye} \ln e_{it} + \alpha_{2i} + \eta_{2t} + \tau_{2it}, \quad (19)$$

with α denoting firm-level and η denoting time fixed effects. This specification deviates from Berner et al. (2022) in two respects. First, we estimate a fixed effects specification in log levels instead of a random intercept model in first differences. Second, we included much less covariates in Equations (18) and (19). Most notably, Berner et al. (2022) included interaction terms of efficiency with growth of R&D, foreign sales, investments, wages and renewables, thus making the elasticities non-linear and dependent on firm characteristics. We opted for a less flexible due to our linear specification but yet more robust unobserved heterogeneity due to our fixed effects setting.

3.5 Industry classification

Our analysis focuses on firms in manufacturing (NACE 10-32) and construction (NACE 41-43). The manufacturing of coke and refined petroleum (19) was excluded for confidentiality reasons and there are no data for the tobacco industry (12). Ideally, one would estimate a stochastic cost frontier model for each industry at the most detailed level. However as is evident from Table 2, the sample size of firms within each 2-digit (not to mention 4-digit) NACE sector is small. First, as outlined in Section (4), the number of firms surveyed for the material input statistics, our source for energy volumes and expenditure, is only around 2,350 each year, not all of which can be matched to the structural business statistics each year. Second, the capital stock was estimated via perpetual inventory method (see Section A.2), for which we restricted the sample to firms covered at least over span of 10 years to avoid estimates biased towards the approximated initial capital stock. Finally, we excluded firms in the data cleaning process outlined in Section (A.3).

The small sample sizes at the NACE 2-digit level may cause problems in specifications that are demanding in terms of parameters, such as a fixed effects translog specification. Hence, we estimated the models for groups of 2-digit NACE sectors based on median firm characteristics. Some studies have argued that only energy-intensive industries monitor their usage of energy and that policy measures are best addressed at them (see Amjadi et al., 2018; Dahlqvist et al., 2021). Other research has emphasised the specific needs for a successful energetic transition by energy intense industries, be it in terms of increased energy need to master

the transition to carbon neutral technologies or the need to be part of integrated energy systems optimizing and interlinking energy use and production in various sectors (cf. Schützenhofer and et. al., 2023). We thus classify industries in line with the median energy intensity observed for each NACE 2-digit sector. We compute the median kWh energy usage per EUR of real output for each industry and group the industries in tertiles. After some consistency checks we obtain three more evenly sized groups of firms that share commonalities in terms of energy- and capital intensity but also in terms of the energy sources used in these sectors (see Table 2). To control for the variation of the composition of energy sources across firms in each of these groups we include the energy shares for electricity, natural gas and oil products in the Translog and Cobb-Douglas energy cost functions estimated in Equations (3) and (4).

With the classification approach outlined in the previous paragraph the group of the most energy intense industries comprises also the food, beverages and textile industries, whereas studies and policy documents commonly refer to the non-mineral products (cement, ceramics, glass), the chemical, the basic metals (steel, non-ferrous metals) and sometimes wood product industries as being energy intense.³ In addition, sector classification also allocates various construction industries to the medium and low energy intensity sectors. Given that the construction sector follows different patterns of energy use and differs in its technical characteristics from more traditional manufacturing sectors, we also report results for these two sector groups separately. Table 2 summarises the classifications and reports key statistics capturing the technological characteristics and energy use patterns in the 2-digit NACE sectors as well as the industry classifications used in the paper. They show that energy intense sectors are typically more capital intense and that they rely on average more heavily on natural gas than less energy intense sectors. The construction sector differs from manufacturing sectors through its intense use of oil products.

³See also (Austrian Productivity Board, 2024, p.121) and (Reinstaller and Sellner, 2025, p.53) for empirical characterisation of the energy intensity distributions of these sectors using firm-level data.

Table 2: Industry statistics by NACE 2-digit sectors and industry classifications. Statistics for 2022.

NACE	avg. energy intensity (kWh/ real production value)	avg. capital intensity ratio capital stock/output	avg. share fuel in total energy use across firms in %*			number of firms
			electricity	nat . gas	oil prod.	
10 - food	0.30	0.58	47.7	31.4	19.4	196
11 - beverages	0.37	1.12	43.8	44.1	9.5	21
13 - textiles	0.38	0.46	43.1	46.4	5.3	18
14 - apparell	0.09	0.28	47.7	22.7	29.6	10
15 - leather prod.	0.15	0.27	53.2	23.6	18.4	8
16 - wood prod.	0.71	0.47	47.1	2.5	19.2	122
17 - paper	1.31	0.59	55.3	31.9	4.3	59
18 - print prod.	0.20	0.66	72.7	19.0	8.3	28
20 - chemicals	0.72	0.48	55.3	31.9	10.6	57
21 - pharmaceuticals	0.27	0.61	55.2	34.7	10.1	17
22 - rubber & plastic	0.24	0.50	69.1	20.8	8.9	96
23 - non-metalic mineral prod.	1.14	0.67	28.4	25.9	38.3	106
24 - basic metals	0.81	0.50	49.9	39.4	5.1	72
25 - fabricated metal prod.	0.24	0.46	55.2	22.8	18.9	190
26 - computer, electronics, optical prod.	0.06	0.26	69.7	13.0	16.3	69
27 - electrical equipment	0.10	0.29	65.7	19.3	12.8	90
28 - machinery and equipment	0.08	0.26	54.4	23.6	19.8	238
29 - road vehicles	0.12	0.32	60.7	21.0	14.9	45
30 - other transport equip.	0.06	0.31	54.9	31.0	14.1	19
31 - furniture	0.16	0.40	48.7	7.4	22.2	40
32 - other manufacturing	0.12	0.58	66.9	14.3	18.1	32
41 - constr. of buildings	0.14	0.45	21.3	3.2	72.3	195
42 - other civil engineering	0.32	0.44	10.8	5.8	83.3	68
43 - spec. constr. activities	0.18	0.50	12.7	5.7	78.5	297
Energy intensity by median energy intensities of sectors*						
Low: 14, 15, 26, 27, 28, 30, 41, 43	0.13	0.38	36.2	12.5	48.7	926
Medium: 18, 21, 22, 25, 29, 31, 32, 42	0.22	0.47	53.6	18.5	24.5	516
High: 10, 11, 13, 16, 17, 20, 23, 24	0.70	0.57	45.8	26.9	18.0	651
Energy intense sectors (narrow definition* and ETS)						
Energy intense: 16, 17, 20, 23, 24	0.92	0.54	45.1	23.1	18.3	416
Firms with plants in ETS	2.18	0.68	34.9	45.8	5.1	46
Construction						
41, 42,43	0.18	0.47	15.5	4.8	76.9	560
By firm size						
Medium	0.29	0.46	41.3	16.7	36.8	1602
Large	0.46	0.46	50.4	24.3	21.6	491

Note: Data Statistics Austria, AMDC. Own calculations. * list of numbers corresponds to NACE sectors listed in the first column.

4 Data

All firm level data used in this analysis were provided by the Austrian Micro Data Centre of Statistics Austria. The principal data source of this analysis are the Structural Business Statistics (SBS). The SBS is an annual survey, covering around 38.000 economically active legal entities (approx. 6% of total firm population as of 2022) in industries B to S (excluding O and S94) of the industry classification NACE 2008.⁴ For firms with 20 or more employees the survey is mandatory, and firms with less employees may be added to reach at least 90% of total sales in each NACE header covered. The variables covered include, production value, sales, employees in full time equivalents (FTE), hours worked, investments, purchase of goods and services and purchase of fuels and are available for the years 2008-2022.

We measure labor input (L) by the hours worked and output via the production value (Y). To derive an estimate of non-energy materials input (M), we subtract the fuels purchases from the purchase of goods and services. Capital stock is derived from the investments applying the perpetual inventory method.⁵ To deflate production value, investments and non-energy material inputs we used the implicit price deflators of the national accounts statistics for output (P1), gross fixed capital formation (P51G) and intermediate consumption (P2) for 74 2-digit NACE 2008 industries available from Statistics Austria.

The second main data source is material input statistics (MIS), which covers the data on energy usage of Austrian firms for the years 2008-2022. In contrast to the SBS where legal units are surveyed, the MIS is based on plants. This means that multiple plants within the MIS may be matched to one legal entity from the SBS. The MIS covers plants active in the NACE 2008 industries B to F (i.e. mining, manufacturing, utilities and construction) with at least 20 employees and 10 million euro total production output (sales and deliveries to other plants within same company), covering around 2,350 of the largest plants of the industry, which corresponds to around 5% of the plant population but 70% of production value.

The data regarding material input as energy usage (i.e. for heating or power generation, but not as an intermediate input) contains both the values (in 1000 EUR) and quantity in physical units (tons, 1000 m³ or MWh), recorded at the CPA 6-digit level. Physical units were converted to net calorific values in GJ. The common quantities and the values are then summed across the 37 different energy sources to arrive at the total quantity (E) and cost (C_e) of energy for each firm-year observation. Energy prices in euro per GJ (p_e) are then computed as unit values, dividing the values by the quantities. Details, including the handling of zero values for own production of renewable energy sources (heating pumps, photovoltaic, wind, water, waste, geothermal and biogas), are included in Appendix A.1. From the detailed energy source level data, we also derived a dummy variable D^{renew} indicating if the firm employed own renewable energy sources.

It should be noted that the following aggregates are often included in energy usage in the MIS: Conversion input, consumption of the energy sector, and losses. We have netted out non-energy consumption. Aggregate energy use values from the MIS thus exceed values reported in the energy balances published by Statistics Austria, as we did not have access to the data to adjust energy use by these factors. The MIS thus captures the gross total energy input at the production level, while energy balances provide the net final energy consumption after accounting for all transformation processes in the energy system. Furthermore, using firm-level energy prices, while introducing rich variation at our level of analysis, may also introduce endogeneity as larger firms may have bargaining power or more choice over rate plans (in case of electricity) and thus larger users are realizing lower prices (see Boyd and Lee, 2019; Reinstaller and Sellner, 2025). Another issue that arises when using an aggregate average energy price at the firm level is that the largest and most

⁴A legal entity is defined as an organizational unit for producing goods or services. It may carry out one or more activities at one or more locations. Economically active units account for employees and/or sales during at least part of the reporting period.

⁵For more details see Appendix A.2.

energy-intensive users tend to use the cheapest type of energy, again lowering the average price with the amount of energy consumption (see Arnberg and Bjørner, 2007). Especially when conducting cross-sectional analysis, these issues will lead to strongly biased and even wrongly-signed price elasticities of energy demand. We address these issues by employing firm-level fixed effects, that to some degree capture the status of a firm as heavy energy user. Furthermore, our detailed dataset permits us to include the energy-mix via the share of natural gas, oil, coal, biofuels in total energy use (with electricity as base). Additionally, we merged data indicating if a plants installation of a firm was registered under the emission trading system of the EU (D^{ETS}).

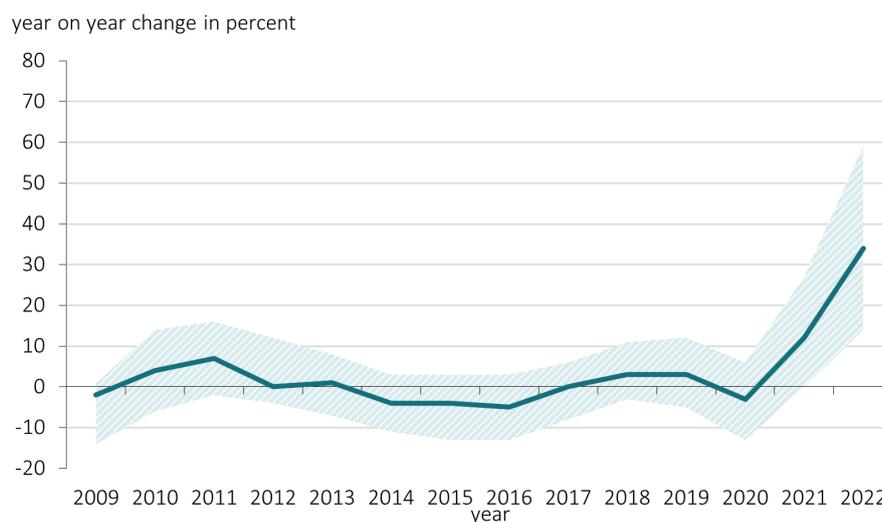
Firm level data are very noisy. As a consequence data cleaning and checking procedures outlined in Appendix A.3 have been applied to the raw data provided by Statistics Austria. In the final data on which the reported results are based 73.4% of all observations are from the manufacturing sector (NACE 10-32). The sectors with the highest number of observations (cf. number of firms for year 2022 in Table 2) are machinery and equipment (NACE 28 - 11.3%), the food industry (NACE 10 - 9.3%) and fabricated metal products (NACE 25 - 9%). Energy intense sectors account for 31% of all observations in the data according to the classification based on median energy intensity and 19.8% following the narrow definition. After data cleaning the panel of firms consists of 1576 firms and 14 periods.⁶ The panel is unbalanced. For 60.7% of firms observations for all periods are available. For another 7.24% of firms observations are complete for 13 periods. For all other firms in the panel the complete set of indicators is available for at least 10 periods of the 14 years covering our sample. Around 6.3% of firms lie on this lower bound imposed by our data cleaning procedures.

⁶The raw data set counts a total of more than 2700 units. The trimmed data set (see Appendix A.3) would count approx. 1100 units.

5 Results

To frame the results discussed in this section, it is worth noting that the energy transition will, on one hand, require substantially higher energy consumption—particularly in the energy-intensive sectors highlighted earlier. On the other hand, the surge in energy costs during the 2022 energy crisis was dramatic. As shown in Figure 1, even in 2021—when energy prices, especially for natural gas, began to climb—average year-on-year energy cost increases in energy-intensive sectors reached 25% (21% median), with the top percentile experiencing spikes of up to 82%. In 2022, prices escalated sharply, leading to even more pronounced cost pressures, as documented by Reinstaller and Sellner (2024, 2025). These developments underscore the critical importance of improving energy efficiency—not only to meet EU and national energy-saving targets but also to cushion short-term price shocks driven by recent geopolitical events.

Figure 1: Development of energy costs over time in energy-intensive manufacturing sectors, 2008-2022.



Note: Data Statistics Austria, AMDC. Own calculations. See Table 2 for the definition of energy intense manufacturing sectors (narrow definition).

Our starting point for the evaluation of the adjustment mechanisms and potential of Austrian firms is the stochastic frontier analysis outlined in Section 3. The results for both the Translog and Cobb–Douglas specifications are presented in Table 3. Because the regression output of the Translog model is difficult to interpret directly, we report only the estimated elasticities for the different explanatory variables, obtained from the linear combination of all interaction terms involving each variable evaluated at the mean log levels of the variables. Columns display the elasticities, while rows indicate the classifications and sectoral subgroups for which the models were estimated. The upper panel of the table shows results from the Translog specification; the lower panel presents results from the Cobb–Douglas model, based on an identical structure.

All models yield coefficients with the expected sign and high statistical significance. We observe violations of concavity requirements in the Translog models especially in the estimation of the energy cost function of firms with low energy intensity (12.02% of observations) as well as for firms in the construction sector (12.14% of observations). The number of concavity violations falls significantly if the year 2022 is dropped from the panel (to zero and 0.56% respectively). This indicates that the increases in volatility in energy prices for the year 2022 are the principal cause for the observed concavity violations. Since the results for the full and shortened panels are largely consistent, we report the findings based on the full panel. Concavity violations are particularly high in sectors with a high heterogeneity of firms as is the case in firm in sectors with low energy intensity and construction. In more homogenous groupings the number drops to below 1%.

The elasticity of energy costs with respect to the normalized firm-level end energy price, output, and

quasi-fixed inputs capital and labor are all positive. For the Translog model, the normalized price elasticities range between 0.73 and 0.77 for industry groups in the median energy intensity classification.⁷ The elasticities estimated from the Cobb-Douglas regressions differ only slightly, highlighting a remarkable consistency between the two models. For the construction sector, price elasticities are lower than in other sectors. The elasticity for the energy intense sector according to the narrow definition takes on a slightly lower value than for energy intense sectors based on median energy intensity. The difference is largely driven by firms in the food, beverage, and textile industries, which are excluded from the narrow definition. For the shortened panel excluding 2022 observations, this discrepancy is similar with overall lower elasticities: 0.627 for sectors classified by median energy intensity versus 0.584 for energy-intensive sectors according to the narrow definition.

The elasticity of energy costs with respect to output varies significantly across sector groups. It tends to be higher in energy-intensive sectors and lower in sectors with intermediate or low energy intensity and in construction. In energy-intensive sectors, a 1% increase in output corresponds to an energy cost increase of nearly 0.5%. This may reflect differences in production technologies – e.g., continuous process technologies are more common in energy-intensive sectors, while discrete processes and inventory use are more prevalent in less energy-intensive sectors. When the panel is shortened to exclude the energy crisis year 2022, the elasticities are 0.498 and 0.449, respectively.

The production factors labor and capital are treated as quasi-fixed inputs, implying that energy costs should respond only weakly to changes in these factors due to adjustment costs. The empirical results are consistent with this assumption. Energy costs are inelastic with respect to both production factors, with elasticities that are consistently higher for labor than for capital. The elasticities of energy costs with respect to labor input (measured as hours worked) are positive and statistically significant across all specifications. In contrast, the estimated coefficients for capital are statistically significant in four out of five specifications using the Translog cost function, and only weakly significant in one specification based on the Cobb–Douglas cost function. This is expected, given the known limitations in the construction of firm-level capital stock measures (see Section A.2 in the Appendix). At the same time, it suggests that the Translog cost function captures underlying heterogeneity in the data more effectively than the Cobb–Douglas specification.

The coefficients for the linear combination of the time-trend components in the Translog specification are statistically significant in four out of five cases and exhibit the expected negative sign. This indicates that continuous technical improvements have a statistically significant albeit economically small cost-reducing effect on energy expenses over time. We rely on results from the Translog specification for the discussion of results in the remainder of this section.

⁷By construction, the coefficients reflect the elasticity of relative energy costs with respect to a relative price (energy prices relative to prices of intermediate consumption). It corresponds to the partial elasticity of energy cost with respect to the energy price.

Table 3: Stochastic frontier regression results

Energy Cost (dependent variable)													
Cost function: Translog													
	p_e		y		L		K		t		N	concavity violation	no efficiency estimate
Energy intensity: Low	0,768	***	0,213	***	0,399	***	-0.018		0.002		7522	904	0
Energy intensity: Medium	0,759	***	0,316	***	0,426	***	0,139	***	-0,004	**	6842	2	0
Energy intensity: High	0,727	***	0,498	***	0,229	***	0,061	*	-0,005	***	7438	46	0
Energy intense sectors (narrow def.)	0,688	***	0,456	***	0,244	***	0,063	*	-0,006	**	4779	40	0
Construction	0,462	***	0,283	***	0,481	***	0,374	***	-0.004	***	4227	513	6
Energy Cost (dependent variable)													
Cost function: Cobb-Douglas													
	p_e		y		L		K		t	t2	N	concavity violation	no efficiency estimate
Energy intensity: Low	0,774	***	0,209	***	0,435	***	-0,026		0,017	-0,002	7522	na	0
Energy intensity: Medium	0,747	***	0,297	*	0,453	**	0,127		0,014	* -0,002	6842	na	0
Energy intensity: High	0,748	***	0,508	***	0,234	***	0,055		0,003	-0,001	7438	na	0
Energy intense sectors (narrow def.)	0,696	***	0,478	***	0,257	***	0,056		0,001	-0,001	*** 4779	na	0
Construction	0,451	***	0,305	***	0,420	***	0,330	*	0,021	** -0,003	4227	na	6

** p<0.01, *** p<0.001

Note: Data Statistics Austria, AMDC. Own calculations. Clustered standard errors at firm level. The columns “concavity violation” and “no efficiency estimate” indicate the number of observations in the sample where we found a violation of concavity in the Translog estimations and the number of observations where it was not possible to obtain an efficiency estimate. The results for the Translog function represent a linear combination of the coefficients obtained for the variable and all related interaction terms and their joint significance.

As outlined in Section 3.1, we recover cost inefficiency terms from the SFA and convert them into efficiency measures to assess energy saving potentials. Figure 2 shows these energy efficiency factors by year and by NACE 2-digit sectors, as well as related sectoral aggregates. Because the distribution of these efficiency terms is exponential by construction, we observe fewer inefficient firms and more firms with intermediate or high efficiency. However, our focus is not on the absolute levels of efficiency but rather on relative positions, which are generally consistent across models with different assumptions about the distribution of inefficiencies. Closer inspection reveals that firms in energy-intensive sectors tend to have higher average efficiency scores which is primarily driven by better performance values in the lower tail of the distribution. This implies that there are fewer inefficient firms in energy-intensive sectors—a plausible finding given the larger share of energy costs in total costs and the stronger incentives for efficiency improvements. This applies also for firms with plants in the ETS. The development of the efficiency distribution over time in turn shows that in the last years covered by the sample overall efficiency has diminished across firms and variation has increased. This is likely related to energy price induced improvements in allocative efficiency, as the decomposition in the following paragraphs suggests.

Table 4 presents the decomposition of changes in energy intensity, as described in Section 3.2. The first column (EIG data) shows the average energy intensity gains (EIG) measured directly from the data, while the second column (EIG predicted) reports the model-predicted values. The difference between the two reflects model error or noise. The predicted EIG values are decomposed into the components described in Section 3.2 allocative efficiency changes (AEC), scale efficiency changes (SEC), quasi-fixed input changes (OIC), technical change (TC), and energy efficiency changes (EEFC), as estimated from the SFA. Positive values indicate a contribution to reduced energy intensity; negative values indicate the opposite. In the upper part the table shows averages of the annual contribution of each of these components over the periods 2009–2020 and 2009–2022 to explicitly account for the potential effect of the energy crisis in 2021 and 2022. The lower part of the table in turn shows the cumulative contributions of each of the components again over the two time periods. This allows us to assess the contribution of energy efficiency improvements to changes in energy intensity over time. We report results both by sector class and by firm size, as well as for firms participating in the EU Emissions Trading System (EU-ETS).

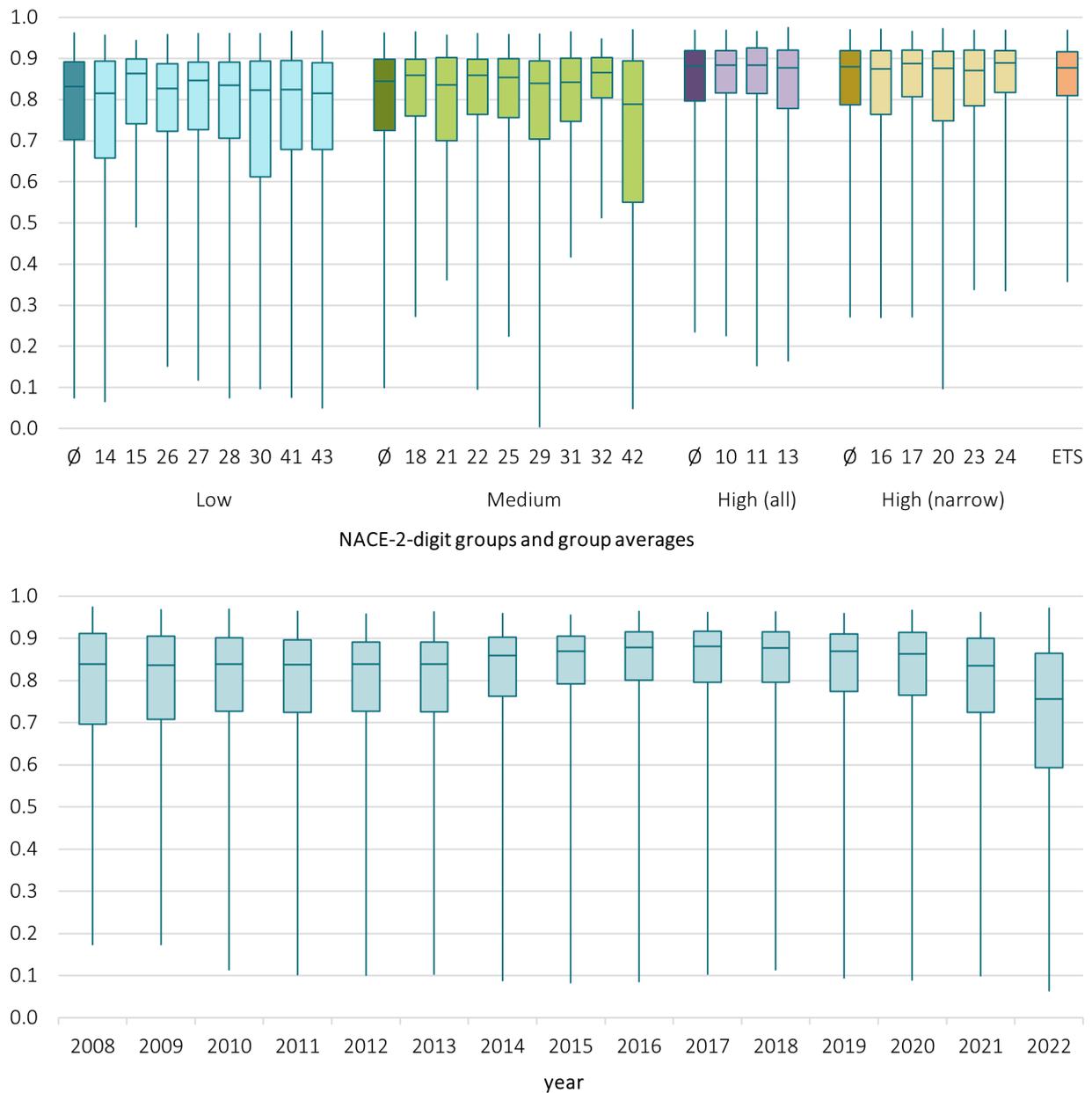
Between 2009 and 2022, energy intensity improved cumulatively by 4.8% across all firms, corresponding to an average annual rate of 0.35% (0.25% for 2009–2020). Developments varied markedly across firm groups: large and energy-intensive firms and those with ETS installations achieved faster improvements, while SMEs and low-intensity sectors lagged behind. The construction sector experienced a sharp deterioration of –27% over the period 2009–2022 and still –8.5% for the subperiod 2009–2020.

Scale effects (SEC) were the dominant driver of improvements in energy intensity. Their contribution averaged 1.19% per year (0.85% for 2009–2020) across all firms, yielding a cumulative effect of 16.7% (10.2% for 2009–2020). These effects were strongest in large firms. They indicate that higher output levels reduce energy intensity through more efficient utilisation of energy, though absolute consumption increases as a result.

Technological change (TC) provided the second-largest contribution to energy efficiency gains in 2009–2022, with an average annual effect of 0.23% and a cumulative improvement of about 3.2%, though contributions before 2020 were only marginally positive. Contributions varied by sector, ranging from negative in low-intensity industries to over 6% in energy-intensive industries and more than 8% in ETS firms.

Energy-efficiency improvements (EEFC) contributed more than TC before 2020 (0.1% per year; cumulative 1.2%), particularly in large and ETS firms. This pattern reversed during the energy crisis, when EEFC turned strongly negative and allocation efficiency (AEC) became positive. A change in energy efficiency due to energy-

Figure 2: Energy efficiency distributions by NACE-2-digit groups and year.



Note: Data Statistics Austria, AMDC. Own calculations. Top: By Nace 2-digit-sector. Bottom: By year, 2008–2022. The averages shows the distribution of the sector groupings in Table 2.

Table 4: Energy intensity gain (EIG) decompositions

Average annual rate of change in percent (2009–2020)							
	EIG		AEC	SEC	OIC	TC	EFFC
	measured	expected					
All firms	0,25	0,22	-0,27	0,85	-0,53	0,07	0,10
Energy intensity: Low	-0,30	-0,16	-0,21	0,88	-0,65	-0,36	0,18
Energy intensity: Medium	0,34	0,16	-0,21	0,93	-0,73	0,20	-0,03
Energy intensity: High	0,70	0,64	-0,37	0,74	-0,23	0,37	0,13
Firm size: Medium	-0,07	-0,04	-0,30	0,83	-0,43	-0,02	-0,12
Firm size: Large	1,02	0,86	-0,19	0,94	-0,79	0,27	0,62
Energy intense sectors (narrow definition)	0,87	0,98	-0,43	0,87	-0,11	0,46	0,19
Firms with plants in ETS	0,32	0,46	-0,33	0,61	-0,44	0,17	0,45
Construction	-0,71	-0,33	-0,08	0,69	-1,23	0,09	0,20
Average annual rate of change in percent (2009–2022)							
	EIG		AEC	SEC	OIC	TC	EFFC
	measured	expected					
All firms	0,35	0,17	0,21	1,19	-0,55	0,23	-0,91
Energy intensity: Low	-0,05	0,00	0,08	1,46	-0,64	-1,85	-0,70
Energy intensity: Medium	0,22	-0,09	0,15	1,23	-0,80	0,40	-1,07
Energy intensity: High	0,83	0,54	0,41	0,88	-0,23	0,48	-0,99
Firm size: Medium	0,03	-0,05	0,20	1,12	-0,41	0,14	-1,10
Firm size: Large	1,09	0,71	0,26	1,39	-0,88	0,43	-0,48
Energy intense sectors (narrow definition)	0,93	0,74	0,49	1,01	-0,17	0,59	-1,18
Firms with plants in ETS	0,92	0,75	0,39	1,14	-0,42	0,30	-0,66
Construction	-1,93	-0,75	-0,10	0,66	-1,31	0,39	-0,38
Cumulated average annual rate of change in percent (2009–2020)							
	EIG		AEC	SEC	OIC	TC	EFFC
	measured	expected					
All firms	3,02	2,65	-3,21	10,22	-6,39	0,79	1,24
Energy intensity: : Low	-3,60	-1,91	-2,57	10,62	-7,80	-4,35	2,20
Energy intensity: Medium	4,05	1,86	-2,48	11,21	-8,80	2,34	-0,40
Energy intensity: High	8,44	7,68	-4,49	8,84	-2,75	4,46	1,61
Firm size: Medium	-0,82	-0,44	-3,58	9,99	-5,14	-0,25	-1,46
Firm size: Large	12,25	10,21	-2,24	11,33	-9,52	3,22	7,41
Energy intense sectors (narrow definition)	10,48	11,77	-5,13	10,45	-1,33	5,46	2,31
Firms with plants in ETS	3,88	5,49	-3,92	7,30	-5,55	2,08	5,35
Construction	-8,48	-3,97	-0,92	8,27	-14,82	1,06	2,44
Cumulated average annual rate of change in percent (2009–2022)							
	EIG		AEC	SEC	OIC	TC	EFFC
	measured	expected					
All firms	4,84	2,37	2,99	16,71	-7,73	3,19	-12,79
Energy intensity: Low	-0,73	0,03	1,09	20,41	-9,02	-2,59	-9,98
Energy intensity: Medium	3,08	-1,20	2,06	17,29	-11,16	5,64	-15,01
Energy intensity: High	11,63	7,59	5,77	12,33	-3,27	6,70	-13,94
Firm size: Medium	0,40	-0,73	2,79	15,71	-5,73	1,97	-15,46
Firm size: Large	15,26	9,93	3,60	19,40	-12,35	5,99	-6,69
Energy intense sectors (narrow definition)	13,07	10,40	6,91	14,08	-2,34	8,28	-16,55
Firms with plants in ETS	12,92	10,45	5,42	15,96	-5,90	4,16	-9,19
Construction	-27,07	-10,44	-1,36	9,20	-18,36	5,45	-5,38

Note: Data Statistics Austria, AMDC. Own calculations. Averages over all years.

cost subsidies appears unlikely in 2022. Applications for these subsidies could only be submitted toward the end of 2022, and payments were made only after final energy bills became available. Thus, no behavioural adjustment in 2022 can be attributed to potential subsidies—especially given that high energy prices already provided strong incentives for efficiency improvements.

Factor input changes (OIC) contributed negatively for most of the period, reflecting increased capital intensity rather than changes in factor quality. This negative effect nearly disappeared in 2022. The results therefore mainly reflect the effects of changes in capital intensity on energy intensity. Historically, the development of energy costs (relative to European competitors) appears to have favoured investment in more energy-intensive technologies. A telling indication is that the persistently negative contribution of factor OIC nearly vanished in 2022.

AEC exhibited persistent inefficiencies: it was negative until 2020, then strongly positive from 2021 as rising energy prices created stronger incentives for energy-intensity reductions. The development of the contribution of allocation efficiency (AEC) to energy intensity reflects the sluggish adjustment of energy consumption to energy price changes at the firm level. This component displays a markedly different pattern before and during the energy crisis (Table 4, 3rd data column). Until 2020, this factor had a consistently negative effect on energy intensity, whereas from 2021 onward it contributed so strongly and positively that it more than offset the negative effects of previous years. Until 2020, comparatively low energy prices likely provided weak incentives for firms to improve their energy intensity. Only with the sharp rise in energy prices beginning in mid-2021 did firms face a strong incentive to reduce energy intensity. As the factor never approaches zero, this points to existing inefficiencies. Possible explanations include limited substitution possibilities between different energy carriers or institutional features of energy pricing and supply contracts.

Overall, our findings align with Adetutu et al. (2020) for the UK (2002–2006), although our estimated contributions – especially from scale efficiency – are lower. The key takeaway is that energy intensity gains in Austrian manufacturing and construction were not driven by energy efficiency improvements. Instead, gains are primarily attributable to scale efficiency and technical change. Hence, firms need high levels of economic activity to reduce their energy intensity – a point with important implications discussed in the concluding section. Across firm groups, large firms and those in energy-intensive sectors achieved the largest reductions in energy intensity, whereas construction and low-intensity sectors saw deteriorations, though they account for a small share of total energy use. Firms with ETS installations reduced energy intensity significantly more than others, driven mainly by technological progress and efficiency gains, underscoring the importance of the EU ETS.

To assess the energy savings attainable under current technologies and practices, we conducted a counterfactual scenario analysis following the approach outlined in Section 3.3. We develop several savings scenarios illustrating the extent to which energy-efficiency measures could help mitigate high energy costs and contribute to national energy-saving targets in the business sector. The results reflect one-off energy-saving potentials under the following assumptions. The first scenario in line with Boyd and Lee (2019) assumes measures enabling firms in the bottom quartile of the efficiency distribution to reach the efficiency level of the median firm within their sector aggregate observed in the year 2022. The second scenario captures a more ambitious case where a measure allows all firms operating below their sector aggregate's median efficiency to move to their sector aggregate's median in 2022.

Table 5 reports actual and counterfactual energy use, net energy savings, and the savings share, disaggregated by sector class, firm size, and ETS participation. Considering the energy efficiency distributions shown in Figure 2 the scenarios do not lead to very different results. In Scenario 1 we estimate an average energy saving potential of 11.7% across all firms, corresponding to 42.6 PJ. The results for Scenario 2 yield savings

Table 5: Counterfactual energy savings, by sector/firm type.

	Scenario 1				Scenario 2		
	Energy use ø 2021/2022 in 1000 GJ	estimated use in 1.000 GJ	difference in 1.000 GJ in %		estimated use in 1.000 GJ	difference in 1.000 GJ in %	
All firms	364 988	322 387	-42 600	-11,7	316 860,1	-48 127,8	-13,2
Energy intensity: Low	17 579	16 382	-1 197	-6,8	16 104,4	-1 474,7	-8,4
Energy intensity: Medium	23 149	20 739	-2 410	-10,4	20 238,2	-2 911,0	-12,5
Energy intensity: High	324 260	285 266	-38 993	-12,0	280 517,5	-43 742,1	-13,5
Firm size: Medium	51 258	43 623	-7 635	-14,8	42 646,6	-8 611,5	-16,8
Firm size: Large	313 730	278 764	-34 966	-11,2	274 213,5	-39 516,3	-12,6
Energy intense sectors (narrow def.)	301 229	267 846	-33 383	-11	262 940,0	-38 289,0	-12,7
Firms with plants in ETS	152 542	145 516	-7 026	-4,6	143 794,1	-8 747,6	-5,8
Construction	9 095	8 511	-584	-6,0	8 460,0	-634,9	-6,6

Note: Data Statistics Austria, AMDC. Own calculations. Calculations show potential one-off saving for efficiency distribution in 2021.

of 13.2% or 48.1 PJ across firms. The difference between these two scenarios would correspond the moving only the firms in the second quartile to median firm efficiency. In this case the energy saving potential would correspond to 5.5 PJ. This can be considered as being the minimum-effort scenario, whereas Scenarios 1 and 2 still imply more involved policy approaches. The results show some variation across sector groups. In absolute terms energy savings are clearly highest for large and energy intense firms for both classifications considered in this paper. Interestingly, ETS-participating firms show only a 4.6% (Scenario 2: 5.8%) savings potential, reflecting a higher efficiency and lower variance than in most other sector groups. This supports the view – also supported by the results in Adetutu et al. (2020) – that carbon pricing provides incentives to enhance energy efficiency. Overall the results are comparable to Boyd and Lee (2019), who estimate a 21.4% savings potential in the U.S. metal-based durable goods sector.

Table 6: Estimations to obtain the rebound effects by sector groups.

Energy demand (dependent variable)										
	TE		p_e		γ		constant		FE	N
Energy intensity: Low	-1,119	***	-0,437	***	0,402	***	-0,971	***	y	7522
Energy intensity: Medium	-1,091	***	-0,472	***	0,538	***	-1,600		y	6842
Energy intensity: High	-1,011	***	-0,566	***	0,612	***	-0,996	***	y	7438
Energy intense sectors (narrow definition)	-1,067	***	-0,629	***	0,531	***	0.304		y	4779
Construction	-1,983	***	-0,747	***	0,509	***	-1,067	*	y	4227
Production value (dependent variable)										
	TE		Energy use				constant			N
Energy intensity: Low	0,776	***	0,682	***			9,277	***	y	7522
Energy intensity: Medium	0,875	***	0,791	***			8,370	***	y	6842
Energy intensity: High	0,619	***	0,568	***			8,491	***	y	7438
Energy intense sectors (narrow definition)	0,478	**	0,438	***			8,952	***	y	4779
Construction	0,556	***	0,277	***			9,716	***	y	4227

** p<0.01, *** p<0.001

Note: Data Statistics Austria, AMDC. Own calculations. Dependent and independent variables in logs. Clustered standard errors at firm level. FE: firm-time fixed effects.

To obtain realistic estimates of potential energy savings, it is essential to account for rebound effects. As outlined in Section 3.4, calculating these effects requires three key elasticities: (i) energy demand with respect to efficiency, (ii) energy demand with respect to output, and (iii) output with respect to efficiency

improvements, controlling for energy demand. Table 6 presents the results from the fixed-effects regressions specified in equations 19. Results show that energy demand is elastic to energy efficiency improvements across sectors. A 1% improvement in energy efficiency in turn increases output by 0.56% in construction and up to 0.87% in medium-intensity industries. Estimated rebound effects range from 14.8% in construction to 43.1% in medium-intensity sectors, and around 23.8% in highly energy-intensive industries (see Table 7). These values lie between the low effects estimated for Germany by Berner et al. (2022) and the higher effects found for Sweden by Amjadi et al. (2018) for Sweden.⁸

Table 7: Estimated rebound effects by sector groups.

Sector/classification	Rebound effect Percent
Energy intensity: Low	27,84
Energy intensity: Medium	43,14
Energy intensity: High	37,48
Energy intense sectors (narrow definition)	23,76
Construction	14,76

Note: Data Statistics Austria, AMDC. Own calculations.

Combining the results from the counterfactual energy saving scenarios shows that rebound effects would reduce net savings to 8.4–9.7%, equivalent to 12.3–14.2% of the final energy consumption reduction mandated by the Austrian Energy Efficiency Act (EEffG) by 2030.

6 Conclusions and policy implications

This paper has examined how changes in energy intensity at the firm level in Austria’s manufacturing and construction sectors from 2008 to 2022 relate to underlying improvements in energy efficiency. We aimed to disentangle genuine efficiency gains from other structural and behavioral drivers of energy use, such as changes in scale, technology, or input substitution. In doing so, we also assessed the untapped potential for energy savings across firms with heterogeneous performance, while accounting for the moderating effect of rebound behavior.

Our empirical results yield several important insights. First, using stochastic frontier analysis and a decomposition of energy intensity gains at the firm level, we find that improvements in energy intensity over the past decade were primarily driven by scale efficiency gains and technical change – not by improvements in energy efficiency proper. In fact, energy efficiency appears to have declined in the latter years of the sample, particularly in non-ETS and less energy-intensive firms. Second, our counterfactual scenario analysis of potential energy savings suggests that if the least efficient firms adopted the practices of median-efficiency firms, an average one-off energy saving between 11.7 and 13.2% could be achieved. After accounting for rebound effects, net savings the net potential savings would amount to between 25 and 29 PJs. This corresponds to between 12.3 to 14.2% respectively of the reduction of final energy consumption mandated by the Austrian Energy Efficiency Act (EEffG). Third, our analysis of rebound effects shows that they are non-trivial but do not eliminate gains. They range ranging from 14.8% in construction to over 43.1% in industries with medium energy intensity. For energy-intensive sectors, the rebound effect ranges between 23.8% and 37.7% depending on the sector definition. These results are broadly in line with patterns found in previous studies.

These findings confirm and extend insights from the existing literature. Similar to Adetutu et al. (2020), we

⁸However, these calculations are not strictly comparable due to difference in methodology.

find that energy efficiency contributes less to energy intensity reductions than scale efficiency and technical change. Our decomposition framework underscores the role of production scale and technological progress as primary levers for reducing energy use per unit of output. Moreover, consistent with earlier work by Amjadi et al. (2018), we observe that rebound effects – although not negligible – do not fully offset the potential savings from energy efficiency improvements. While not explicitly estimating rebound effects for firms participating in the EU ETS we find that they tend to be more efficient and show lower energy saving potentials, lending further empirical support to the hypothesis that carbon pricing and emissions trading schemes create incentives for sustained efficiency improvements.

From a policy perspective, several conclusions can be drawn. First, the evidence clearly suggests that Austria's manufacturing and construction sectors still possess considerable potential for energy efficiency gains – especially among lagging firms in energy intense sectors. However, realising this potential requires targeted support, including better access to information, improved financing options to address liquidity constraints, and mechanisms to overcome behavioral and organizational inertia. Second, because scale efficiency and technical change and not energy efficiency improvements have driven most changes in energy intensity, policy frameworks should support long-term investment in innovation and productive capacity. Measures that enhance firm competitiveness may, indirectly, be more effective in lowering energy intensity than narrowly defined efficiency programs.

Third, rebound effects must be considered in any realistic energy efficiency policy. While they do not negate the value of efficiency improvements, they reduce net savings and must be accounted for in impact assessments. Carbon pricing can provide incentives for efficient energy use by firms during rebounds periods.

Finally, our results highlight an important strategic consideration: if the path to net-zero requires substantial increases in energy use in energy-intensive manufacturing sectors – as projected – then the burden of reducing energy consumption must also be shared by other sectors such as transport, buildings, and residential consumption. Energy efficiency improvement need to be part of a broader, economy-wide strategy to balance increased clean energy demand with system-wide reductions in wasteful use.

An important shortcoming of this analysis is its partial equilibrium character. We do not consider spillovers or indirect effects as well as adjustments or interactions between firms. However, the study presents the most accurate estimates of potential energy savings using firm-level data for Austria to date. This evidence may inform future work using more aggregate, general equilibrium models.

7 Declarations

This research project was conducted with data from the Austrian Micro Data Center (AMDC). The AMDC is a research data infrastructure facility of Statistics Austria that enables research on micro data processed in compliance with data protection regulations (Fuchs et al., 2024).

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Appendix

A Data Appendix

A.1 Energy expenditures and prices

The material input statistics (MIS) records whether the plant uses the production input as an energy source (i.e. for heating or power generation) or otherwise. Since we are interested in energy consumption we only retained material inputs used for energy generation. Since the MIS surveys plants, but we match based on legal entities ids, the MIS may contain duplicate entries regarding the usage of a specific energy source in a given year. We treat exact quantity and value for a specific energy source usage and given year reported by two plants within one legal entity as double reporting (i.e. the plant reported a single energy usage for the whole legal entity) and removed full duplicates. The same procedure was applied to partial duplicates, where either the reported quantity or (non-zero) value was identical for the same legal entity and year.

As a next step, we converted the recorded units (either tons, 1000 m³ or MWh) of 37 different energy sources used to the net calorific values in Gigajoule (GJ), using the conversion factors from the Austrian energy accounts of Statistics Austria. Energy values reported in the tables correspond to 1000 GJ or 1 TJ.⁹

We then calculated unit values by dividing the values in euro by the quantity in GJ. These unit values are zero for own energy production from renewable sources. As our stochastic frontier cost function approach cannot handle zero energy costs, we interpolated the unit values for these energy sources by related market-priced energy sources. For own electricity production (heating pumps, photovoltaic, wind, water, geothermal) interpolated the unit values with median unit values of purchased electricity of firms with a similar energy demand. This is important, as the data clearly show lower unit values for firms with larger energy demand, hinting at quantity discounts and bargaining power. For the energy sources of waste and biogas we employed a similar procedure using purchased biofuels with the same recorded unit (i.e. tons for waste and 1000 m³ for biogas). Using the interpolated unit values we calculated the interpolated or market-price based energy costs for firms with own energy-production.

Finally, the values and quantities were aggregated to total energy costs and five broad categories used in International Energy Agency (2023): 1) electricity, 2) natural gas, 3) oil products, 4) coal and coal products and 5) biofuels. After this aggregation the unit values were recomputed.

A.2 Capital stock for the structural business statistics

We cannot approximate the capital stock via total fixed assets, since we do not have access to firm level balance sheet data. Therefore, we compute the real net capital stock for Austrian firms from their investments (taken from the SBS) via the perpetual inventory method (PIM).¹⁰ The law of motion of the capital stock is given by

$$K_{t,i,s} = K_{t-1,i,s}(1 - \delta_s) + I_{t,i,s}, \quad (20)$$

whereas $K_{t,i,s}$ is the real net capital stock, δ_s is the geometric depreciation rate and $I_{t,i,s}$ is real gross fixed capital formation of firm i in industry s and in year t .

The productive net capital stock at the end of the period $t = 1$ can be written as the accumulated depreciated investments of the previous periods

⁹Available online here <https://www.statistik.at/fileadmin/pages/99/AustriaDatenPublikation.ods>.

¹⁰(See for example Appendix B in Lutz, 2016).

$$K_{t=1,i,s} = I_{t=0,i,s} + I_{t=-1,i,s}(1 - \delta_s) + I_{t=-2,i,s}(1 - \delta_s)^2 + \dots = \sum_{n=0}^{\infty} I_{t=-n,i,s}(1 - \delta_s)^n. \quad (21)$$

Assuming real investments in industry s grow at an annual rate of g_s we have

$$K_{1,i,s} = I_{0,i,s} \sum_{n=0}^{\infty} \left[\frac{(1 - \delta_s)}{(1 + g_s)} \right]^n = I_{0,i,s} \frac{(1 - g_s)}{(g_s + \delta_s)}. \quad (22)$$

So the real net capital stock at the beginning of the initial period $t = 1$ is given by

$$K_{1,i,s} = \frac{I_{1,i,s}}{(g_s + \delta_s)}. \quad (23)$$

However, utilizing just the first observed investment for estimating the initial capital stock may lead to severely biased estimates, since investments at the firm level can be lumpy and very volatile. We thus follow Lutz (2016) and use the average investment calculated as

$$\hat{I}_{1,i,s} = \frac{\sum_{t=0}^n \frac{I_{t+1,i,s}}{(1+r)^t}}{n}. \quad (24)$$

For discounting we use the composite (short and long run) lending rate for non-financial corporations for Austria from the ECBs Statistical Data Warehouse. The geometric average (1995-2022) annual real capital stock growth rate g_s is estimated from the real net capital stock data from annual national accounts at the 64 2-digit NACE 2008 industry level from Eurostat (*nama10nfa_s,t*). As a depreciation rate we use the average geometric rate by industry. Statistics Austria derives the industry level capital stock assuming that investments are evenly distributed within the year, according to the following formula (see Huber, 2015, page 479)

$$K_{t,s} = K_{t-1,s}(1 - \delta_s) + I_{t,s}(1 - \delta_s)^{0.5}, \quad (25)$$

which we solve for the depreciation rate

$$\delta_s = \frac{-2K_{t,s}K_{t-1,s} + 2K_{t-1,s}^2 - I_{t,s}^2 + I_{t,s}(4K_{t,s}K_{t-1,s} + I_{t,s}^2)^{0.5}}{2K_{t-1,s}^2}. \quad (26)$$

Industry data on gross fixed capital flows ($I_{t,s}$) are again taken from Eurostat (*nama10nfa_fl*). We take the median depreciation rate for each industry over the period 1995-2021.

Applying the PIM, the capital stock in earlier periods of the sample is strongly driven by the initial estimate. Ideally, one would apply the method to a long time series and drop the first 10-20 years to mitigate the bias. Unfortunately, our data covers the years 2008 to 2022, i.e. 15 years at max, which renders such a procedure infeasible. However, to mitigate the problem to some extent, we restrict our sample to firms that are at least 10 years in the sample and have non-zero investments at least half the time. Since the PIM requires balanced yearly data, we applied linear interpolation to data for firms with missing periods, dropping firms with more than one year missing between their first and last reported year.

A.3 Data cleaning

Since firm level data can be very noisy and we cannot rule out data errors, we carried out a number of plausibility checks and data cleaning steps prior to the econometric analysis. We have therefore explored several data cleaning approaches. In a first approach we purged the data set of extreme and unplausible values.

In line with Haller and Hyland (2014), we removed firms that show a capital-to-output ratio larger than 7 at any year. The ratio was computed using the real net capital stock derived from the PIM and the sales deflated by industry output prices. In a next step, we cleaned firms that show very high annual growth or steep declines in our main variables in one or more years. In some cases a steep decline is followed by a strong increase, or vice versa, hinting at a recording error (wrong digit position). We inspected the distribution of growth rates and set 250% as maximum and -80% as minimum growth. This rule was then applied to real production value, total energy costs, non-energy materials input and the quasi-fixed inputs labour and capital stock. We further removed firms that in some year have a cost-over-sales ratio of more than 2, cost share of labour of more than 99% or below 0.1%, a cost share of energy of more than 60% or an cost share of energy of more than 99%. We then removed firms with very large or small energy prices. Specifically, we dropped firms from the sample with a unit values of total energy consumption smaller than the first or larger than the 99th percentile of the distribution in one year.

While being rigorous this data cleaning approach leads to the loss of a large number of firms (approx. 400 accounting for approx. 5300 observations of 25000 for the untrimmed sample). In addition, it also leads to the exclusion of a number of large energy consumers in the sample. We therefore adopted a winsorising approach where instead of dropping observations with extreme values we replaced them with the value observed either at the 1% or the 99% quantile of the distribution of a variable in each year depending on whether outliers were on the lower or upper end of the distribution. This allows us to keep the firms that would be dropped due to trimming in the sample. Independently of the data cleaning approach, we kept only firms with at least 10 observations in the 14 years covering our sample in order to be able to best exploit the panel structure of the data. In this way about 500 firms drop out of the sample.

An assessment of the various data sets shows that independently of the cleaning approach chosen the results of the SFA are very consistent for the energy intense industry groupings, as well as the industry group with low energy intensity and the construction sector. The data cleaning has the strongest impact on the industry group with intermediate energy intensity where consistent, stable and robust estimates across regression models are obtained only for the winsorised data. We therefore have opted to use and report results for the winsorised data set.

B Technical Appendix: Translog Cost Function Elasticities with Normalized Prices

We use a Translog energy cost function with two variable inputs (energy and materials) and two quasi-fixed inputs (capital and labor). Let:

- p_{it}^e : price of energy
- p_{it}^m : price of materials
- y_{it} : output
- K_{it} : capital (quasi-fixed)
- L_{it} : labor (quasi-fixed)
- t : time

We normalize all costs and prices by the material input price p_{it}^m to ensure linear homogeneity of the cost function in prices by construction. Define:

$$\tilde{C}_{it} = \frac{C_{it}}{p_{it}^m}, \quad \tilde{p}_{it}^e = \frac{p_{it}^e}{p_{it}^m}$$

The normalized Translog cost function in equation (3) then reads:

$$\begin{aligned} \ln \tilde{C}_{it} = & \alpha_i + \alpha_1 \ln \tilde{p}_{it}^e + \beta_1 \ln y_{it} + \phi_K \ln K_{it} + \phi_L \ln L_{it} + \theta t \\ & + \frac{1}{2} \zeta t^2 + \frac{1}{2} \alpha_{11} (\ln \tilde{p}_{it}^e)^2 + \alpha_y \ln \tilde{p}_{it}^e \ln y + \frac{1}{2} \beta_{11} (\ln y_{it})^2 \\ & + \alpha_K \ln \tilde{p}_{it}^e \ln K_{it} + \alpha_L \ln \tilde{p}_{it}^e \ln L_{it} + \beta_K \ln y_{it} \ln K_{it} + \beta_L \ln y_{it} \ln L_{it} \\ & + \frac{1}{2} \phi_{K1} (\ln K_{it})^2 + \frac{1}{2} \phi_{L1} (\ln L_{it})^2 + \phi_{KL} \ln K_{it} \ln L_{it} \\ & + \theta_K \ln K_{it} \cdot t + \theta_L \ln L_{it} \cdot t + u_{it} + v_{it} \end{aligned}$$

with $\ln \tilde{C}_{it} = \ln C_{it} - \ln p_{it}^m$. From this function the elasticities used in the energy intensity decomposition are then obtained as follows:

- **Normalised Energy Price Elasticity:**

$$\varepsilon_{\tilde{p}_{it}^e} = \frac{\partial \ln C_{it}}{\partial \ln \tilde{p}_{it}^e} = \alpha_1 + \alpha_{11} \ln \tilde{p}_{it}^e + \alpha_y \ln y_{it} + \alpha_K \ln K_{it} + \alpha_L \ln L_{it}$$

- **Output Elasticity:**

$$\varepsilon_{it}^y = \frac{\partial \ln C_{it}}{\partial \ln y_{it}} = \beta_1 + \beta_{11} \ln y_{it} + \alpha_y \ln \tilde{p}_{it}^e + \beta_K \ln K_{it} + \beta_L \ln L_{it}$$

- **Capital Elasticity:**

$$\varepsilon_{it}^K = \frac{\partial \ln C_{it}}{\partial \ln K_{it}} = \phi_K + \phi_{K1} \ln K_{it} + \alpha_K \ln \tilde{p}_{it}^e + \beta_K \ln y_{it} + \phi_{KL} \ln L_{it} + \theta_K \cdot t$$

- **Labor Elasticity:**

$$\varepsilon_{it}^L = \frac{\partial \ln C_{it}}{\partial \ln L_{it}} = \phi_L + \phi_{L1} \ln L_{it} + \alpha_L \ln \tilde{p}_{it}^e + \beta_L \ln y_{it} + \phi_{KL} \ln K_{it} + \theta_L \cdot t$$

- Elasticity with respect to time (embodied and disembodied non-neutral technical change):

$$\epsilon_{it} = \frac{\partial \ln C}{\partial t} = \theta + \theta_K \ln K_{it} + \theta_L \ln L_{it} + \zeta \cdot t$$

where all parameters $\alpha, \beta, \phi, \theta$ are then recovered from the estimation.

C Technical Appendix: Derivation of the energy intensity gain decomposition

Dynamic changes of energy intensity at the firm level

The normalized cost function is given by:

$$\tilde{C}_{it}^e = \tilde{c}(\tilde{p}_{it}^e, y_{it}, K_{it}, L_{it}, t) \cdot \exp(u_{it} + v_{it})$$

where $\tilde{c}(\cdot) = c(p_{it}^e, p_{it}^m, y_{it}, K_{it}, L_{it}, t) / p_{it}^m$ is the cost function normalized by the price of materials p_{it}^m . Taking logs of both sides:

$$\ln \tilde{C}_{it}^e = \ln \tilde{c}(\tilde{p}_{it}^e, y_{it}, K_{it}, L_{it}, t) + u_{it} + v_{it}$$

Following Adetutu et al. (2020) we take the time derivative:

$$\begin{aligned} \frac{d \ln \tilde{C}_{it}^e}{dt} &= \frac{\partial \ln \tilde{c}}{\partial \ln \tilde{p}_{it}^e} \cdot \frac{d \ln \tilde{p}_{it}^e}{dt} + \frac{\partial \ln \tilde{c}}{\partial \ln y_{it}} \cdot \frac{d \ln y_{it}}{dt} + \frac{\partial \ln \tilde{c}}{\partial \ln K_{it}} \cdot \frac{d \ln K_{it}}{dt} + \\ &\quad \frac{\partial \ln \tilde{c}}{\partial \ln L_{it}} \cdot \frac{d \ln L_{it}}{dt} + \frac{\partial \ln \tilde{c}}{\partial t} + \frac{du_{it}}{dt} + \frac{dv_{it}}{dt} \end{aligned}$$

Since:

$$\begin{aligned} \tilde{p}_{it}^e &= \frac{p_{it}^e}{p_{it}^m} \Rightarrow \ln \tilde{p}_{it}^e = \ln p_{it}^e - \ln p_{it}^m \\ \Rightarrow \frac{d \ln \tilde{p}_{it}^e}{dt} &= \frac{d \ln p_{it}^e}{dt} - \frac{d \ln p_{it}^m}{dt} \end{aligned}$$

Define the elasticities:

$$\tilde{\epsilon}_{it}^e = \frac{\partial \ln \tilde{c}}{\partial \ln \tilde{p}_{it}^e}, \quad \epsilon_{it}^y = \frac{\partial \ln \tilde{c}}{\partial \ln y_{it}}, \quad \epsilon_{it}^K = \frac{\partial \ln \tilde{c}}{\partial \ln K_{it}}, \quad \epsilon_{it}^L = \frac{\partial \ln \tilde{c}}{\partial \ln L_{it}}, \quad \epsilon_{it} = \frac{\partial \ln \tilde{c}}{\partial t}$$

Substituting these into the derivative we get:

$$\begin{aligned} \frac{d \ln \tilde{C}_{it}^e}{dt} &= \tilde{\epsilon}_{it}^e \cdot \left(\frac{d \ln p_{it}^e}{dt} - \frac{d \ln p_{it}^m}{dt} \right) + \epsilon_{it}^y \cdot \frac{d \ln y_{it}}{dt} + \epsilon_{it}^K \cdot \frac{d \ln K_{it}}{dt} \\ &\quad + \epsilon_{it}^L \cdot \frac{d \ln L_{it}}{dt} + \epsilon_{it} + \frac{du_{it}}{dt} + \frac{dv_{it}}{dt}. \end{aligned}$$

As approximation to changes between discrete time steps we write:

$$\begin{aligned} \Delta \ln \tilde{C}_{it}^e &= \tilde{\epsilon}_{it}^e \cdot (\Delta \ln p_{it}^e - \Delta \ln p_{it}^m) + \epsilon_{it}^y \cdot \Delta \ln y_{it} + \epsilon_{it}^K \cdot \Delta \ln K_{it} \\ &\quad + \epsilon_{it}^L \cdot \Delta \ln L_{it} + \epsilon_{it} + \Delta u_{it} + \Delta v_{it} \end{aligned}$$

which corresponds to equation (7).

EIG Decomposition

From the definition:

$$e_{it} = \frac{C_{it}^e}{p_{it}^e} \Rightarrow \ln e_{it} = \ln C_{it}^e - \ln p_{it}^e \Rightarrow \Delta \ln e_{it} = \Delta \ln C_{it}^e - \Delta \ln p_{it}^e$$

Since $C_{it}^e = p_{it}^m \cdot \tilde{C}_{it}^e$

$$\ln C_{it}^e = \ln p_{it}^m + \ln \tilde{C}_{it}^e \Rightarrow \Delta \ln C_{it}^e = \Delta \ln p_{it}^m + \Delta \ln \tilde{C}_{it}^e$$

So substituting for $\ln C_{it}^e$ in the definition of $\ln e_{it}$ energy intensity gain is:

$$\text{EIG}_{it} = \Delta \ln y_{it} - \Delta \ln e_{it} = \Delta \ln y_{it} - (\Delta \ln p_{it}^m + \Delta \ln \tilde{C}_{it}^e - \Delta \ln p_{it}^e) = \Delta \ln y_{it} - \Delta \ln \tilde{C}_{it}^e + \Delta \ln \tilde{p}_{it}^e$$

Plugging in the definition of $\Delta \ln \tilde{C}_{it}^e$ from above we finally get:

$$\begin{aligned} \text{EIG}_{it} = \Delta \ln y_{it} - [\tilde{\varepsilon}_{it}^e \cdot (\Delta \ln p_{it}^e - \Delta \ln p_{it}^m) + \varepsilon_{it}^y \cdot \Delta \ln y_{it} + \varepsilon_{it}^K \cdot \Delta \ln K_{it} \\ + \varepsilon_{it}^L \cdot \Delta \ln L_{it} + \epsilon_{it} + \Delta u_{it}] + \Delta \ln \tilde{p}_{it}^e \end{aligned}$$

Group terms:

$$\text{EIG}_{it} = (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e + (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it} - (\varepsilon_{it}^K \cdot \Delta \ln K_{it} + \varepsilon_{it}^L \cdot \Delta \ln L_{it}) - \epsilon_{it} - \Delta u_{it}$$

which corresponds to equation (9).

$$\boxed{\text{EIG}_{it} = \text{AEC}_{it} + \text{SEC}_{it} + \text{OIC}_{it} + \text{TC}_{it} + \text{EEFC}_{it}}$$

Component Overview

Table 8: Components of the normalized energy efficiency gain decomposition

Term	Interpretation
$\text{AEC}_{it} = (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e$	Allocative Efficiency Change
$\text{SEC}_{it} = (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it}$	Scale Effect Component
$\text{OIC}_{it} = -(\varepsilon_{it}^K \cdot \Delta \ln K_{it} + \varepsilon_{it}^L \cdot \Delta \ln L_{it})$	Other Inputs Contribution
$\text{TC}_{it} = -\epsilon_{it}$	Technical Change
$\text{EEFC}_{it} = -\Delta u_{it}$	Energy Efficiency Frontier Change

Aggregation

Following Adetutu et al. (2020) we construct a Törnqvist index to obtain aggregate EIG components from the firm level EIG components (indexed i) as follows:

$$\begin{aligned} \text{AEC}_t &= \sum_i (1 - \tilde{\varepsilon}_{it}^e) \cdot \Delta \ln \tilde{p}_{it}^e \approx \frac{1}{2} \sum_i [(1 - \tilde{\varepsilon}_{it}^e) + (1 - \tilde{\varepsilon}_{it-1}^e)] \cdot [\ln \tilde{p}_{it}^e - \ln \tilde{p}_{it-1}^e] \\ \text{SEC}_t &= \sum_i (1 - \varepsilon_{it}^y) \cdot \Delta \ln y_{it} \approx \frac{1}{2} \sum_i [(1 - \varepsilon_{yit}) + (1 - \varepsilon_{yit-1})] \cdot [\ln y_{it} - \ln y_{it-1}] \\ \text{OIC}_t &= -\sum_i \sum_{k \in K, L} (\varepsilon_{it}^k) \Delta x_{it}^k \approx -\frac{1}{2} \sum_i \sum_k [(\varepsilon_{kit}) + (\varepsilon_{kit-1})] [\ln x_{ikt} - \ln x_{ikt-1}] \\ \text{TC}_t &= -\sum_i (\epsilon_{it}) \approx -\frac{1}{2} \sum_i (\epsilon_{it} + \epsilon_{it-1}) \\ \text{EEFC}_t &= -\sum_i (\Delta u_{it}) \approx -\sum_i \ln (CE_{it}/CE_{it-1}) \end{aligned}$$