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Global energy efficiency improvement: a mixed panel model approach

par

Vladislav Portniaguine

Mario Samano

Olivier Bahn

HEC Montréal

Directeurs de recherche

Sciences de la gestion

Spécialisation Économie Appliquée

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Résumé

Ce mémoire modélise le paramètre d'Amélioration Autonome de l'Efficacité Énergétique (AEEI), un élément crucial de la modélisation à long terme des systèmes énergétiques et de l'adaptation climatique, qui quantifie le taux auquel les économies améliorent leur conversion de l'énergie primaire en valeur ajoutée finale indépendamment des effets liés aux prix, aux revenus, à la structure et aux politiques. Des estimations distinctes du paramètre sont obtenues pour chacune des quinze régions du monde définies dans le modèle d'évaluation intégrée AD-MERGE 2.0 en utilisant une spécification de variable latente dérivée de l'estimateur de groupes moyens augmentés (Augmented Mean Groups). Les résultats de ces modèles sont comparés aux spécifications traditionnelles de tendance déterministe dans un cadre de groupes moyens et montrent des estimations plus stables et réalistes. Enfin, un cadre de modèle mixte, qui fait la moyenne des résultats de plusieurs modèles, est utilisé pour obtenir des estimations consensuelles à la fois au niveau régional et mondial. Cette méthodologie vise à isoler l'impact exclusif du progrès technologique sous-jacent et à offrir aux chercheurs un cadre potentiel pour valider les calibrations des paramètres dans un cadre empirique unifié.

Abstract

This thesis models the Autonomous Energy Efficiency Improvement (AEEI) parameter, a critical element of long-term energy system and climate adaptation modeling which quantifies the rate at which economies improve their conversion of primary energy into final value added independent of price, income, structural, and policy effects. Separate parameter estimates are obtained for each of the fifteen world regions defined in the AD-MERGE 2.0 Integrated Assessment Model by utilizing a latent variable specification derived from the Augmented Mean Groups panel estimator. Results from these models are benchmarked to traditional deterministic trend specifications in a Mean Groups framework and shown to deliver more stable and realistic estimates. Finally, a mixed-model framework that averages multiple model results is used to derive consensus estimates at both a regional and global level. This methodology seeks to isolate the exclusive impact of underlying technological progress and to offer researchers a potential framework for validating parameter calibrations within a unified empirical framework.

Contents

List of Tables

List of Figures

List of Abbreviations

AEEI Autonomous Energy Efficiency Improvement

CDP Common Dynamic Process

UEDT Underlying Energy Demand Trend

CES Constant Elasticity of Substitution

ESUB Elasticity of Substitution

ITC Induced Technical Change

MG Mean Groups

AGM Augmented Mean Groups

ARDL Autoregressive Distributed Lag

CGE Computable General Equilibrium

IAM Integrated Assessment Model

LMDI Logarithmic Mean Divisia Index

IDA Index Decomposition Analysis

LOCF Last Observed Carried Forward

FOCB First Observed Carried Backward

WB World Bank

WDI World Development Indicators

CMO Commodity Markets Outlook

UNSD United Nations Statistical Division

NIA National Income Accounts

IEA International Energy Agency

WEB World Energy Balances

FEC Final Energy Consumption

TES Total Energy Supply

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1 Introduction

Energy security and climate adaptation are among the most pressing concerns that individual nations and humanity as a whole must face in the coming decades. It is therefore critically important to understand the nature of energy use and the progress of energy efficiency improvements that have been made in recent years, how they differ among regions, and at what rate they could be expected to continue in the coming future. This thesis seeks to complement the existing literature on this subject by modeling the Autonomous Energy Efficiency Improvement parameter (AEEI), a concept that refers to changes in energy demand that are not directly attributable to price and income effects and that is often used as a proxy for broad energy efficiency improvements across entire sectors or economies.

The "classic" AEEI parameter focuses solely on changes in energy intensity, defined as energy used per dollar of GDP, net of price and income effects. However, depending on the modeling framework it can be extended to net out other effects such as those of changing energy generation mix, output structure, or government policy (Kaufman, 2004). This thesis is focused specifically on "passive" energy efficiency that evolves through organic market competition, the gradual renewal of the capital stock, and the general advancement of scientific knowledge. Thus, in addition to the standard price and income effects this thesis will seek to control for changes in economic structure and energy policy. Structural change is a particularly important factor as changes in energy intensity can be caused by transition to service economies and by the relocation of energy-intensive manufacturing across countries, which can mask underlying changes in energy efficiency (Moreau et al., 2019).

Properly accounting for the AEEI remains an unresolved issue in both empirical energy modeling (Liddle, 2023) and theoretical models (Eckaus and Sue Wing, 2007). Recent literature employs various strategies to model this parameter including econometric estimation, structural modeling, and expert opinion. A major debate in the energy efficiency literature is how best to specify the AEEI: using an endogenous specification tied to price or income, or an exogenous specification via a deterministic or stochastic time trend (Webster et al., 2008; Hunt et al., 2003). This thesis uses panel econometric techniques to model the AEEI in 15 major regions for the years 1995-2021 using both deterministic and stochastic exogenous trends in a panel regression setting. The regions correspond to those presented in the latest AD-MERGE 2.0 Integrated Assessment Model (IAM) (Amirmoeini et al., 2024), and data for them is constructed by aggregating regional indicators across a total pool of 93 countries.

Given the inherent uncertainty in estimating such a broadly defined concept at such a high level, a number of model specifications are used to cross-validate the results. This thesis begins by using pooled OLS models with fixed effects to understand the behavior of control variables. However, pooled models have several major limitations, specifically the assumption of homogeneous effects across panel units as well as potential bias caused by cross-sectional dependence (Pesaran and Smith, 1995; Bond and Eberhardt, 2009). Furthermore, the time dummies used to control for cross-sectional effects in pooled models interfere with the estimation of exogenous time trends, which makes them unsuitable to elicit the AEEI parameter. To address these challenges, this thesis leverages the Mean Groups (MG) estimator first introduced by Pesaran and Smith (1995) as well as the recent Augmented Mean Groups (AMG) estimator introduced by Bond and Eberhardt (2009) and Eberhardt and Teal (2010). The MG model extends the traditional panel models by averaging together coefficient estimates from individual regressions. The AMG model further extends the MG model by first estimating a stochastic trend that represents the evolution of an underlying latent variable assumed to correlate across panel units. This trend is termed the common dynamic process (CDP) and is incorporated in a second-stage MG regression to control for dynamic cross-sectional effects (Bond and Eberhardt, 2009). This thesis follows Eberhardt and Teal (2010) in interpreting the latent variable as a form of factor productivity, in this case representing the productivity of energy flows in the wider economy, thereby serving as a proxy for the AEEI. Baseline estimates of the AEEI using deterministic time trends in an MG setting are used to benchmark the AMG results.

To better isolate the energy efficiency effect, it is important to account for changes in energy intensity caused by structural changes. A two-step strategy is employed to achieve this. First, index decomposition analysis (IDA) via the logarithmic mean divisia index (LMDI) is used to decompose changes in energy intensity into a structural component, driven by changes in the financial contribution between sectors, and an intensity component, driven by the changes in energy intensity of the sectors themselves (Ang, 2004; 2005). The intensity component of the index decomposition better approximates underlying energy efficiency; however, given the high level of aggregation of the sectors used in the decomposition, a substantial amount of structural changes within sectors remains in the resulting decomposed series (Voigt et al., 2014). Thus, the direct share of industry in total energy demand is used as an additional control variable in the final regressions to capture any remaining structural effects that were not accounted for in the index decomposition. An additional variable controlling for the share of energy supplied by nuclear and renewable sources is used as a proxy for government energy policy in the energy system. In order to overcome potential limitations of small regional sample sizes and uncertainty in model specification, model averaging techniques are used to generate consensus estimators across a range of model specifications for the world as a whole and for each region separately (Buckland, 1997; Hansen, 2007; Greene, 2003).

Overall, the primary research goal of this thesis is to assess whether panel regression techniques of the kind described above can provide a unified empirical framework to corroborate AEEI parameter values derived from theoretical models. The results indicate that, with certain caveats, this appears to be the case. The rest of this thesis is organized as follows: Section 2 presents the literature review on existing energy intensity studies, including a discussion of the AEEI in theoretical models of climate change and energy policy, critiques around its existing formulation, the adjacent literature on empirical estimation, commonly identified determinants of energy intensity, and the important tendencies in recent decades. Section 3 describes the data set used in this thesis and explains how the variables were constructed. Section 4 outlines the methodology used. Section 5 presents and discusses the results. Finally, Section 6 concludes by answering the research question and discussing the broader implications of the findings.

2 Literature Review

This section reviews the fundamental concepts and debates in the current literature regarding the modeling of energy efficiency improvements. It starts with the theoretical concept of autonomous energy efficiency, its definition, use in the current literature, commonly assumed values, and critiques. It then proceeds to examine the empirical literature on modeling energy efficiency and the value this literature holds in understanding the theoretical models, including the adjacent literature on price and income elasticity and the wider discussion on determinants of efficiency changes. It concludes with a presentation of the stylized facts of energy efficiency trends in the world, including convergence in energy efficiency trends among regions and the impact of offshoring and rebound effects on accurate measurement of energy efficiency.

2.1 AEEI in Modeling Technological Change

To my knowledge, the concept of autonomous energy efficiency improvement was first mentioned in the work of Edmonds and Reilly (1983), who introduced a model for studying the consequences of long-term carbon abatement in the global economy. Although they did not explicitly give it a name, the authors left room in the model for a parameter meant to represent technological progress independent of price signals. This parameter is important in the model's long-term projections as it allows for the modeling of gradual improvements in energy use efficiency that occur due to technological advancements, behavioral changes, or other non-price factors. In the model proposed by Edmonds and Reilly, the efficiency parameter can be adjusted to reflect different scenarios of technological change, and it can be switched on or off to assess the impact of automatic efficiency gains on energy demand. When active, the parameter serves to reduces energy consumption for a given level of economic activity at a fixed rate over time, thus playing a pivotal role in scenarios exploring future energy use and policy impacts, allowing modelers to simulate either a world where energy efficiency continues to improve autonomously or one where such improvements stagnate.

Since its introduction, there has been an ongoing debate about what this parameter should represent, how to set its value, or whether it should exist at all. Two literature surveys conducted by Jacobsen (2001) and Löschel (2002) offer an extensive discussion of the state of modeling of technological change in large-scale energy and climate models of the time, including a discussion of what had then come to be termed the AEEI parameter. They summarize it as a heuristic measure that captures technological advancements leading to a decoupling of economic growth from energy use. According to their review, researchers typically treat the AEEI as either a constant or as following a nonlinear time trend within their models. It is usually included as a distinct coefficient within production or cost functions, and can be dis-aggregated to reflect sector-specific technological change or specified at the economy-wide level to capture structural shifts in the economy that influence energy consumption. For instance, in Constant Elasticity of Substitution (CES) production functions, AEEI is often modeled as cost-diminishing technical change, reflecting the idea that technological improvements inherently lead to less energy being required per unit of output for any given level of energy prices.

AEEI remains a prominent concept in recent literature. In a comprehensive survey of commonly used tools for modeling industrial transformation by Elberry et al. (2024), AEEI is highlighted as one of the most frequently mentioned tools for modeling technological change in the context of energy and climate economics. The authors emphasize that AEEI continues to be widely used in Computable General Equilibrium (CGE) models, Integrated Assessment Models (IAMs), and other large-scale economic models that seek to model long-run policy scenarios such as the impact of carbon taxes and climate adaptation strategies. Due to their stylized and simplified nature, all of these models continue to incorporate an AEEI parameter to capture the autonomous improvements in energy efficiency that are expected to occur independently of price and policy interventions. To obtain parameter values AEEI is often calibrated based on historical data, but it can be adjusted within models to explore different scenarios of technological progress.

The survey by Elberry et al. also explores the relationship between AEEI and related empirical concepts such as endogenous technical change, learning-by-doing, and learning-by-searching. While AEEI is often exogenously set and reflects historical trends within the context of a specific modeling framework, the related empirical concepts offer a more dynamic representation of technological progress, where improvements in energy efficiency are driven by ongoing investments in R&D, accumulation of production experience, and economies of scale. The distinction between these approaches is crucial, as it affects the interpretation of model outcomes and the policy recommendations derived from them. Elberry et al. note that there is growing interest in using endogenous and semi-endogenous forms of technological change to capture more dynamic interactions between energy efficiency improvements and economic factors. Specifically, the authors highlight that 22% of the tools they reviewed incorporate endogenous technological change, allowing the AEEI to provide a more realistic and flexible representation of how technological progress can evolve in response to economic activities and policy interventions. However, the implementation of such endogenous approaches is still relatively limited, with the majority of models relying on simpler, exogenous specifications of the AEEI.

To illustrate the role of the AEEI in a modern IAM, a visual schematic of the MACRO module from the AD-MERGE 2.0 model (Amirmoeni et al., 2024) is shown in Figure 1, reproduced here with the authors' permission. This module shows various elements of the economic and energy system and their interactions in terms of providing inputs to production, generating pollutants, calculating externalities and damages, and the overall impact of these elements on climate and welfare. For our purposes, the two most prominent elements are the ESUB and AEEI. ESUB refers to elasticity of substitution and refers to the ability to substitute energy inputs to production for labor and capital. This factor is assumed to be heavily affected by price (Bataille et al., 2006), as relatively more expensive energy would incentivize agents to develop technological innovations aimed at economizing on energy use. The second factor is AEEI, which represents a more passive rate of technological innovation that is part of the general operation of market competition and advancement of human knowledge. There is obviously a strong interaction between these two components, which is a prominent feature of both the theoretical and empirical literature reviewed here.

Despite the ubiquity of the AEEI in the literature, there is at present no consensus on how exactly to model energy efficiency improvement, nor is there an empirical explanation that has definitively resolved the best approach to modeling this parameter (Webster et al., 2008; Liddle, 2023). The choice of AEEI values is typically guided by the specific type of model in question and the level of sectoral disaggregation. For instance, the original MERGE IAM proposed by Manne et al., (1995) sets the AEEI at 0.5% below the annual growth rate of income. Bataille et al. (2006) and Webster et al. (2008) both provide summaries of commonly used AEEI parameter values in IAMs at the time of their publications. Webster et al. (2008) cite a range of models with AEEI values for

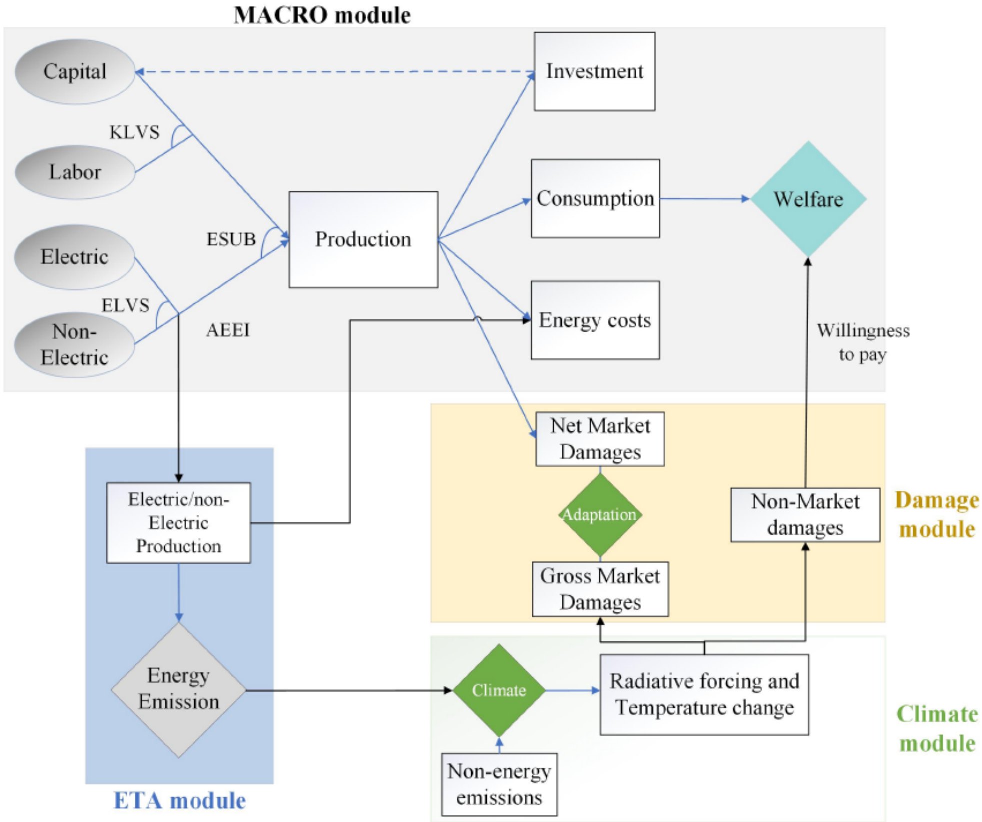

Figure 1: MACRO module from AD-MERGE 2.0 Model

Source: Amirmoeni et al. (2024).

different regions varying from 1% to 2.6% in more optimistic scenarios, and from 0.00% to 0.25% per year in more pessimistic cases. In their own derivations, Webster et al. (2008) demonstrate that when estimating a simple empirical model of energy use with price and income elasticities and an exogenous time trend, the coefficient of the time trend is either insignificant when income elasticity is allowed to vary, or else yields AEEI values of 2% or 0.5% when the income elasticity is fixed at 1 or 0.5, respectively. Bataille et al. (2006) analyze the commonly used calibration of the MIT-EPPA model, citing AEEI figures of 1.98% for China, 1.43% for India, 1.301% for the United States (though this value is assumed to decrease over time), 1.210% for other OECD countries, and 1.1% for the rest of the world. According to the authors, these values are set through expert elicitation and literature review. Their own model seeks to elicit an AEEI value for the Canadian economy via a calibration exercise, and yields an economy-wide value of 0.57% under market clearing conditions.

Recent studies further explore the variability in AEEI values across different sectors and regions, underscoring the complexity and context-specific nature of modeling autonomous energy efficiency improvements. Van Ruijven et al (2010) explore the potential evolution of global residential energy use in the TIMER 2.0 global energy model with assumed AEEI values of 0.5% to 1.5%. Steinbuks and Neuhoff (2014) focus on efficiency improvements of the capital stock in the OECD manufacturing industry and find values ranging from 2% to 4% energy efficiency growth per year. Fujimori et al. (2016) test AEEI values for the global economy in a hindcasting exercise aimed at validating the finding of the AIM/CGE (Asia-Pacific Integrated Models / Computable General Equilibrium) IAM. They use staggered, income-dependent values set to 1%, 1.5%, and half of GDP growth for GDP growth rates of 0-3%, 3-5%, and over 5% respectively, and find that this model accurately reproduces global aggregate trends but diverges in reproducing regional trends. Wang et al. (2022) replicate the same approach to modeling the AEEI as Fujimori et al. (2016) but specific to the Chinese economy. Timilsina et al. (2021) offer a novel approach to calibrating the AEEI values for the Chinese economy, combining a top-down approach leveraging macroeconomic data and a bottom-up approach that starts with dis-aggregated sectors to arrive at an economy-wide value of 1.5%. Finally, Zhang et al. (2024) study the potential changes to fossil fuel trade and emissions caused by Russia-EU energy decoupling in a dynamic general equilibrium model with AEEI values between 0.5% and 3% for different sectors and regions, though it is not immediately clear which exact sectors or regions are associated with what value or how the values were derived.

2.2 Critiques of the AEEI concept

There have been a number of critiques of the concept of autonomous efficiency improvements. In the aforementioned literature surveys, Jacobsen (2001) and Löschel (2002) both identify significant challenges and limitations in the measurement and application of AEEI. A primary concern is the difficulty in accurately quantifying technological change due to its inherently complex and multifaceted nature. Technological improvements are not uniform across sectors or regions, leading to variability in the effectiveness of AEEI as a predictive tool. This heterogeneity complicates the task of setting a universally applicable AEEI parameter within models. Furthermore, there is an ongoing debate about whether efficiency improvements should be treated as an exogenous factor specified by the researcher or be derived endogenously from within the model's own assumptions. While traditionally considered exogenous, some argue that technological change should be modeled endogenously, allowing for feedback mechanisms where policy measures and market conditions influence the rate and direction of technological advancements. Another problem identified by the authors is the potential for misrepresenting the effects of technological change when using a constant AEEI. Real-world technological progress is often nonlinear, with periods of rapid advancement followed by slower growth, which a constant AEEI fails to capture accurately. This misalignment can over- or under-estimate future energy demand, affecting the reliability of long-term energy projections. Finally, the surveys also highlight the issue of policy relevance. As AEEI is a simplification, its application in policy analysis can be problematic. Policymakers may rely on these models for decision-making, but the assumptions underlying AEEI may not hold in practice, particularly in dynamic and rapidly evolving technological landscapes. The surveys suggest that more sophisticated approaches, possibly incorporating endogenous technological change or varying the AEEI values across sectors and time, could enhance the robustness of these models.

The problems identified have led some authors to conclude that AEEI in its existing form is not a useful concept or cannot be measured accurately. Kaufman (2004) offers a description of AEEI as a time trend "left over" after other factors affecting energy demand have been accounted for, and argues that this is not a satisfying approach to modeling technological change. He argues that this formulation lacks a clear causal mechanism, and that a proper modeling of technological change should be more explicit about what exactly is changing in either the underlying structure of the energy system or in household consumption behaviour. To demonstrate this, he specifies a model of the US Energy/GDP ratio across the 20th century and uses a Vector Error Correction Model (VECM) to demonstrate that all long-term energy intensity reductions can be understood as the equilibrium relationship between energy use and shifting household preferences, changes in the fuel mix away from coal towards higher-quality fuels, and the impact of energy prices. He argues that, to the extent that there is an autonomous component, it is a stochastic trend representing short-term fluctuations around a long-term equilibrium defined by the underlying structure of energy consumption and production, which is the true measure of long-run energy intensity declines.

Dowlatabadi and Oravetz (2006) also challenge the concept of AEEI, but from the angle of indistinct boundaries between price-induced changes and autonomous changes. They argue that the separation between AEEI and price-induced energy efficiency improvements is not as clear-cut as often assumed. The authors suggest that many factors traditionally lumped into AEEI, such as changes in energy-using behaviors or technological adoption, could be influenced by price signals, thereby questioning whether efficiency changes are truly "autonomous" or are simply the result of long-run price induced changes. They propose a more integrated approach that considers the interaction between price and non-price factors in driving energy efficiency improvements. This approach would involve the use of more granular data and the development of models that capture the feedback loops between energy prices, technological change, and consumer behavior.

Webster et al. (2008) focus on the inconsistency of AEEI when compared across different income levels and regions. They argue that AEEI, as commonly applied, fails to account for the varying income elasticity of energy demand, leading to overgeneralized assumptions in energy models. According to Webster et al., the AEEI is often assumed to be constant across different contexts, which oversimplifies the complex relationship between income growth, energy use, and efficiency improvements. As an alternative, they propose formulating energy efficiency improvements directly through the mechanism of income elasticity by recalibrating models to account for different income levels and their associated energy demand patterns, thereby providing a more accurate representation of energy efficiency dynamics. In two separate runs of MIT's EPPA long-term emissions model, they demonstrate that while both an exogenous and endogenous formulation of the AEEI yield similar predictions in the short-term, they diverge in their long-term predictions with the exogenous formulation yielding exaggerated predictions of energy efficiency growth compared to an endogenous parameter that varies with income growth.

Though not fundamentally discounting the whole concept, two studies by Eckaus and Sue Wing (2007) and Sue Wing (2008) caution about how exactly AEEI values should be specified. Their work identifies key drivers of energy intensity in the U.S. economy, including technological advancements, structural changes in the economy, and sector-specific shifts in energy consumption patterns. Historically, structural changes, such as the transition from manufacturing to less energy-intensive service industries, played a significant role in reducing energy intensity. However, over time, the emphasis shifted toward improvements within sectors, driven by technological innovation and increased energy efficiency in industrial processes. These changes are typically measured through the decline in energy-output ratios across various sectors, indicating how much energy is required to produce a unit of output. For example, Eckaus and Sue Wing highlight that by the late 20th century, energy-output ratios in U.S. industries had decreased significantly, reflecting both the impact of technological progress and the broader economic shift towards less energy-intensive activities. The authors argue that this evolution suggests that models projecting future energy use should account for both the historical role of structural changes and the continued impact of technological advancements. In light of these facts, they caution that commonly applied uniform AEEI values in models may need to be revisited, with a potential move toward more sector-specific AEEI values that better capture the nuanced drivers of energy efficiency.

2.3 Empirical studies on energy efficiency

The debate on properly incorporating autonomous energy efficiency improvements in policy analysis models is adjacent to the debate on modeling technological change in econometric studies. In fact, as Elberry et al. (2024) point out, AEEI and technological change are essentially the same concepts, with the difference in nomenclature primarily the result of the specific context in which they are used. Technological change is not directly observable and is therefore modeled through various proxies. Many of the empirical studies that incorporate proxies for technology are primarily focused on finding the values of other parameters, most commonly price and income elasticities of energy demand, and hence focus on the best way to specify technology changes as a control variable (eg., Parker and Liddle, 2016; Liddle and Sadorsky, 2020). Others focus on trying to model technological change itself through latent variables (eg., Jin and Jorgensen, 2010). This literature is directly relevant to the empirical methodology used in this thesis, and hence a deeper discussion will be presented in the Methodology section. However, the key points of this debate are still worth mentioning here to highlight the parallels with the theoretical debate around modeling the AEEI.

An early example of the work on technology changes is the study by Jones (1994), which incorporates many of the themes in this strand of literature. The study concerns the question of whether exogenous time trends should be included in empirical models of energy demand. It specifies an autoregressive distributed lag (ARDL) model analyzing the income and price elasticity of US energy demand with and without a time trend, and finds that the inclusion of the trend stabilizes the estimated price elasticity from implausibly high figures to a more reasonable range of values. Jones proposes that this trend accounts for the progress of technical change, and that models that fail to incorporate such trends should be considered invalid on both empirical and theoretical grounds, as they overstate elasticity estimates and imply that declining energy prices could lead to negative technical progress. However, Jones admits that in the long-run it remains difficult to precisely disentangle price-induced technical change (ITC) and autonomous technological progress, and the researcher must therefore walk a fine line between overstating price elasticities by failing to control for this effect and overstating the role of technological progress if the proxy for it is mis-specified.

The debate surrounding the modeling of ITC in the long-run then focuses on the effects of asymmetric prices. Gately and Huntington (2002) argue for the inclusion of asymmetric price responses, showing that energy demand reacts differently to price increases than to decreases. They posit that this asymmetry is crucial for accurately capturing ITC, as it reflects the reality that technological and behavioral changes driven by price increases are not fully reversible when prices drop. Huntington (2006) furthers this argument by suggesting that price asymmetry better explains long-term energy demand trends compared to models using fixed time effects, which may confound ITC with other exogenous factors. In contrast, Adeyemi and Hunt (2007) explore these models in the context of OECD industrial energy demand and find that while asymmetry and time dummies are statistically significant, they may function more as substitutes than complements. Their work raises questions about whether exogenous trend specifications are necessary or if price asymmetry alone sufficiently captures ITC, suggesting a more nuanced approach may be needed to account for sector-specific characteristics. These authors collectively advance the discussion by highlighting the importance of considering both price asymmetry and potential exogenous trends, while also questioning the one-size-fits-all application of these models across different sectors.

In parallel to the debate over the proper way to incorporate price effects, Hunt et al. (2003) focus on the best way to represent the exogenous time trend formulation. They argue that the main problem with the traditional use of an exogenous trend was the assumption of a deterministic time trend, which is both a theoretically and empirically problematic way to represent energy demand. Instead, they argue for the use of a stochastic time trend that they label the Underlying Energy Demand Trend (UEDT), which they show is superior both to a deterministic time trend or a cointegrating estimation in modeling energy demand as it produces well-specified models that are free from the serial correlation and non-normality in residuals produced by more rigid techniques, and offers more reliable parameter estimates. According to their findings, empirical evidence from UK energy demand data across various sectors consistently favors stochastic formulations, underscoring their robustness and adaptability in accurately modeling energy demand trends.The UEDT methodology they developed is now a standard approach in the literature, and recent studies such as Alarenan et al (2020) and Javid et al (2022) have successfully applied it to modeling energy demand in Pakistan and Saudi Arabia, respectively.

Adeyemi and Hunt (2014) merge the two strands of this debate in a study of energy demand in the OECD manufacturing sector. They argue that a model of energy demand with both price asymmetry and a stochastic UEDT is the most general case, and that assumptions such as price symmetry, deterministic trends, or the absence of exogenous trends are limited versions of this general case achieved via imposed parameter restrictions. They then proceed to test which is the preferred model for each of the 15 countries in their sample, starting from the most general case and only imposing additional restrictions if accepted by the data. They find that a model with both price asymmetry and a stochastic trend is the preferred model in almost all cases, highlighting the complementary nature of this specification. They also note, however, that in this specification the UEDT encompasses behavioral and structural changes as well as the role of technological progress, implying that additional controls would be needed to isolate the impact of technological progress specifically.

Several other studies effectively corroborate this conclusion. Hunt and Ryan (2015) model energy as derived demand, and show that the inclusion of a either a nonlinear exogenous time trend (t and t^2) or a stochastic UEDT improves the power of their model by accounting for technological progress. Jin and Jorgensen (2010) shift the focus on estimating the impact of technological progress itself by specifying it as a latent factor that evolves according to a stochastic trend and thereby estimating improvements in technology in various industrial sectors of the US economy. Finally, Parker and Liddle (2016) use both asymmetric prices and a common dynamic process, a stochastic trend derived from cross-sectional time dummies in a first-stage panel regression, to control for the influence of technological changes and economic shocks driven by global trade, economic integration, and knowledge spillover in a panel study of energy-efficiency in OECD manufacturing. The discussion in the Methodology section demonstrates that the last two approaches are complementary, and can be combined to form the model derived in this thesis.

2.4 Determinants of energy intensity

Having established the parameters of the debate and the theoretical and empirical frameworks within which energy efficiency studies are framed, I now turn to a review of the modeling of price and income elasticities specifically and the determinants of energy efficiency more generally. Income and price elasticity are especially important since in the most basic empirical estimation they are the sole control variable used to estimate the AEEI, which is simply defined as all energy demand changes not caused by price and income changes (Liddle 2023). If we are interested in more granular estimates of AEEI as a representation of technological progress, then it is important to control for other effects such as structural shifts and fuel mixes (Kaufman, 2004), and the existing literature can provide a sense of which variables to use for these purposes. The studies reviewed in this section either model energy demand directly or model the energy intensity of GDP, defined as energy used per dollar of final value added, which represents the inverse of energy efficiency and is commonly used in efficiency studies.

Early factors impacting energy intensity were identified by Kaufman (1992), who found that a greater output share of industry and purchases of more energy-intensive goods tended to increase energy intensity while higher energy prices and a transition to higher-quality fuels tended to decrease it. Many findings since then have confirmed these early insights, and have added several more factors not considered by Kaufman. A complete list of studies reviewed is presented in Table 1. For the purpose of this thesis, the key takeaway is the importance of controlling for industry output share through index decomposition or direct modeling approaches, and the significant impact of cross-border trade and capital flows in driving energy efficiency improvements. The latter insight is crucial as this thesis leverages cross-sectional dependence in energy intensity trends to elicit the AEEI on the assumption that global technological trends are at least partially synchronized.

Study	Methodology	Sample	Factors	Causality
Mielnik and Goldemberg (2002)	Regression Analysis	20 developing countries (1987-1998)	Foreign Direct Investment (FDI)	FDI has a negative effect on energy intensity, likely due to the adoption of modern technologies brought by FDI
Metcalf (2008)	Econometric Analysis, Decomposition Methodology	U.S. state-level data from 1970 to 2001	Energy prices, Per capita income, Capital-labor ratio, Population growth, Climate variables	Higher energy prices and rising per capita income lead to lower energy intensity, primarily through improvements in energy efficiency. Capital-labor ratio and population growth have mixed effects.
Song and Zheng (2012)	Decomposition Analysis and Econometric Analysis	Provincial-level data from China (1995-2009)	Income, Energy prices, Capital-labor ratio, Urbanization, Policy	Rising income reduces energy intensity, while energy prices have a limited effect. Urbanization and capital-labor ratio show mixed effects. Policy reduces energy intensity mainly through efficiency improvements.
Wang (2013)	Decomposition Analysis	Cross-country data from 100 countries (1980-2010)	Technological progress, Capital-energy ratio, Labor-energy ratio, Output structure	Technological progress, capital accumulation, and changes in output structure reduce energy intensity, while labor-energy ratio increases it.
Voigt et al. (2014)	Decomposition Analysis	40 major economies (1995-2007)	Structural changes, Technological improvements	Technological improvements generally reduce energy intensity, while structural changes have mixed effects depending on the country.
Jimenez and Mercado (2014)	Decomposition Analysis, Panel Data Regression, Synthetic Control Method	75 countries, with a focus on Latin American countries (1971-2010)	Per capita income, Petroleum prices, Fossil fuel energy mix, GDP growth	Per capita income and petroleum prices reduce energy intensity. Fossil fuel energy mix and GDP growth have mixed effects.
Filipovic et al. (2015)	Panel Data Analysis	EU-28 member states (1990-2012)	Energy prices, Energy taxes, GDP per capita, Final energy consumption per capita, Growth of gross inland consumption	Energy prices, energy taxes, and GDP per capita have a negative impact on energy intensity, while final energy consumption per capita and growth of gross inland consumption have a positive impact.
Atalla and Bean (2017)	Decomposition Analysis, Panel Data Regression, Cluster Analysis	39 countries (1995-2009)	Energy prices, Income per capita, Industrial share of GDP, Investment to capital ratio, Total degree-days	Higher energy prices and income per capita increase energy productivity (reduce energy intensity). Higher industrial share reduces energy productivity. Investment and total degree-days have mixed effects.
Mahmood and Talat (2018)	Panel Data Regression	19 European countries (1995-2015)	GDP growth rate, Population growth rate, Energy taxes, Energy prices	GDP growth rate has a negative effect on energy intensity, population growth rate has an insignificant effect, and energy taxes and prices reduce energy intensity.
Antonietti and Fontini (2019)	Dynamic Panel GMM	120 countries (1980-2013)	Oil price, GDP growth, Population density, Industrial structure	Higher oil prices and GDP growth reduce energy intensity. Population density and industrial structure have mixed effects.
Deichmann et al. (2019)	Piecewise Linear Regression, Index Decomposition	137 countries (1990-2014)	GDP per capita, Structural change, Energy efficiency	GDP per capita has a negative effect on energy intensity with a threshold effect at $5,000. Structural change and energy efficiency improvements reduce energy intensity.
Jain and Goswami (2021)	Index Decomposition Analysis, Panel Data Regression	South Asian countries (1990-2014)	Endowment of energy resources, Renewable energy production, Crude oil price, Population density, GDP per capita	Endowment of energy resources and renewable energy production increase energy intensity, while crude oil price, population density, and GDP per capita decrease it.

Continued on next page

Table 1: (Continued)

Study	Methodology	Sample	Factors	Causality
Liao et al. (2022)	OLS Fixed Effects Model, Instrumental Variable Analysis	64 large economies (1972-2019)	Investment-GDP ratio, GDP per capita, Population density	Higher investment-GDP ratio increases energy intensity. GDP per capita and population density have mixed effects.
Sun et al. (2022)	Logarithmic Mean Divisia Index (LMDI) Approach, Regression Analysis	30 Emerging Market Countries (1971-2016)	Energy price, Technological progress, Urbanization, Industry structure, Net energy exporter status	Energy price increases reduce energy intensity. Technological progress and urbanization reduce energy intensity, while net energy exporter status has mixed effects.
Djeunankan et al. (2023)	FMOLS, DOLS, CCR, AMG, Mediation Analysis	93 countries (1995-2015)	Economic complexity, Per capita GDP, Population density, Trade openness	Economic complexity, GDP per capita, and population density increase energy efficiency, while trade openness reduces it.

Table 1: Summary of Studies on Energy Intensity

2.5 Global energy intensity trends

This literature review concludes with a discussion of the key stylized facts identified in current energy efficiency trends. Specifically, it concerns the questions of rebound effects that act to counteract energy efficiency savings by increasing energy consumption in response to more efficient technology, the tendencies for offshoring and changes in global industrial structure, and the convergence of energy efficiency trends within and across regions. An understanding of these tendencies provides important context for analyzing and interpreting the results of this thesis.

Rebound effects

The rebound effect, a phenomenon where gains in energy efficiency lead to increased energy consumption, poses significant challenges for achieving energy reduction goals, and the three papers under review critically examine this effect from different perspectives. Herring (2006) offers a foundational critique of energy efficiency, arguing that it often leads to higher overall energy consumption due to economic and behavioral response. He suggests that the anticipated energy savings from efficiency improvements are frequently offset by increased demand, particularly in energy-intensive sectors. Stern (2020) expands on this critique by examining the economy-wide rebound effect. He utilizes a macroeconomic model to assess how energy efficiency improvements across various sectors influence overall energy consumption and economic output. Stern's findings indicate that while sector-specific efficiency gains can lead to modest energy savings, the cumulative effect across the economy often results in negligible reductions or even increases in total energy use. This economy-wide perspective underscores the limitations of sectoral approaches and the necessity of considering broader economic interactions when evaluating energy efficiency policies. Building on these analyses, Brockway et al. (2021) provide a comprehensive review of rebound effect studies. They find that rebound effects can vary significantly depending on factors such as the structure of the economy, energy prices, and technological advancements, but that their overall impact can erode as much as half of any reduction in energy demand achieved through efficiency improvements. Collectively, these findings suggest that aggregate data may understate the impact of technological progress as rebound effects will offset a substantial part of energy efficiency improvements.

Offshoring

Offshoring, the process of structural change whereby countries relocate lower-value added (and generally energy-intensive) industries to other countries can have a substantial impact on energy intensity without changing energy efficiency. The four studies reviewed here collectively argue that offshoring distorts the true picture of energy efficiency and intensity, leading to an overestimation of the benefits of energy efficiency policies when evaluated at a national level. Lan et al. (2016) use structural decomposition analysis to evaluate global energy footprints between 1990 and 2010, revealing that affluent countries tend to offshore their energy-intensive production to less developed nations, resulting in an apparent but misleading reduction in domestic energy intensity. The findings suggest that true efficiency gains are often overstated, as they fail to consider the global context of energy usage. Hardt et al. (2018) provide a focused analysis of the UK, comparing the impacts of offshoring against domestic efficiency improvements. By decomposing the UK's energy consumption, they show that although domestic energy use has decreased, the global energy footprint linked to UK consumption has not. This indicates that energy demand has been transferred to other countries, suggesting that offshoring is the primary driver of perceived efficiency gains. Moreau and Vuille (2018) find a similar effect in Switzerland and, in a subsequent paper, Moreau et al. (2019) explore the broader

European context. They identify a trend of "virtual decoupling," where reductions in domestic energy intensity are primarily the result of offshoring energy-intensive activities rather than true efficiency improvements. Their analysis suggests that the structural effects of globalization, such as the shift from manufacturing to services and the relocation of heavy industry, are the main drivers behind the apparent decline in energy intensity across Europe. These studies emphasize the pivotal role of industrial offshoring in structural changes and underscore the importance of controlling for the share of industry in output when modeling energy intensity.

Convergence

The question of global and regional convergence in energy intensity trends has been a significant area of study, with various researchers examining whether countries and regions are moving towards similar levels of energy efficiency. This body of work explores whether convergence exists, and if so, among which regions it is most apparent. The five papers under review provide a comprehensive analysis of these trends.

Duro et al. (2010) investigate the inequality in energy intensity levels among OECD countries, employing a methodology that quantifies the dispersion of energy intensity over time. Their findings suggest a trend towards convergence within the OECD, with disparities in energy intensity gradually decreasing. This convergence is attributed to shared technological advancements, similar policy frameworks, and the structural shift from manufacturing to service-based economies. However, the degree of convergence varies among member countries, reflecting differences in economic structures and energy policies. Liddle (2010) expands this analysis by examining energy intensity convergence on a global scale, using a large data set spanning 111 countries from 1971 to 2006. His study identifies significant regional differences in convergence trends. While OECD and Eurasian countries show clear signs of continued convergence, with energy intensities aligning more closely over time, regions like Sub-Saharan Africa, Latin America, and the Middle East and North Africa (MENA) display either no convergence or divergence. Liddle's work highlights the role of economic structure and energy efficiency practices in driving these trends, noting that trade and technology transfer among OECD and Eurasian countries have facilitated convergence, whereas other regions lag behind due to less integration into global markets and technological advances.

Jakob et al. (2012) provide a broader perspective by linking convergence in energy use to economic growth patterns across countries. Their analysis shows that while there is some evidence of convergence in energy intensity at a global level, this is primarily driven by economic growth rather than explicit energy policies. The paper argues that economic growth in developing countries often leads to increased energy efficiency as these countries industrialize and adopt more advanced technologies. However, the pace of convergence is uneven, with faster progress observed in countries that are more integrated into the global economy.

Mulder and de Groot (2012) focus on energy intensity across different sectors and countries, exploring whether convergence is occurring within specific economic sectors. Their findings indicate that convergence is more likely in less energy-intensive sectors, such as services, where technological diffusion and global trade have led to more uniform practices across countries. In contrast, energy-intensive sectors like manufacturing show less evidence of convergence, as these sectors are more influenced by local factors such as energy prices and domestic policy environments. This sectoral analysis provides a nuanced view of convergence, suggesting that while some global convergence is occurring, it is highly sector-specific.

Balado-Naves et al. (2023) take a more recent and spatial approach to the study of energy intensity convergence, incorporating spatial spillovers into their analysis. They find that convergence is not only a result of direct technological and policy changes within countries but also of spatial interactions where neighboring countries or regions influence each other's energy intensity through trade, policy diffusion, and shared infrastructure. Their study reveals that regions with strong economic ties and shared borders, such as those within the European Union, tend to exhibit stronger convergence patterns. However, regions that are more isolated or less integrated into global networks show weaker or no convergence trends.

Together, these studies illustrate that global and regional convergence in energy intensity is influenced by a multitude of factors, including economic structure, technological diffusion, trade integration, and spatial interactions. Convergence appears more pronounced in regions and sectors that are highly integrated into global markets and where technological advancements are more readily adopted. Conversely, regions and sectors that are less integrated or more energy-intensive exhibit slower or no convergence. These trends have important implications for this thesis, as the methodology employed here leverages cross-border technology trade as the foundation for its latent variable representation and relies on international convergence in energy intensity trends to obtain accurate estimates. Heterogeneity in regional convergence trends implies that parameter estimates must be treated cautiously, as some regions yield more robust estimates than others.

3 Data and Variable Construction

The data set used in this thesis is compiled from multiple sources to ensure comprehensive coverage of the necessary variables. Information on total energy supply by source and energy use by sector comes from the International Energy Agency's (IEA) *World Energy Balances* (International Energy Agency, 2023). GDP at purchasing power parity (PPP) and population data are sourced from the World Bank's World Development Indicators (WDI) (World Bank, 2023a). Energy price data come from the World Bank's Commodity Market Outlook database (World Bank, 2023b). Data on total value added and value added breakdown by sector, as well as exchange rates and implicit price deflators, are obtained from the United Nations' National Income Accounts (NIA) (United Nations Statistics Division, 2023). The data is aggregated at an annual level for the years 1995-2021, which covers the period from the consolidation of the post-Soviet republics and the rapid rise of international trade through the COVID-19 shock and recovery. Data are aggregated from the national level to build separate data sets for each of the 15 regions of the AD-MERGE 2.0 model, giving a balanced panel data set of 405 total observations with 27 years per region.

Prior to aggregation, all data underwent thorough visual inspection to identify and remove countries with clear data problems and anomalies, such as anomalous spikes, discontinuities, or incompleteness in the key variables of GDP and total energy supply. Via this process, the data set was narrowed down to 93 major countries, which include the majority of the global economy. Energy source data was treated separately as the IEA practice is to record missing values whenever a country does not have a particular energy source (for example, nuclear power), leading to a higher proportion of missingness. For these series, countries with all missing values or with missing values where the energy supply clearly originated from or headed to zero were imputed with a value of zero for the missing component. In other cases missing values were imputed using either linear interpolation or Last Observed Carried Forward / First Observed Carried Backward (LOCF / FOCB) for edge cases. These methods were chosen for their ease of implementation and acceptable levels of bias (Moritz and Bartz Beielstein, 2017). In addition to imputing energy source data, several countries required imputation in their Agriculture and the so-called 'Non-Energy' sector energy consumption data. Given the marginal nature of these sectors in the overall energy use profile and the need to have complete series for chained index decomposition, maintaining the completeness of the sample was prioritized over potential bias from imputation.

3.1 Regional aggregation

Once cleaned and imputed, all country-level data were aggregated into 15 regions to align with the structure of AD-MERGE 2.0. A map of these regions is show in Figure 2, reproduced here with the authors' permission. A summary of the regional energy and GDP coverage of my final sample is shown in Table 2, with the full list of retained countries and their respective regions presented in the appendix. To give an idea of how this coverage aligns with overall global economic activity, Figure 3 shows the total world share of GDP and Energy use by region for 2019, built from the complete sample available from the IEA and WDI. As one would expect, the United States, China, and Western Europe account for over half of the world's economic activity; however, aggregating individual countries into larger macro-regions creates groupings that are more comparable to one another in terms of size versus what we would see if we were trying to directly compare countries on the scale of, for instance, China and Lithuania.

Most of the data are additive across countries which made the aggregation process relatively straightforward, though with two important caveats. First, financial value added by sector in the NIA data is only available in nominal dollars, and was first multiplied by each country's PPP adjustment factor obtained from the WDI data set to convert it into real units. A second important caveat is the construction of the aggregate energy price indices which required special attention due to the non-additive nature of real price data. The details of these transformations are presented below, as is a discussion of the index decomposition methodology employed to isolate the sector intensity and structural components behind energy intensity changes.

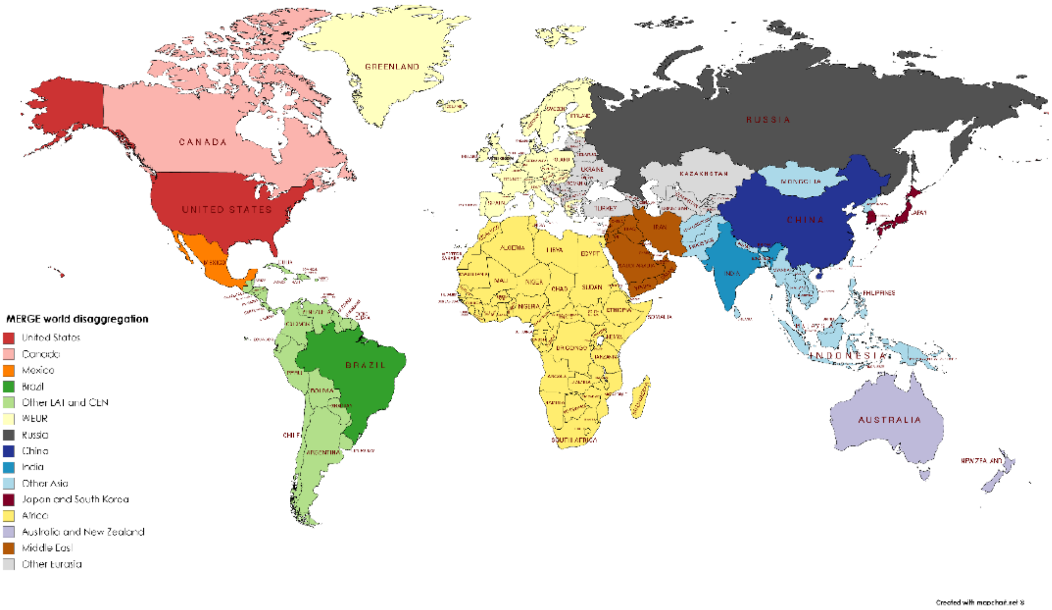

Figure 2: Region Map from AD-MERGE 2.0 Model

Source: Amirmoeni et al. (2024).

Label	Region	Energy	GDP
AFR	Africa	81%	82%
ANZ	Australia and New Zealand	100%	100%
BRA	Brazil	100%	100%
CAN	Canada	100%	100%
CHN	China	100%	100%
CLA	Other Central and Latin America	73%	79%
IND	India	100%	100%
JSK	Japan and South Korea	100%	100%
MEA	Middle East	84%	79%
MEX	Mexico	100%	100%
OAS	Other Asia	93%	93%
OEA	Other Eurasia	98%	98%
RUS	Russia	100%	100%
USA	USA	100%	100%
WEU	Western Europe	99%	99%

Table 2: Summary of Regional Energy and GDP Coverage

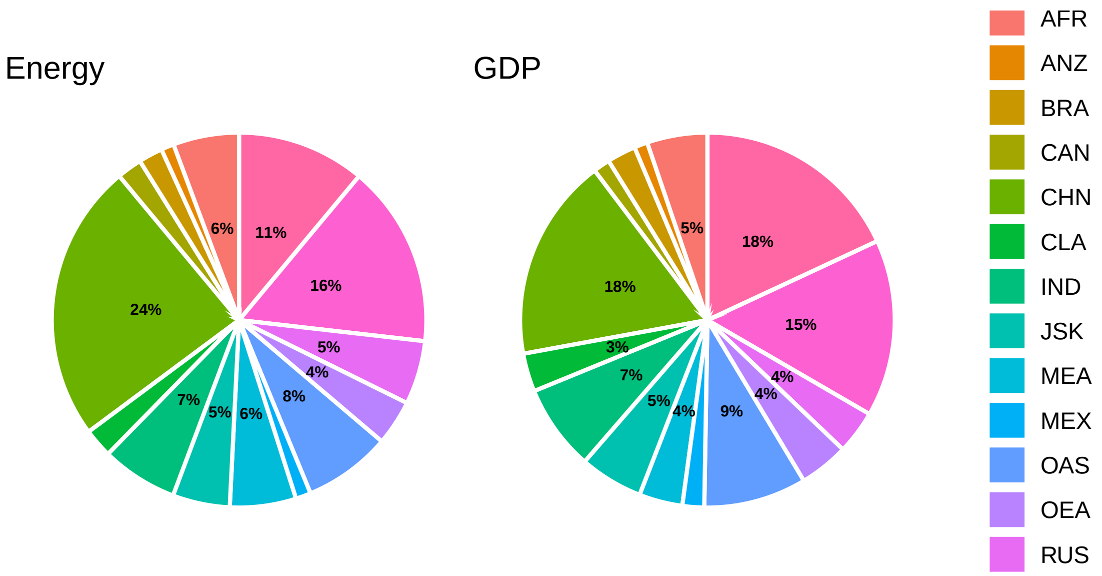

Figure 3: Regional Shares of Global Energy Use and GDP in 2019

3.2 Sector value added and energy data

Sector-specific data in this study consists of two types - financial value added and energy use. Value added by sector is available in nominal current dollars in the NIA data set. To make it comparable across regions and sectors, it was first re-based to constant 2021 dollars using the PPP-adjustment factors obtained from the WDI. This process is imperfect, as there is no guarantee that an aggregate PPP adjustment factor will apply uniformly across all sectors (Kander, 2005). However, I believe that any inaccuracy in this adjustment process will be smaller than the problems created by using nominal values, as GDP measurement can vary widely across vintages and methodologies (Semieniuk, 2024) and the World Bank's methodology brings these closer into line with a comparable uniform measure of real value added that is additive across countries, and therefore represents the measure of GDP used in this thesis. Sector value added data is available according the ISIC Revision 3 classification which consists of Agriculture, Manufacturing, Mining and Utilities, Construction, a merged line for Transport, Storage, and Communication, a merged line for Trade and Hospitality, and Other Services. To make them comparable to their corresponding sectors in the IEA data, these lines were merged together to create the three main sectors: Agriculture, used directly as a stand-alone line; Industry, representing the sum of Manufacturing, Mining and Utilities, and Construction; and Services, representing the sum of the remaining sectors including transportation. It would have been preferable to keep services and transport separate as transport is itself a major consumer of energy, but unfortunately the presence of the rapidly growing sector of digital communications in the Transport, Storage, and Communication value added line makes this direct comparison impossible.

The structure of the energy data is somewhat complicated and requires deeper explanation. The World Energy Balances data set provides two commonly used metrics of total energy use: Total Energy Supply (TES) and Final Energy Consumption (FEC). TES represents the total amount of primary energy supplied to an economy over a period of time from all sources, and represents primary energy production plus net energy imports and net draw downs on stockpiles, minus marine and aviation bunkers. FEC represents the final amount of energy consumed by end sectors including industry, transportation, residential, agriculture, and services sectors. The key difference between the two metrics is the treatment of intermediate stages of energy used in the generation of electricity and heat (mostly electricity) and the production of energy products. In the energy balances, energy used for energy transformation is recorded as a negative, and the net energy use in transformation is subtracted from TES to obtain FEC. For this reason, studies such as Deichmann et al. (2019) which explicitly model energy use by sectors as independent variables use FEC as the numerator in their energy intensity series, as according to them this avoids complexities in aligning the energy balance accounting. Those studies that use TES as their numerator, such as Antonietti and Fontini (2019), do not focus on decomposing energy use into its component sectors as that is not the focus of their analysis.

This thesis focuses on the energy efficiency of the economic system as a whole, and thus it is critical to model the energy intensity of Total Energy Supply. However, in order to perform index decomposition analysis, energy used in the economy needs to be aligned to corresponding sectors of financial value added in the NIA data. As the data do not align perfectly, certain assumptions need to be made to best align the sectors. The key caveat is the treatment of energy used in intermediate energy transformation. In the energy balances data, energy used for transformation in the electrical and energy industry sectors is treated as an intermediate loss, but from a financial standpoint, these operations generate corresponding value added. However, while electricity generation and energy products are both forms of secondary energy from the standpoint of energy accounting, they differ substantially in terms of the distribution of value added of the attendant infrastructure. For example, a report by Alahdad et al. (2020) found that in Canada in 2019, electricity generation accounted for 1.8% of GDP while the energy products sector accounted for 7.7%. The energy balances data for the same year shows that 15% of Canada's primary energy was consumed by electricity generation while 19% was consumed by the energy products industry. Thus, while the share of energy use is very similar between the two sectors, the share of financial value added retained by the energy products sector is much greater than that by the electricity generation sector.

To address this discrepancy, a split strategy was followed when mapping energy use to end sectors. The absolute value of energy used by the energy industry in transformation was mapped to the industry sector to reflect the high-value added nature and diverse industrial processes used in the production of manufactured goods such as coke and refined petroleum products. This mapping corresponds organically to the various mining and processing activities involved in energy products transformation, whose corresponding financial lines in the chemical and mining industries are part of total industry value added in the NIA data. By contrast, the absolute value of electricity and heat production losses were distributed across sectors in proportion to their shares of final electricity and heat consumption. This reflects the undifferentiated homogeneous nature of electricity and heat as an intermediate energy flow, with utilities retaining a tiny fraction of the economy's financial value disproportionate to their share of energy contribution.

The alternative option of assigning all losses in energy conversion to the industry sector would reflect the status of utilities in the industry value added line, but would vastly impact the share of energy used by the industrial sector in the economy in a way that would obfuscate important energy efficiency gains achieved by that sector. Specifically, the electrification of the economy and attendant increase in energy efficiency of end-use sectors could be obscured by the growing energy consumption of the industrial sector if all energy used in electricity transformation was assigned to it. Since the majority of financial value added of electricity use is retained by the end consumer, it makes more sense to map energy transformation losses to those same sectors when aligning energy and financial data. This approach ensures energy use and value added are matched as closely as possible when performing index decomposition.

Following the process outline above, energy use was grouped into three sectors: Industry, Services (including Transport), and Agriculture. Industry is the sum of final energy consumption by the Industry line plus final energy consumption by the Non-Energy line which primarily represents auxiliary processes used by Industry, plus the energy used in energy products transformation. Services is the sum of final energy consumption by the Residential, Commercial and Public Services, and Transport lines. Agriculture is a standalone sector. Primary energy used in electricity and heat generation was then distributed across the aggregated sectors in proportion to their share of final electricity and heat consumption. A complete breakdown of sectors available in the energy balances data and corresponding mappings to the NIA financial value added data is shown in Table 3.

3.3 Energy intensity index

As demonstrated in Table 1 of the literature review section, index decomposition analysis (IDA) is a ubiquitous feature of energy efficiency studies. The most commonly used IDA methodology is the Logarithmic Mean Divisia Index (LMDI), extensively discussed by Ang (2004; 2005), Ang et al. (2009) and Ang et al. (2010). These studies compare the LMDI to a number of other index decomposition techniques and find that it satisfies the important properties of perfect decomposition and reversibility, meaning it does not leave any unexplained residual term as part of the decomposition methodology and does not depend on the choice of a base year. Despite this latter property, Ang et al. (2010) nevertheless suggest the use of a chained index that decomposes changes across adjacent time periods rather than performing decomposition relative to one fixed period to ensure the greatest accuracy. Ang et al. (2010) also highlight the ubiquitous use of the LMDI across organizations and demonstrate multiple cases, such as the application of LMDI in the IEA and EU-ODEX accounting systems to analyze energy efficiency trends across several sectors, as well as its use in Australian studies to compute energy savings and energy performance indicators.

The purpose of index decomposition is to decompose changes of an energy aggregate between any two periods into a series reflecting the shifting energy intensities of the disaggregated sectors and a series reflecting their relative contribution to the aggregate (Ang

Flow Type	**Energy Flow**	**Corresponding NIA Sector**
Supply	Total energy supply	Total Value Added
Electricity generation	Main activity producer electricity plants	Distributed according to sectors' shares of final electricity consumption
	Autoproducer electricity plants	
	Main activity producer CHP plants	
	Autoproducer CHP plants	
	Main activity producer heat plants	
	Losses	
Energy products	Coke ovens	Industry
	Gas works	
	Blast furnaces	
	Oil refineries	
	Other transformation	
	Energy industry own use	
Final energy consumption	Construction	Industry
	Mining and quarrying	Industry
	Manufacturing	Industry
	Transport	Services
	Residential	Services
	Commercial and public services	Services
	Agriculture/forestry	Agriculture
	Non-energy use	Industry

Table 3: IEA Energy Flow Sector Mapping

2004, 2005). For example, we can use it to understand whether declines in energy intensity between two periods are the result of shifts in economic structure, such as a declining financial weight of the industrial sector, or the result of changing energy intensity within the industrial sector, which should more closely resemble technical change. A detailed derivation of the LMDI is found in Ang (2005) and is worth replicating here to understand how the data in this thesis will be treated. Assume V is an energy aggregate influenced by n factors, denoted by $x_1, x_2, \ldots, x_n$. The aggregate variable V can then be expressed as:

$$V = \sum_i V_i = \sum_i x_{1,i} x_{2,i} \cdots x_{n,i} \tag{1}$$

The total change in V from an initial period 0 to a final period T can be expressed as a ratio:

$$\Delta V_{\text{tot}} = \frac{V^T}{V^0} = \frac{\sum_i V_i^T}{\sum_i V_i^0} \tag{2}$$

In the multiplicative LMDI approach, we decompose this ratio into the product of the effects of the individual factors:

$$\Delta V_{\text{tot}} = \Delta x_1 \Delta x_2 \cdots \Delta x_n \tag{3}$$

where Δx_k is the effect of the k-th factor and is given by:

$$\Delta x_k = \exp\left(\sum_i \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)} \ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right)\right) \tag{4}$$

Here, $L(a, b)$ represents the logarithmic mean of a and b, defined as:

$$L(a, b) = \frac{a - b}{\ln a - \ln b} \tag{5}$$

For the specific case of decomposing changes in energy consumption into activity (D_{act}), structure (D_{str}), and intensity (D_{int}) effects, the total energy consumption E can be expressed as:

$$E = \sum_i Q_i S_i I_i \tag{6}$$

Where Q_i represents the activity level of sector i. The share of sector i in total activity Q is given by $S_i = \frac{Q_i}{Q}$. Additionally, the energy intensity of sector i is denoted by $I_i = \frac{E_i}{Q_i}$. The decomposition of the change in total energy consumption from period 0 to period T is then given by:

$$D_{\text{tot}} = \frac{E^T}{E^0} = D_{\text{act}} D_{\text{str}} D_{\text{int}} \tag{7}$$

where the components are defined as follows:

$$D_{\text{act}} = \exp\left(\sum_i \frac{L(E_i^T, E_i^0)}{L(E^T, E^0)} \ln\left(\frac{Q^T}{Q^0}\right)\right) \tag{8}$$

$$D_{\text{str}} = \exp\left(\sum_i \frac{L(E_i^T, E_i^0)}{L(E^T, E^0)} \ln\left(\frac{S_i^T}{S_i^0}\right)\right) \tag{9}$$

$$D_{\text{int}} = \exp\left(\sum_i \frac{L(E_i^T, E_i^0)}{L(E^T, E^0)} \ln\left(\frac{I_i^T}{I_i^0}\right)\right) \tag{10}$$

These formulas allow us to isolate the impact of changes in overall activity D_{act}, sectoral structure D_{str}, and sectoral intensity D_{int} on the total energy consumption. Note that some authors use the terms for structure and activity interchangeably. In practice, most of the studies are concerned with analyzing just the structural and intensity components, since the activity component is just a balancing term that keeps the series stable at a fixed value. In this thesis, the focus is on understanding efficiency changes, hence the focus will be on decomposing total changes in energy intensity (defined as energy consumption per dollar of GDP, or E/Q in the index decomposition terminology) into $Dint$ and $Dstr$ where the sectors i represent Industry, Services, and Agriculture as derived above, the sector financial shares S_i are the shares of final value added in GDP, and the sector intensities I_i are the kJ of total energy supplied to each sector divided by the final dollar value added of each sector.

Decomposition was performed using manual code implemented in R. Chained decomposition was used to comply with the best practices described in Ang et al. (2010), meaning that each period was decomposed relative to the previous period. To ensure that my final results can be interpreted as the AEEI which represents direct changes in energy efficiency, the resulting decomposition series (which represents ratios of one period versus another) was then recursively projected onto the original energy intensity series starting with the value in 1995 to obtain "counterfactual" series via the formulae:

$$EI_t^{Int} = EI_{t_0} \times \prod_{k=t_0+1}^{t} D_{int,k} \tag{11}$$

$$EI_t^{Str} = EI_{t_0} \times \prod_{k=t_0+1}^{t} D_{str,k} \tag{12}$$

Here EI_t^{Int} represents the evolution of energy intensity in a scenario in which there are no structural changes *between* sectors, while EI_t^{Str} represents energy intensity in a scenario in which there are no intensity changes *within* sectors. The resulting decompositions for each region are shown in Figure 4, where the scales are normalized to 1 at the base year for ease of visual comparison.

There are several important observations to make regarding the decomposition plot. Sectoral intensity is clearly the dominant component driving overall intensity shifts in all regions except Brazil. This finding aligns with the literature; indeed, the decomposition plots closely resemble those in Jiminez and Mercado (2014), despite differences in data, regional aggregation, and the choice of index decomposition technique. However, caution is needed before interpreting this as an improvement in energy efficiency. As Jiminez and Mercado note, the effectiveness of index decomposition relies heavily on the granularity of sectoral dis-aggregation. More detailed dis-aggregations at the sub-sector level (e.g., metals, chemicals, transport) in studies such as Voigt et al. (2014) tend to reveal a greater role for structural shifts in explaining energy intensity changes than is visible in studies using high-level aggregates. Unfortunately, the more detailed sectoral dis-aggregations necessary for such analysis are not available for this breadth of data, which requires focusing on more targeted sets of countries, such as the manufacturing sectors of the 15 OECD economies studied by Parker and Liddle (2016). Nonetheless, even with more granular decomposition, Parker and Liddle's findings support the consensus that sector intensities are the dominant driver of aggregate intensity.

It is also important to consider the critique by Kander (2005), who argues that financial aggregates are problematic for inferring changes in underlying energy efficiency. She suggests that these aggregates can be misleading because the price of manufactured goods tends to fall relative to services due to faster productivity growth in manufacturing. This causes an apparent stagnation or decline in the financial share of manufacturing, accompanied by stability or even expansion in real output. Consequently, when measured in constant prices, the relative share of manufacturing remains stable, contradicting the notion of a real shift to a service economy that would imply reduced material and energy demands. To address this issue, this thesis employs the share of industry in energy consumption as an additional layer of structural controls, ensuring that any effects not captured through index decomposition are accounted for by changes in the real physical use of energy. However, this strategy also carries risks, as changing energy shares may reflect differential growth in energy productivity. A further discussion of this issue is provided in the Methodology section.

3.4 Energy price index

Energy price is a critical control variable for any attempt to model the AEEI, as short-term price increases may cause greater relative output declines in energy-intensive industries while long-term increases incentivize investment in energy efficiency technology. Unfortunately, detailed data on energy prices by country were not available for this study. Instead, country-specific price indices were constructed following the methodology outlined by Antonietti and Fontini (2019), who used the real exchange rates of local currency to the dollar to construct country-specific price indices for the price of oil. The methodology was adjusted to better reflect the impact of prices on energy use by replacing the consumer price index (CPI) used in calculating real exchange rates with the implicit price deflator (IPD). The IPD measures the overall price level of all domestically produced final goods and services in the economy, and allows for assessing the broader impact of energy price

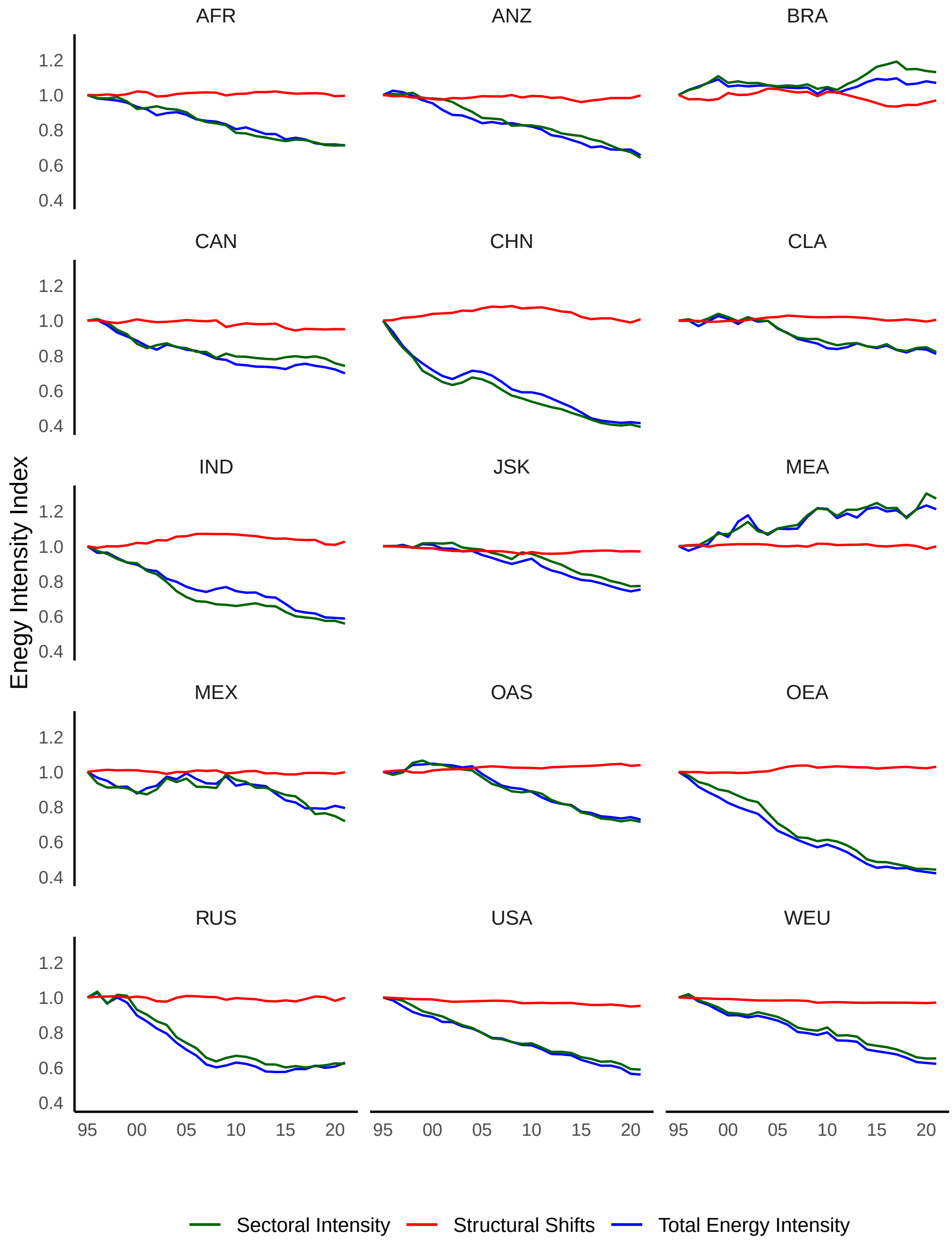

Figure 4: Energy Intensity Decomposition by Region

changes in the economy as a whole rather than the more narrow focus on final consumer prices in the CPI. Data on both the IPD and exchange rates come from the NIA. The original IPD is indexed to 2015 which was re-based to 2021 to align with the GDP PPP data.

The resulting formula was generalized to construct price indices for each of the three major traded international commodities: oil, gas, and coal. The prices for these are available from the CMO data. For oil and coal, a simple average of world prices was used. For gas, countries were assigned to one of three gas hubs (HH, TTF, JKM) based on their region to better reflect the fragmented nature of the natural gas market, and the details of this mapping are presented in the appendix. Regional-level price indices were then constructed as a weighted sum of local real commodity prices multiplied by the shares of their respective fuels in the overall regional energy mix.

Thus, for any individual country j, the price index for commodity i is given by the formula:

$$P_{i,j} = \left(\frac{P_i^{\$} \times \mathrm{ER}_j^{\mathrm{LCU}/\$}}{\frac{\mathrm{IPD}_j^{\mathrm{LCU}}}{100}} \right) \times \left(\frac{\mathrm{IPD}^{\$}}{100} \right) \tag{13}$$

Where $P_{i,j}$ represents the price index of commodity i for country j, reflecting the real cost of commodity i in terms of a base year's purchasing power. The notation $P_i^{\$}$ refers to the annual price of commodity i in US dollars. The term $\mathrm{ER}_j^{\mathrm{LCU}/\$}$ denotes the annual exchange rate from US dollars to the local currency unit (LCU) for country j, indicating how many LCUs one US dollar can purchase. The variable $\mathrm{IPD}_j^{\mathrm{LCU}}$ represents the annual Implicit Price Deflator in the local currency units for country j. Finally, $\mathrm{IPD}^{\$}$ is the annual Implicit Price Deflator for the United States. Both IPD's were normalized to 2021 to align energy prices with the constant 2021 dollars used to measure GDP.

Once price indices are calculated for each commodity, a complete energy price index for every region R can be constructed by taking the weighted sum of the commodity price indices for each country $j \in \mathbb{R}$ and the share of each respective commodity c_i (coal, oil, and natural gas) in the overall regional fuel mix F_R:

$$P_R^{\mathrm{Energy}} = \sum_i \sum_j \left(\frac{c_{ij}}{F_R} \right) P_{ij} \tag{14}$$

The resulting index for each region is shown in Figure 5. To ensure comparison across fuel carriers, all commodity prices were first converted into \$/MJ using the EIA's energy conversion calculator (U.S. Energy Information Administration, 2024) Note that this formula implies a marginal cost of zero for other energy sources, such as biomass and waste, renewables, hydro, and nuclear power. This is not entirely accurate, but the costs for larger projects are primarily capital and maintenance costs as the fuel itself is either a tiny fraction of costs (nuclear) or non-existent for other renewables sources, while the price for biomass and waste is assumed to be generally cheaper than that for fossil fuels in countries that use them to a substantial degree. Thus, while the cost of missing fuel vectors is not zero, it is lower than that of the fossil fuels measured, and thus the formula will capture this effect. Another limitation of this index is the absence of electricity price data or data on energy subsidies. Taken together with the high-level of aggregation, this price index must be understood as an imperfect but necessary approximation.

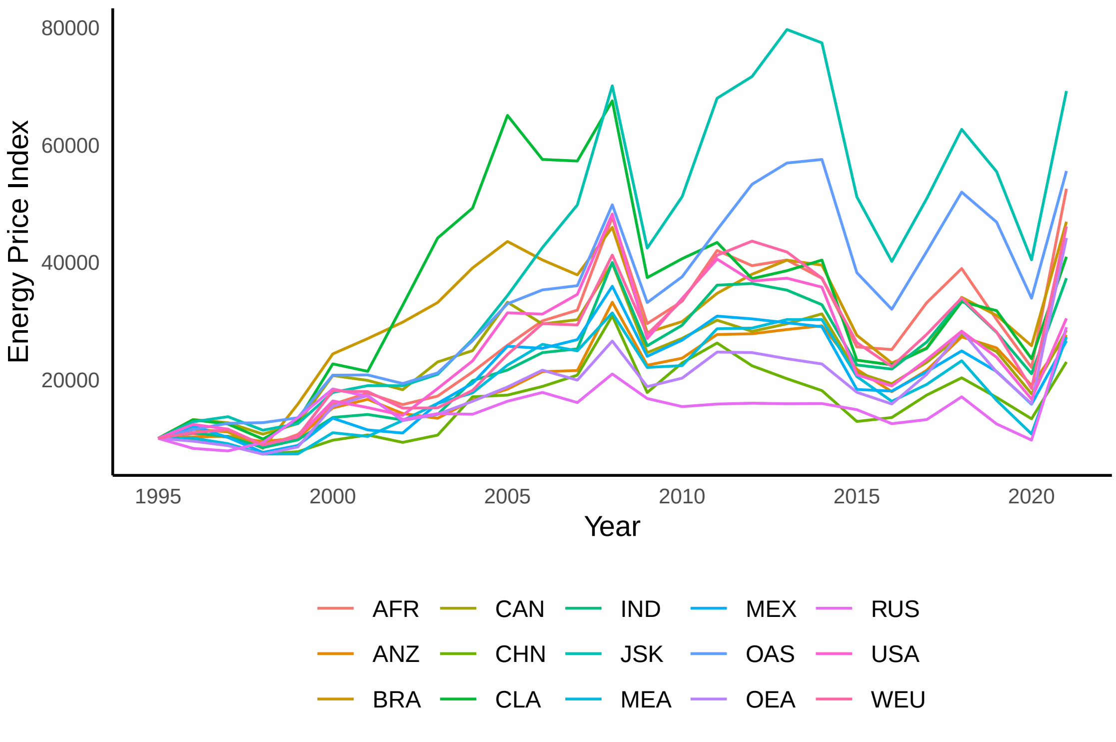

Figure 5: Real Energy Price Index

Finally, in order to model the impact of price asymmetry as suggested by Adeyemi and Hunt (2014), the resulting price indices were split into asymmetric components representing accumulating sequences of price increases and decreases, respectively. These components were constructed following Liddle and Sadorsky (2020) as:

$$P_t^+ = \sum_{j=1}^{t} \max(\Delta P_j, 0) \tag{15}$$

$$P_t^- = \sum_{j=1}^{t} \min(\Delta P_j, 0) \tag{16}$$

Where P_t^+ is the accumulating series of price increases and P_t^- is the accumulating series of price decreases. This formulation represents the notion that price increases may induce structural changes to the energy system that are not reversed when prices decline. The findings in Adeyemi and Hunt (2014), Parker and Liddle (2016), and Liddle and Sadorsky (2020), among others, all speak to the importance of controlling for price asymmetry in energy efficiency and demand studies.

3.5 Other data and variable tables

The other data used in this study consists of controls for income and fuel mix. Income is measured as GDP PPP per capita in constant 2021 international dollars. In terms of fuel mix, share of nuclear and renewables in the overall energy mix was selected as the main control variable, as it is most likely to correlate with the wider effort at energy transition and hence can serve as a proxy for energy policy. Detailed tables of the energy supply and energy demand structures of each region are available in the appendix.

To interpret model coefficients as elasticities, all values including sector and fuel shares as well as the index-decomposed energy intensity series were transformed into logarithms. Since the logarithm of zero is undefined and since the logarithm function changes concavity about the point $x = 1$, share data was converted into basis points on a 10,000 point scale and all values less than 1 on this scale (less than 0.01% on the original scale) were set to 1. This ensures that the logarithmic transformation preserves a value of zero as the base of the scale. The price index was also transformed to avoid values less than 1, and the energy intensity of GDP was converted into KJ/$. Summary tables of the final variables used in my models are presented in Tables 4 and 5.

Variable	Min	Max	Mean	SD
Energy intensity	2394	13132	4862	1779
Intensity decomposition	2448	13132	4905	1771
Structural decomposition	2924	14224	6107	2778
Energy price index	7312	79669	24731	13363
Sum of price increases	0	150918	32557	27493
Sum of price decreases	-91722	0	-17826	18869
Income	2530	70174	26461	18105
Share of energy demand by industry	30	70	46	7
Share of energy supplied by nuclear and renewables	0	23	9	6

Table 4: Descriptive Statistics of Variables

Symbol	Variable (Transformed)	Calculation
EI	log energy intensity	Energy intensity in kJ / GDP PPP in constant 2021 $
EI^{Int}	log intensity decomposition	Counterfactual series of energy intensity if only sector intensities changed
EI^{Str}	log structural decomposition	Counterfactual series of energy intensity if only sector shares changed
P	log energy price index	Local currency real energy prices weighted by fuel share
P^{+}	sum of log price increases	Sum of accumulated energy price increases
P^{-}	sum of log price decreases	Sum of accumulated energy price decreases
Y	log income	GDP PPP per capita in constant 2021 $
ED^{Ind}	log share of energy demanded by industry	Share of total energy demand by the industrial sector, including the energy products industry
ES^{NR}	log share of energy supplied by nuclear and renewables	Share of total energy supply from nuclear, hydro, geothermal, solar, wind, and other (SWO)

Table 5: Variable Symbols and Definitions

4 Methodology

This thesis uses panel data techniques to elicit AEEI estimates in a global setting. Since the AEEI is not directly observable, this poses a major challenge. Most of the literature on empirically modeling energy efficiency, such as Hunt et al. (2003), does so for a given country with a long time series and can therefore use structural time series techniques to elicit the unobservable stochastic trend component that represents technological changes alongside other factors. Those studies that model AEEI at a global level, such as Fujimori et al. (2016), do so within the context of theoretical CGE or IAM models, and derive the AEEI from model calibration or by setting fixed parameter values and testing the fit of the resulting predictions. This thesis is therefore in a narrow niche that seeks to elicit both global and regional values for the AEEI in a unified and purely empirical framework. To my knowledge, I have not found any other work that attempts to tackle the question in this exact manner. That said, there are cross-country panel studies that model the impact of income and prices on energy efficiency and demand, and which use a control structure that I believe can be re-purposed to elicit the desired results.

In terms of the existing literature this thesis most closely aligns with the work of Parker and Liddle (2016) and Liddle and Sadorsky (2020) who investigate global energy trends using the Augmented Mean Groups (AMG) estimator developed by Bond and Eberhardt (2009) and Eberhardt and Teal (2010). AMG is an extension of the Mean Groups (MG) estimator of Pesaran and Smith (1995), originally developed to overcome the bias caused by imposing homogeneous restrictions on heterogeneous coefficients in a pooled OLS panel regression. MG models involve estimating separate regressions for each panel unit, which are assumed to represent idiosyncratic local effects. The estimates are then averaged to elicit a common mean effect. This methodology is effective when all slopes are heterogeneous, but can fail to detect the true strength of homogeneous effects when they exist (Pesaran et al., 1999) and can suffer from cross-sectional dependence among panel units, which can bias the averaged results (Bond and Eberhardt, 2009). To overcome this bias, Bond and Eberhardt proposed the AMG estimator, which augments the classic MG estimator with an underlying stochastic trend termed the common dynamic process that represents an accumulating sequence of commonly correlated shocks that affect all panel units and evolve over time, and which is presented in detail in the next section.

4.1 Derivation of the AMG estimator

Bond and Eberhardt (2009) propose the following two-step procedure designed to address cross-sectional dependence in panel data models. In the first step, a pooled OLS regression augmented with time dummies is calculated in differences. The coefficients of the differenced dummies are then collected into a single vector called the common dynamic process (CDP). This vector is then appended to the individual panel units, and individual regressions are run to calculate the Mean Groups estimator. To see how this works formally, consider a panel data model:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}, \tag{17}$$

where y_{it} is the dependent variable for unit i at time t, x_{it} is the independent variable, α_i is the unit-specific intercept, β_i is the unit-specific slope coefficient, and u_{it} is the error term. To account for cross-sectional dependence, we assume that the error term u_{it} can be decomposed as:

$$u_{it} = \lambda_i f_t + \epsilon_{it}, \tag{18}$$

where f_t is a latent variable representing an unobserved common factor that is assumed to correlate across panel units, λ_i is the factor loading, ϵ_{it} is the idiosyncratic error term. f_t is assumed to evolve according to the process:

$$f_t = \rho f_{t-1} + \eta_t, \tag{19}$$

Which includes the potential for non-stationarity when $\rho = 1$. It is important to note that the estimator remains consistent in this situation. The first step of the AMG procedure then involves estimating the common dynamic process f_t. This can be done by running a pooled regression with time dummies D_t on the differenced variables:

$$\Delta y_{it} = \beta_i \Delta x_{it} + \sum_{t=2}^{T} \delta_t \Delta D_t + \nu_{it}, \tag{20}$$

where δ_t are the coefficients on the time dummies, and ν_{it} is the differenced error term. Notice that in this model the matrix of the time dummies $\mathbf{D}$ will take the form:

$$\begin{pmatrix} 1 & 0 & \dots & \dots & 0 & 0 & 0 \\ -1 & 1 & \dots & \dots & 0 & 0 & 0 \\ 0 & -1 & \dots & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & & & & \vdots \\ 0 & 0 & \dots & \dots & 1 & 0 & 0 \\ 0 & 0 & \dots & \dots & -1 & 1 & 0 \\ 0 & 0 & \dots & \dots & 0 & -1 & 1 \end{pmatrix} \tag{21}$$

That is, the differenced time dummies are not purely instantaneous shocks but rather the accumulation of shocks over time. The estimated time dummy coefficients $\hat{\delta}_t$ are then collected into a vector representing the CDP, with $\hat{\delta}_1 = 0$ to initialize the process:

$$\hat{\boldsymbol{\delta}} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_T \end{bmatrix} \tag{22}$$

Whose entries are assumed to represent the underlying common factor:

$$\hat{f}_t = \hat{\delta}_t. \tag{23}$$

In the second step, the estimated common dynamic process $\hat{f}_t$ is included as an additional regressor in the original model:

$$y_{it} = \alpha_i + \beta_i x_{it} + \gamma_i \hat{f}_t + \epsilon_{it}. \tag{24}$$

The model is then estimated separately for each cross-sectional unit i, and the individual coefficients $\hat{\beta}_i$ are averaged to obtain the AMG estimator:

$$\hat{\beta}_{AMG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}_i. \tag{25}$$

This procedure yields consistent and unbiased estimates of the long-run parameters β_i in the presence of cross-sectional dependence, non-stationarity, and heterogeneous slopes. However, its performance can degrade in the presence of reverse causality, if the number or nature of the common factor is mis-specified, or in very small sample sizes (Bond and Eberhardt, 2009). With these caveats in mind, we now turn to the derivation of the AEEI parameter estimates from these estimated common factors.

4.2 Derivation of the AEEI parameter estimate

The AMG methodology has been successfully applied to global energy studies. Parker and Liddle (2016) use the AMG estimator to investigate the impact of energy prices on energy efficiency in the manufacturing sectors of 15 OECD economics. Liddle and Sadorsky (2020) study the impact of price and income asymmetry on energy demand in a global panel of 91 countries. Both methodologies include asymmetric price changes, and Liddle and Sadorsky finds these to be highly significant. Liddle and Sadorsky study energy demand directly, while Parker and Liddle first use LMDI decomposition to decompose their energy intensity series into an intensity component, which they term the efficiency component, and a structural component. Both studies find high statistical significance for the CDP coefficient, and both authors suggest that the CDP in this setting represents shared global or regional economic forces, such as technological advancements, policy changes, or market conditions, that simultaneously influence energy efficiency and demand across multiple countries or sectors. Thus, the CDP in such studies has a similar intepretation as the UEDT in Hunt et al. (2003), only it is estimated via cross sectional time dummies rather than in a structural time series framework.

In both Parker and Liddle (2016) and Liddle and Sadorsky (2020), the CDP is used as a control variable to account for cross-sectional dependence, and is not the focus of the study. However, in the original presentation of the AMG methodology, Eberhardt and Teal (2010) focus on modelling the unobserved latent variable f as that component of a country's manufacturing Total Factor Productivity (TFP) that is driven by international technology trade, foreign investment, and the general progress of technological knowledge that is assumed to correlate across countries. That is, their study focuses on understanding the behavior of the common dynamic process itself rather than passively incorporating it as a control variable in the regression, and treats it as a latent variable that represents accumulating technological progress.

This thesis will follow the structure of Parker and Liddle (2016) in using an AMG framework with asymmetric prices to model the index-decomposed series of energy intensity. However, following Eberhardt and Teal (2010; 2019), I will shift the focus to understanding the behavior of the common dynamic process itself. Specifically, I will treat the latent variable f as representing the accumulation of general technological advancement, cross-border knowledge spillover, and macroeconomic shocks that affect energy intensity changes. Between any two periods $t-1$ and t, the expected evolution of this process then becomes $\mathbb{E}[\Delta \hat{f}_t]$. In order to isolate the secular trends in technological progress that represent autonomous energy efficiency improvement from other shocks that impact energy intensity but are unrelated to energy efficiency, I will further decompose the common dynamic process into a deterministic and stochastic component. The derivations that follow are based on the methods presented in the Time Series Econometrics course by Dr. Giacomo Candian in the Winter 2021 semester.

To give a concrete analogy, it useful to first consider what exactly is happening when we estimate the "classic" AEEI by using solely a deterministic trend formulation of the kind presented in Webster et al. (2008), where E is energy demand:

$$E_t = \beta_1 P_{t-1} + \beta_2 Y_{t-1} + \gamma t + \epsilon_t \tag{26}$$

When we treat the term γ as representing the long-run estimate of the AEEI parameter (hereafter denoted $\hat{A}$), we are implicitly saying that our expectation of the future evolution of autonomous energy efficiency improvement is that of the estimated response of energy demand (or energy efficiency) $\hat{\gamma}$ to a deterministic trend with an expected difference of one. Explicitly:

$$\hat{A} = \hat{\gamma}\mathbb{E}[\Delta t] = \hat{\gamma}(1) = \hat{\gamma} \tag{27}$$

This is trivial, but is worth mentioning as it is the basis for the methodology used to estimate the AEEI in this thesis. Specifically, I treat the unobserved latent variable f from the AMG estimator as following a random walk with drift:

$$f_t = \mu + \rho f_{t-1} + \eta_t, \tag{28}$$

Since the AMG estimator is robust to unit root processes (Eberhardt and Teal, 2010), it should admit such a formulation. In fact, the graph of the CDP presented in Eberhardt and Teal clearly shows a stochastic process with a strong underlying time trend. If the process has a unit root then $\rho = 1$, then the common dynamic process can be modeled as:

$$f_t = \mu + f_{t-1} + \eta_t, \tag{29}$$

which when differenced yields

$$\Delta f_t = f_t - f_{t-1} = \mu + \eta_t, \tag{30}$$

If we assume that $\eta_t \sim \mathrm{N}(0, \sigma^2)$ and is independent and identically distributed (i.i.d.), then the differenced process becomes a constant μ with white noise disturbances, that is $\mathbb{E}[\eta_t] = 0$. Since these disturbances are symmetric about 0, they will tend to cancel out as our time span $T \to \infty$. Thus, at any point in time, our expectation $\mathbb{E}[\Delta f_t]$ can be derived as:

$$\begin{aligned}
\Delta f_t &= \mu + \eta_t && (31)\\
\mathbb{E}[\Delta f_t] &= \mathbb{E}[\mu + \eta_t] && (32)\\
&= \mu + \mathbb{E}[\eta_t] && (33)\\
&= \mu + 0 \quad (\text{since } \mathbb{E}[\eta_t] = 0) && (34)\\
\mathbb{E}[\Delta f_t] &= \mu, \quad \forall t && (35)
\end{aligned}$$

If $\hat{\gamma}_i$ is the estimated coefficient on the CDP for an individual panel unit, then plugging in the expected difference of the estimated process $\mathbb{E}[\Delta \hat{f}]$ into equation (27) in place of $\mathbb{E}[\Delta t]$ yields the long-run AEEI estimate $\hat{A}_i$ for region i:

$$\hat{A}_i = \hat{\gamma}_i \mathbb{E}[\Delta \hat{f}] = \hat{\gamma}_i \hat{\mu} \tag{36}$$

Where $\hat{\mu}$ is the estimated mean of the CDP in first differences, and represents the drift component of the random walk. Following the Augmented Mean Groups methodology, our global estimator then becomes:

$$\bar{A} = \frac{1}{N}\sum_{i=1}^{N} \hat{A}_i = \frac{1}{N}\sum_{i=1}^{N} \hat{\gamma}_i \hat{\mu} = \bar{\gamma}\hat{\mu} \tag{37}$$

Conceptually, this means that if our latent variable f represents the full range of commonly correlated shocks that affect energy intensity across all panel units, including business cycles, trade flows, and technological changes, then we can further decompose our estimate of $\hat{f}$ into a purely stochastic component $\hat{\eta}$ that represents business cycles and other idiosyncratic disturbances that impact energy use but are not related to technological changes, and a deterministic trend component $\hat{\mu}$ that represents the underlying long-run evolution in energy efficiency technology. The locally estimated $\hat{\gamma}_i$ will then represent the strength with which individual regions respond to this underlying efficiency trend, while the average estimator $\bar{\gamma}$ measures the strength of response in the world economy as a whole. The separate estimation of global mean technology evolution $\hat{\mu}$ and regional response parameters $\hat{\gamma}_i$ also allows for a more accurate representation of regional dynamics when technological changes are heterogeneous across regions.

Equations (36) and (37) will be estimated for each region individually and for the world as a whole, and represent the primary result of this thesis. Essentially, they blend the energy efficiency study of Parker and Liddle (2016) with the latent representation of technological progress via a stochastic trend with drift that is found in Jin and Jorgensen (2010), estimated by explicitly analyzing the common dynamic process in an approach inspired by Bond and Eberhardt (2009), and Eberhardt and Teal (2010; 2019).

4.3 Model control structure

If AEEI represents that which is "left over" after other factors have been accounted for (Kaufman, 2004), then the interpretation of the AEEI should very much depend on what type of controls are included in the model during estimation. The common formulation of the AEEI is that it absorbs all effects not related to price and income (Liddle, 2023). However, this can vary by model - for instance, the schematic for the TIMER model found in van Ruijven et al. (2010) clearly shows that AEEI impacts energy demand through a channel that runs parallel to sectoral change, meaning that it nets out structural shifts as well. Indeed, if AEEI is to represent changes in technology specifically, then at least some kind of structural control will have to be included in the empirical setup.

As described in the data section, the first layer of structural controls is the LMDI decomposition used to construct the dependent variable EI^{Int}, which nets out changes in the financial contribution of various sectors to focus on changes in intensities within those specific sectors. However, due to the high level of aggregation when using total Industry, Services, and Agriculture in the decomposition, substantial residual structural changes will remain within the the series (Voigt et al., 2014; Kander, 2005). For this reason, although I also use LMDI I am not comfortable directly calling my dependent variable "efficiency" in the same manner as Parker and Liddle (2016), who use a much more granular index decomposition of the manufacturing industry into its sub-sectors. Instead, I use the share of energy demanded by industry ED^{Ind} as an additional variable to control for structural changes. To make my AEEI estimate "autonomous" of government policy as well, I use the share of energy supply by nuclear and renewables, ES^{NR}, as a proxy for government energy policy.

Both of these controls are imperfect as they are likely to absorb many adjacent correlated effects. For example, the changing share of energy demanded by industry ED^{Ind} may be the result of structural changes due to industrial offshoring, but may also represent differential rates of energy efficiency improvement in the industry sector versus other sectors. Likewise, while the changing share of energy supplied by nuclear and renewables ES^{NR} may represent government policy directed at stimulating energy efficiency more generally, it may absorb many adjacent effects such as the broader trend towards energy efficiency driven by electrification and the independent choices of market actors to invest in variable renewable sources (VRE), which is becoming a common feature of the energy generation landscape (Amirmoeni et al., 2024).

Additional consideration must be paid to the temporal dynamics of the model. The high persistence of energy intensity is clearly visible in the regional energy intensity plots that were presented in Figure 4. To control for this, studies such as Parker and Liddle (2016) include a lag of the dependent variable in their AMG framework. However, since the process I am modeling is unobserved and represents the exogenous variation in energy intensity not accounted for by my control variables, there is a risk that introducing a lagged dependent variable might absorb much of the very effect I am looking to measure. Furthermore, lagged dependent variables introduce additional complexities in deriving long-run coefficients and their variances, and in general the proliferation of control variables in panel units of 27 observations each may cause the models to become overfit at the individual region level, even if not necessarily at the aggregate level. Finally, given the heterogeneous slope estimates in a Mean Groups framework, there is no way of telling *a priori* which model specification is the best fit for each region, and while some may fit better others may destabilize the estimates.

Instead of trying to overcome these complexities by estimating a single optimal global model, I chose to use a mixed-model approach. Specifically, I estimate multiple model specifications for each panel unit and for the world as a whole, then average the resulting coefficient estimates to generate consensus estimates within model classes and across all models. This methodology offers significant advantages, particularly in contexts where the true model specification is unknown and sample sizes are small. Buckland (1997) argues that when the true model is complex or unknown, approximating reality with simpler models through a mixed-model approach provides a more robust solution. This is especially relevant when data are sparse, as it avoids the pitfall of overfitting and acknowledges the potential for multiple models to approximate different aspects of the data. Furthermore, Hansen (2007) demonstrates that model averaging can achieve lower mean squared errors compared to selecting a single best model, thereby improving overall estimation accuracy in finite samples. This approach allows for the incorporation of model selection uncertainty, leading to more reliable inferences than those obtained by traditional model selection methods alone.

For simplicity, I opted to average my models using the weighted least squares (WLS) methodology where the weights are the inverse variances of the individual estimates, ensuring that my consensus models assign greater weight to estimates with better fits (Greene, 2003). Following the approach in Eberhardt (2012) I implement this averaging by regressing the weighted coefficient estimates on a constant. Thus, for a given vector of intercept estimates $\boldsymbol{\beta}$, a vector of ones $\mathbf{1}$, and a diagonal matrix of weights $\mathbf{W}$ containing the inverse variances, my WLS consensus estimator is given by:

$$\hat{\beta}_{\text{WLS}} = \left(\mathbf{1}^{\top}\mathbf{W}\mathbf{1}\right)^{-1}\mathbf{1}^{\top}\mathbf{W}\boldsymbol{\beta} \tag{38}$$

I estimate a total of 24 models to elicit the AEEI from various angles. To serve as a control group, I estimate 8 Mean Groups models with deterministic time trends termed MG-T, that replicate the traditional setup for estimating the AEEI. All models have a matrix of controls $\mathbf{X} = [\mathbf{P}^{+} \mid \mathbf{P}^{-} \mid \mathbf{Y}]$ which contains controls for asymmetric price and income effects. The models are then partitioned into two groups, static (MG-TS) and dynamic (MG-TD) indicating the absence or presence of a lagged dependent variable. For each group, I specify four structural control specifications: (1) with no structural controls, (2) with controls for the share of industry in energy demand only, (3) with controls for the share of nuclear and renewables in energy supply only, and (4) with both sets of structural controls. Structural control variables are contained in the matrix $\mathbf{S} = \left[\mathbf{ED}^{Ind} \mid \mathbf{ES}^{NR}\right]$. Thus, the equation for a generic MG-T model for region i becomes:

$$EI_{it}^{Int} = \phi EI_{it-1}^{Int} + \mathbf{X_{it}}\boldsymbol{\beta}^{\top} + \mathbf{S_{it}}\boldsymbol{\theta}^{\top} + \gamma_i t + \epsilon_{it} \tag{39}$$

Where ϕ, θ_1, and θ_2 are restricted to 0 depending on the model specification.

Eight AMG and eight AMG with trend (AMG-T) models are specified following this same template. In the case of the basic AMG model, the deterministic trend component of the MG-T model is replaced by the common dynamic process $\hat{f}$ estimated from a first stage regression in differences containing the same set of control variable as the second-stage model, thus giving the general AMG specification:

$$EI_{it}^{Int} = \phi EI_{it-1}^{Int} + \mathbf{X_{it}}\boldsymbol{\beta}^{\top} + \mathbf{S_{it}}\boldsymbol{\theta}^{\top} + \gamma_i \hat{f}_t + \epsilon_{it} \tag{40}$$

In the case of the AMG-T model, the AMG model is extended to include an deterministic time trend, and thus represents a hybrid of the MG and AMG specification. This possibility was allowed by Eberhardt and Teal (2010) who suggested that the inclusion of additional local time trends might boost the signal from the CDP by netting out local idiosyncrasies. The formulation of the generic AMG-T model then becomes:

$$EI_{it}^{Int} = \phi EI_{it-1}^{Int} + \mathbf{X_{it}}\boldsymbol{\beta}^{\top} + \mathbf{S_{it}}\boldsymbol{\theta}^{\top} + \gamma_i \hat{f}_t + \alpha_i t + \epsilon_{it} \tag{41}$$

Note that $\hat{\gamma}_i$ will be the estimated coefficient of the time trend in the MG-T model and the estimated coefficient of the CDP in the AMG and AMG-T models. This is done to emphasize the role of these terms as estimates for the AEEI in their respective specifications. Note also that, in the case of the AMG-T model, the deterministic trend is appended after the first-stage estimation of the CDP has been completed. For ease of reference, the model control structures are summarized in Table 6.

Once individual panel units are estimated, I calculate my "vertical" AMG coefficient estimates across regions according to equation (25), and then calculate model consensus estimates "laterally" for each region and for the world according to equation (38). In the case of dynamic models, long-run coefficients are derived as $\hat{\beta}(1-\hat{\phi})^{-1}$ to account for the persistence of shocks. Standard errors are then calculated via the Delta method as in Parker and Liddle (2016). I implement this via the **msm** package in R.

4.4 Implementation

Stata's **xtmg** package developed by Eberhardt (2012) allows for the estimation of MG and AMG models and allows access to both the aggregate and individual-level results, but does not allow access to the CDP estimated in the first-stage regression. Thus, I wrote custom script in R to replicate these estimators, and validated the group-level and aggregate results against those obtained in Stata to ensure accuracy in implementation. In the case of AMG, the overall structure is that described by Eberhardt - I first estimate a pooled OLS manually augmented with time dummies in first differences, then I estimate group-level regressions. If trends are present in the AMG model, they are appended after the estimation of the CDP. Standard errors are calculated relative to a z-distribution to comply with the procedure in the **xtmg** package.

Model	Trend	CDP	Dynamic	Demand	Supply
MG-TS(1)	X				
MG-TS(2)	X			X	
MG-TS(3)	X				X
MG-TS(4)	X			X	X
MG-TD(1)	X		X		
MG-TD(2)	X		X	X	
MG-TD(3)	X		X		X
MG-TD(4)	X		X	X	X
AMG-S(1)		X			
AMG-S(2)		X		X	
AMG-S(3)		X			X
AMG-S(4)		X		X	X
AMG-D(1)		X	X		
AMG-D(2)		X	X	X	
AMG-D(3)		X	X		X
AMG-D(4)		X	X	X	X
AMG-TS(1)	X	X			
AMG-TS(2)	X	X		X	
AMG-TS(3)	X	X			X
AMG-TS(4)	X	X		X	X
AMG-TD(1)	X	X	X		
AMG-TD(2)	X	X	X	X	
AMG-TD(3)	X	X	X		X
AMG-TD(4)	X	X	X	X	X

CDP is the common dynamic process. Dynamic refers to the presence of a lagged dependent variable. Demand refers to controls for share of industry in energy demand. Supply refers to controls for share of nuclear and renewables in the energy supply.

Table 6: Model Structure Summary

5 Results

5.1 Exploratory analysis

Prior to obtaining my main results, I ran pooled OLS models with fixed effects in levels and differences without any exogenous trends to get a sense of the behavior of my control variables. The overall panel model specification is:

$$EI_{it}^{Int} = \mathbf{G_{it}}\boldsymbol{\beta}^{\top} + \mu_i + \theta_t + \epsilon_{it} \tag{42}$$

Where $\mathbf{G_{it}}$ is a matrix of various control variables, μ_i are country fixed effects and θ_t are time fixed effects. Country fixed effects are present in all level model runs. Controls are layered progressively starting with price (1), income (2), structural controls (3), and time fixed effects (4). All models are run with and without price asymmetry and in levels and differences. The results are presented in Table 7 for levels and Table 8 for differences.

Table 7: Panel Results - Levels

	No Price Asymmetry				Price Asymmetry			
Variable	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P_t	-0.1672***	-0.0216	-0.0122	0.0008				
	(0.0376)	(0.0231)	(0.0237)	(0.0538)				
P_t^+					-0.0722**	-0.0129	-0.0093	0.0058
					(0.0182)	(0.0175)	(0.0223)	(0.0668)
P_t^-					0.0894*	0.0516	0.0215	-0.0158
					(0.0322)	(0.0253)	(0.0310)	(0.0983)
Y_t		-0.5008***	-0.5513***	-0.5059**		-0.4005***	-0.4967***	-0.5083**
		(0.0789)	(0.0886)	(0.1368)		(0.0834)	(0.1181)	(0.1372)
ED_t^{Ind}			0.7407*	0.6331			0.6217	0.6417
			(0.2851)	(0.3270)			(0.3149)	(0.3326)
ES_t^{NR}			0.0152	0.0271			0.0148	0.0282
			(0.0757)	(0.0801)			(0.0733)	(0.0802)
Time effects	No	No	No	Yes	No	No	No	Yes
Adj R^2	0.85	0.94	0.95	0.95	0.91	0.95	0.96	0.95
Within R^2	0.26	0.72	0.78	0.47	0.57	0.75	0.78	0.48

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered at the region level. Sample size N = 405. All variables have been within-transformed to remove country fixed effects. The dependent variable is EI_t^{Int}.

Table 8: Panel Results - Differences

	No Price Asymmetry				Price Asymmetry			
Variable	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ΔP_t	-0.0088	0.0093	0.0072	0.0280*				
	(0.0052)	(0.0047)	(0.0045)	(0.0125)				
ΔP_t^+					0.0048	0.0129	0.0146	0.0422*
					(0.0082)	(0.0085)	(0.0074)	(0.0177)
ΔP_t^-					-0.0290*	0.0035	-0.0049	-0.0039
					(0.0118)	(0.0098)	(0.0093)	(0.0267)
ΔY_t		-0.4108***	-0.4307***	-0.4399***		-0.4068***	-0.4226***	-0.4467***
		(0.0511)	(0.0556)	(0.0559)		(0.0502)	(0.0546)	(0.0599)
ΔED_t^{Ind}			0.2176*	0.2372**			0.2202*	0.2398**
			(0.0800)	(0.0726)			(0.0792)	(0.0725)
ΔES_t^{NR}			-0.0663*	-0.0672*			-0.0689*	-0.0685*
			(0.0256)	(0.0263)			(0.0255)	(0.0272)
Constant	-0.0140***	-0.0055	-0.0039		-0.0172***	-0.0065	-0.0058	
	(0.0032)	(0.0029)	(0.0028)		(0.0040)	(0.0036)	(0.0032)	
Time effects	No	No	No	Yes	No	No	No	Yes
Adj R^2	0.00	0.23	0.30	0.31	0.01	0.23	0.30	0.33

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered at the region level. Sample size N = 390. The dependent variable is ΔEI_t^{Int}.

The most salient feature of these results is the behavior of the price variable. When calculated in levels (as opposed to differences - all models are in logs) price behaves as expected when included alone, with price increases associated with energy intensity declines. There is also some evidence of price asymmetry, though price decreases seem to have a stronger effect than price increases. However, these effects disappear as soon as income is controlled for. Income is the dominant variable in all models where it is present, and is associated with a strong decline in energy intensity as is expected in the literature (see Table 1 in the literature review section). Price becomes statistically insignificant whenever income is present, and reverses sign when time fixed effects are controlled for. The share of industry in output tends to increase energy intensity as one would expect, but is usually not statistically significant. The share of nuclear and renewables in the energy mix has the wrong sign, but the confidence bounds are so wide that this coefficient is effectively meaningless.

The situation changes somewhat when we calculate the model in differences. Differencing the variables renders them stationary and removes any unit roots, thus controlling for potential spurious correlations, but removing long-run effects. The share of nuclear and renewables now has the right sign as it is associated with reductions in energy intensity and is faintly significant. Share of industry remains positive, is statistically significant and is "boosted" in both magnitude and significance when time effects are controlled for. Income remains the dominant effect and consistently negative. However, the price signal remains very weak and is generally pointing in the "wrong" direction, with energy price increases associated with increasing rather than decreasing energy intensity.

There are several reasons why price might behave this way. The first is the hypothesis of homogeneous slopes, which is inherent in the pooled OLS model and assumes that all countries will respond the same way to price signals. We know this is not true, and studies such as Mukhamediyev et al. (2023) highlight the differences in energy price response among energy exporters and energy importers, with the latter obviously more affected. If so, then using a Mean Groups framework should help, as it allows for heterogeneous responses. Second, there is the possibility of interaction between price and other variables. Kilian (2008) and Kilian and Zhou (2023) explore the impacts of energy price shocks on the US economy and find that the timing of these shocks relative to the business cycle plays a critical role in determining their effects. During periods of economic expansion, industries may absorb higher energy costs without reducing energy consumption, leading to an increase in energy intensity. Additionally, the sectoral responses to price shocks are crucial, as energy-intensive industries, particularly those with limited substitution possibilities, may continue or even increase their energy use despite rising prices. This sectoral rigidity, combined with the cyclical nature of the economy, can result in an overall increase in energy intensity, which diverges from the theoretical expectation of a decrease. Finally, Liddle and Hasanov (2020) point out that while using highly aggregated energy prices helps control for endogeneity between price and energy demand, it may obscure important underlying effects and cause price elasticities to be insignificant in regression results. Their study used country-level aggregations, so any aggregation problems will be even worse when using macro-regions as this thesis does.

There is one more thing to note in the exploratory results. In the differenced pooled OLS model, the constant term is equivalent to a first-differenced time trend, and can therefore serve as a proxy for the AEEI. This gives us our first "glimpse" of what the global AEEI value should be - specifically, we should expect a value in the range of -0.0172 and -0.0039. With these preliminary results in mind, we now turn to our main results.

5.2 Main results

This section presents the results from estimating the MG-T, AMG, and AMG-T models as described in the methodology section. Table 9 shows the global results for the MG-T models specified in equation (39), while Tables 10 and 11 present the results for the AMG and AMG-T models specified in equations (40) and (41). Before running the models, I tested for cointegration and cross-sectional dependence to better understand the relationships among my variables and across panel units. Westerlund's cointegration test (Westerlund, 2007) on control structures (1) and (4) failed to reject the null hypothesis of no cointegration, with panel test statistics of -0.937 and -3.687, and p-values above 0.99, suggesting no long-term equilibrium relationship among the variables. However, Pesaran's cross-sectional dependence test results (Pesaran, 2004), shown in Table 12, indicate strong cross-sectional dependence for all variables except industry. These findings suggest that any long-term drivers in the model likely stem from unobserved common factors rather than an equilibrium relationship among the variables themselves. Moreover, the strong correlation among regions underscores the suitability of the AMG approach, which is robust to these common factors.

	Static models				Dynamic models			
Variable	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Trend$	-0.0081	-0.0069	-0.0091	-0.0078	-0.002	-0.0015	-0.0011	-0.0009
	(0.0053)	(0.0046)	(0.006)	(0.0049)	(0.0026)	(0.0034)	(0.0026)	(0.0031)
EI_{t-1}^{Int}					0.5391***	0.4658***	0.4735***	0.4271***
					(0.0628)	(0.0585)	(0.0608)	(0.0622)
P_t^+	0.0185	0.0143	0.0196	0.0172	0.0086	0.0076	0.0118	0.0112
	(0.0201)	(0.0175)	(0.0181)	(0.0175)	(0.0099)	(0.0095)	(0.0085)	(0.0091)
P_t^-	0.0146	-0.0019	0.0079	-0.0096	0.0016	-0.0061	-0.0073	-0.0141*
	(0.0204)	(0.021)	(0.0192)	(0.0181)	(0.0108)	(0.0102)	(0.0094)	(0.0084)
Y_t	-0.3623***	-0.3568***	-0.3755***	-0.3852***	-0.2482***	-0.2674***	-0.2789***	-0.3105***
	(0.0925)	(0.0934)	(0.1085)	(0.0868)	(0.0553)	(0.0673)	(0.0561)	(0.0621)
ED_t^{Ind}		0.1545		0.1533		0.1176		0.1592***
		(0.1088)		(0.1121)		(0.0817)		(0.0578)
ES_t^{NR}			-0.1261***	-0.1203***			-0.1259***	-0.1212***
			(0.0467)	(0.0443)			(0.0395)	(0.038)
N	405	405	405	405	390	390	390	390
RMSE	0.0244	0.0215	0.0211	0.0193	0.0173	0.0159	0.015	0.014

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All models include a constant. The dependent variable is EI_t^{Int}.

Table 9: MG-T Results Summary

	Static models				Dynamic models			
Variable	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDP	0.9542***	0.8185***	1.1153***	1.0605***	0.6814**	0.6534**	0.7924***	0.8454***
	(0.3068)	(0.2437)	(0.2689)	(0.2078)	(0.3256)	(0.3118)	(0.2591)	(0.2649)
EI_{t-1}^{Int}					0.561***	0.512***	0.4749***	0.4179***
					(0.0624)	(0.0613)	(0.0641)	(0.0678)
P_t^+	0.0517*	0.0436**	0.0625***	0.0567***	0.0356**	0.0339**	0.0451***	0.0459***
	(0.0266)	(0.0211)	(0.0237)	(0.0187)	(0.0174)	(0.0158)	(0.0136)	(0.0126)
P_t^-	0.004	-0.0059	-0.0047	-0.0197	0.0024	-0.0041	-0.0004	-0.0056
	(0.018)	(0.0158)	(0.0165)	(0.0134)	(0.0067)	(0.0083)	(0.0101)	(0.01)
Y_t	-0.417***	-0.4215***	-0.4231***	-0.4451***	-0.2266***	-0.254***	-0.2456***	-0.2839***
	(0.0618)	(0.0686)	(0.052)	(0.0573)	(0.0449)	(0.0464)	(0.0455)	(0.0466)
ED_t^{Ind}		0.1057		0.1659		0.0864		0.1808***
		(0.1162)		(0.1162)		(0.062)		(0.0503)
ES_t^{NR}			-0.1399***	-0.1237**			-0.1139**	-0.1104**
			(0.0492)	(0.0546)			(0.0451)	(0.0502)
N	405	405	405	405	390	390	390	390
RMSE	0.0239	0.022	0.0213	0.0195	0.0165	0.0157	0.0145	0.0137

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All models include a constant. CDP is the common dynamic process. The dependent variable is EI_t^{Int}.

Table 10: AMG Results Summary

	Static models				Dynamic models			
Variable	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDP	0.9347***	0.9074***	1.0691***	1.0504***	0.9392***	0.9422***	0.9564***	0.994***
	(0.2764)	(0.2174)	(0.1985)	(0.1609)	(0.3069)	(0.2697)	(0.2337)	(0.2204)
$Trend$	-0.0028	-0.0028	-0.0027	-0.0024	0.003	0.0023	0.0032	0.0029
	(0.0055)	(0.0049)	(0.0054)	(0.0048)	(0.0036)	(0.0046)	(0.0033)	(0.0039)
EI_{t-1}^{Int}					0.4681***	0.4021***	0.4212***	0.3689***
					(0.0654)	(0.0664)	(0.0662)	(0.0694)
P_t^+	0.0435*	0.0432**	0.0561***	0.0538***	0.0376**	0.0378**	0.0442***	0.0449***
	(0.0225)	(0.0186)	(0.0203)	(0.0169)	(0.0179)	(0.016)	(0.0138)	(0.0128)
P_t^-	0.0019	-0.0139	0.0046	-0.0131	0.0141	0.0009	0.0104	0.0009
	(0.0198)	(0.0202)	(0.019)	(0.0177)	(0.011)	(0.0108)	(0.011)	(0.0099)
Y_t	-0.4085***	-0.3995***	-0.422***	-0.4422***	-0.2875***	-0.2926***	-0.2968***	-0.3277***
	(0.0909)	(0.0963)	(0.09)	(0.0772)	(0.0575)	(0.081)	(0.0533)	(0.0647)
ED_t^{Ind}		0.1038		0.1635		0.1002		0.1839***
		(0.1114)		(0.1093)		(0.0825)		(0.0543)
ES_t^{NR}			-0.1155***	-0.1126***			-0.1213***	-0.1199***
			(0.0436)	(0.0436)			(0.0381)	(0.0393)
N	405	405	405	405	390	390	390	390
RMSE	0.0214	0.0198	0.0195	0.0181	0.0153	0.0142	0.0137	0.0128

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All models include a constant. CDP is the common dynamic process. The dependent variable is EI_t^{Int}.

Table 11: AMG-T Results Summary

	EI^{Int}	P_t^+	P_t^-	Y_t	ED^{Ind}	ES^{NR}
CD-test	25.17***	52.22***	52.38***	49.18***	-0.28	15.70***
p-value	0.000	0.000	0.000	0.000	0.779	0.000

Null hypothesis: no cross-sectional dependence.

Table 12: Results of Peseran's Cross-Section Dependence Test

We can see from Tables 9, 10, and 11 that the AMG models consistently outperform the MG models. While the lagged dependent variable, income, and the share of energy from nuclear and renewable sources is significant across all simple MG models, all of them have insignificant price elasticities and trend coefficients. Furthermore, although all trends are pointing down, the magnitude of their coefficients is substantially diminished by the inclusion of a lagged dependent variable, confirming my concern that the two would interfere with one another. Looking at the AMG models, we see that the magnitude and significance of the income coefficient remains quite strong across all models and is quite similar to that of the MG models. Likewise, the structural control variables retain the correct signs and have similar magnitudes and significance levels across all model types.

The two major differences between the MG and AMG models are the estimates for price and income. The high significance of the CDP coefficient in the AMG models suggests that they are robust to the issue of conflating the exogenous trend and endogenous income effects highlighted by Webster et al. (2008) and which is clearly the case for the MG models. The inclusion of a lagged dependent variable does reduce the magnitude of the coefficient, although the impact on measuring the AEEI is unclear as the same lagged dependent variable may have boosted the mean of the underlying CDP. Price becomes significant in the AMG estimator with clear signs of asymmetric price effects; however, the signs are "wrong" relative to what theory would predict, meaning that the aggregated effect of energy price increases across the whole world remains associated with increases rather than decreases of energy intensity in this model, potentially due to the reasons highlighted in the exploratory analysis section. Finally, within the AMG models, the inclusion of a time trend along the CDP does not seem to affect results.

Overall, the results are strongly in favor of the AMG models, which were designed to handle precisely the kind of cross-sectional dependence we see in this data. The significance of the CDP term in all model results suggest that leveraging this cross-sectional dependence has allowed us to extract valuable information regarding the underlying evolution of energy intensity trends, and the constancy of the income and structural control coefficients across MG and non-AMG models suggest that these trends are primarily related precisely to those unobserved components that we were seeking to estimate. Before we proceed to derive the model AEEI estimates, however, we must make sure that the CDP estimated in these models conforms to our model assumptions.

5.3 Analysis of the CDP

In order to derive the AEEI using the mean of the common dynamic process, we must be sure the process follows a random walk with drift that is mean-stationary with normal i.i.d. disturbances to conform to the assumptions that underlie the derivations presented in the methodology section. To do this, it is helpful to visualize the process itself. Figure 6 shows an example of CDP evolution in levels and first differences for the AMG-S1 model, with the dashed line indicating the differenced mean. The CDP graph for all other models is qualitatively similar, and the distribution of shocks about the mean of the differenced processes is shown in Figure 7. Based on visual inspection, the process clearly conform to our assumptions - all the CDP estimates are symmetrical about a constant mean that ranges from -0.009 for static specifications to -0.007 for dynamic specifications. That is, we are looking at a process that represents an accumulating sequence of underlying shocks to energy intensity with a an average disturbance of 0.7% to 0.9% and that remains steady across time. Note that the CDP distributions presented in Figure 7 are for the AMG without trend models, since the AMG-T models append the trend after the first-stage estimation and therefore have identical CDP's for identical control specifications.

To formally test the assumptions of stationarity and normality, I employed the Phillips-Perron (PP) test for residual stationarity and the Jarque-Bera (JB) test for residual normality. The PP test was chosen for its robustness to serial correlation and heteroskedasticity in the error terms, which are common issues in time series data, particularly when dealing with small sample sizes (Phillips and Perron, 1988). The null hypothesis of the PP test is that the differenced CDP series has a unit root, indicating non-stationarity. Table 13 indicates that this hypothesis is rejected at the 5% level for all model specifications, implying the CDP series are indeed mean-stationary. In parallel, I ran the Jarque-Bera (JB) test to assess the normality of the residuals. The JB test examines skewness and kur-

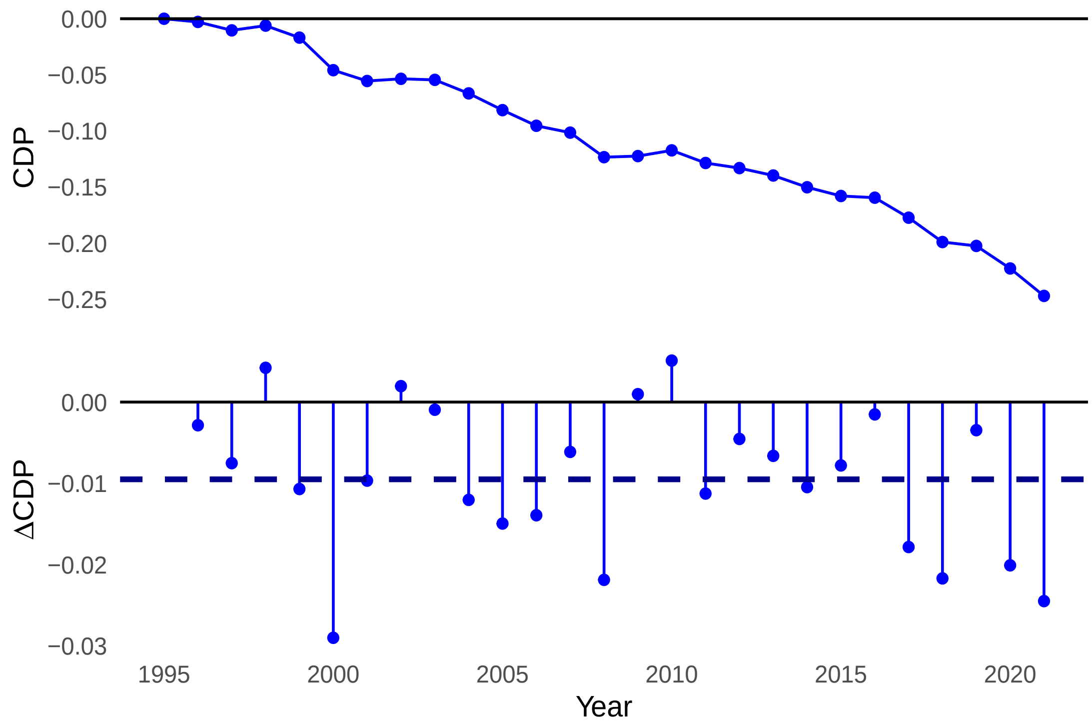

Figure 6: CDP Evolution - AMG-S1 Model

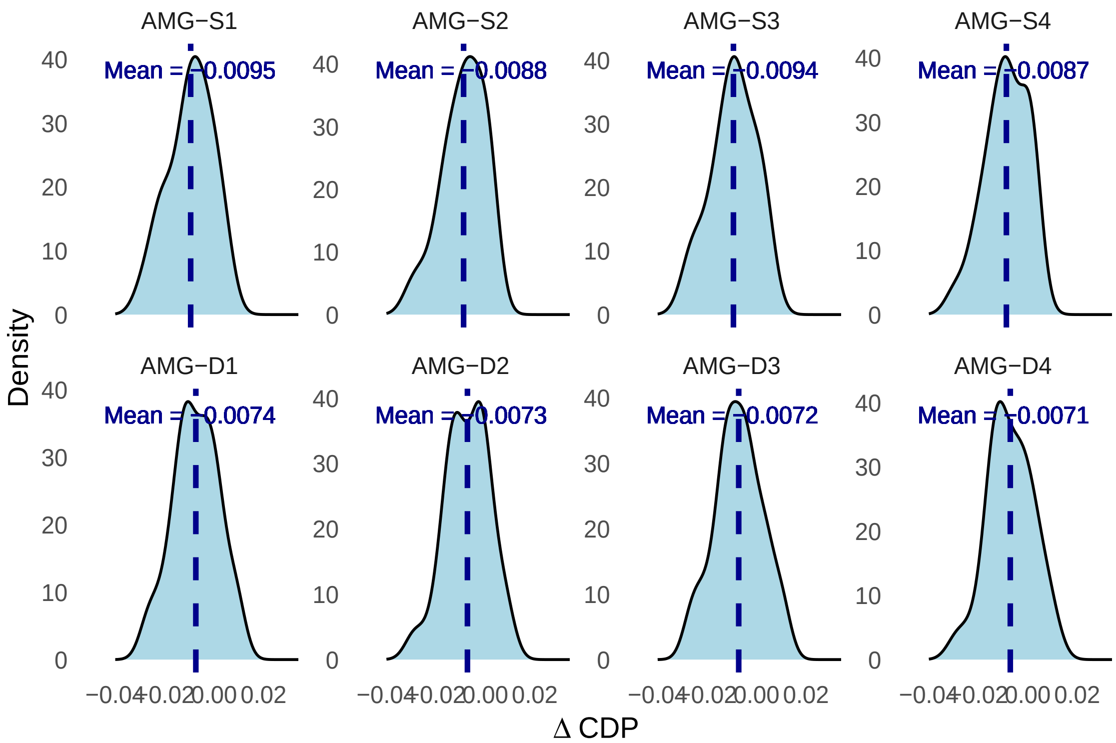

Figure 7: CDP Distributions by Model Specification

tosis, with a null hypothesis being that the residuals are normally distributed. The large p-values in Table 13 indicate that we fail to reject this hypothesis and hence can assume stationarity. Together with the visual inspection, the test results confirm that the CDP is a sequence of normally-distributed shocks about a stationary mean, indicating that the underlying process conforms to the assumption of a random walk with drift necessary to use the CDP in the derivation of long-run AEEI estimates.

Model	PP_Statistic	PP_p_value	JB_Statistic	JB_p_value
AMG-S1	-20.5*	0.0214	0.978	0.613
AMG-S2	-21.8*	0.0138	1.74	0.418
AMG-S3	-20.9*	0.0194	0.863	0.649
AMG-S4	-22.1*	0.0124	1.23	0.542
AMG-D1	-20.7*	0.0205	0.334	0.846
AMG-D2	-20.9*	0.0193	0.386	0.824
AMG-D3	-21.1*	0.0180	0.260	0.878
AMG-D4	-21.3*	0.0168	0.137	0.934

Note: The null hypothesis of the Phillips-Perron (PP) test is that the series has a unit root (i.e., it is non-stationary). The null hypothesis of the Jarque-Bera (JB) test is that the series is normally distributed.

Table 13: Results of Phillips-Perron and Jarque-Bera Tests

5.4 AEEI estimates

We now turn to the main result of this thesis - the derivation of the global and regional AEEI results from the model results in the previous section. As described in the methodology section, AEEI estimates for MG models are simply the coefficients of the time trend, while for the AMG models they represent the coefficient of the CDP multiplied by the mean of the process in first differences. For dynamic models, coefficients are adjusted to account for the persistence of shocks by dividing the coefficient value by $(1 - \hat{\phi})$ to obtain the long-run estimates, where $\hat{\phi}$ is the coefficient on the lagged dependent variable. Standard errors in this case are obtained via the Delta method, which accounts for the variance and covariance between variables. This method is necessary because it provides an accurate estimate of the joint standard error when parameters are correlated, ensuring that their inter-dependencies are properly reflected, and is the basis for calculating long-run errors in studies such as Parker and Liddle (2016).

The derived AEEI coefficients are presented in Table 14. As in the main results, the coefficients on the time trends in the MG models are not significant, and the slope estimates in the dynamic models remain much smaller than those in static models even after adjusting for long-term effects. By contrast, the estimates from the AMG models are significant across all model formulations. Interestingly, the estimates from the static AMG models with and without trend are similar in magnitude to those in the simple MG model. This suggests that the issue with modeling the AEEI is not the absence of a deterministic underlying trend in technological progress, but rather the presence of stochastic noise that obscures this trend. Controlling for this noise in an AMG setting allows us to elicit much cleaner parameter estimates. Another interesting effect seen in these results is that while the presence of a lagged dependent variable tends to absorb part of the exogenous variation attributed to the trend in the MG model, it actually seems to slightly boost the magnitude of the results in the AMG models, suggesting that the AMG estimates remain robust in dynamic specifications. Finally, the addition of an exogenous time trend in the AMG framework also seems to slightly boost the signal from the CDP, especially for dynamic models. This could indicate that the trend partly controls for rebound effects or other local idiosyncratic effects that cause divergence from the underlying global efficiency trend.

Having examined the global means, we now turn to the regional estimates. For ease of presentation, the full list of results is in the appendix, and Figure 8 presents AEEI estimates averaged within each model class - MG-T S/D, AMG S/D, and AMG-T S/D, for a total of six averages of four models each. AEEI estimates were derived for each model specification first and then averaged. At this stage the means represent simple averages as we are exploring model behavior and want to retain a view of the model spread. The means and 90% confidence intervals are derived by regressing the models on a constant, and the confidence intervals should be understood as representing the strength of the model consensus. Note that for India and China there are outliers that are not presented on the charts.

Model Type	Static models (1)	(2)	(3)	(4)	Dynamic models (1)	(2)	(3)	(4)
MG-T	-0.0081	-0.0069	-0.0091	-0.0078	-0.0043	-0.0028	-0.0021	-0.0016
	(0.0053)	(0.0046)	(0.006)	(0.0049)	(0.0172)	(0.0063)	(0.0134)	(0.0055)
AMG	-0.0091***	-0.0072***	-0.0104***	-0.0092***	-0.0115**	-0.0097**	-0.0109***	-0.0103***
	(0.0029)	(0.0021)	(0.0025)	(0.0018)	(0.0057)	(0.0048)	(0.0038)	(0.0034)
AMG-T	-0.0089***	-0.008***	-0.01***	-0.0091***	-0.0131***	-0.0114***	-0.012***	-0.0112***
	(0.0026)	(0.0019)	(0.0019)	(0.0014)	(0.0046)	(0.0035)	(0.0032)	(0.0028)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For MG models, AEEI is equal to the estimated coefficient of the time trend. For AMG models, AEEI is derived as the estimated coefficient of the common dynamic process multiplied by the mean of the process in first differences. For dynamic models, the coefficients have have been multiplied by $\hat{\alpha}(1-\hat{\phi})^{-1}$ to derive long-run estimates, where $\hat{\alpha}$ is the estimated coefficient on the model-specific AEEI proxy and $\hat{\phi}$ is the estimated coefficient of the lagged dependent variable. Standard errors for dynamic models were calculated via the Delta method. The suffix "-T" on the model type indicates the presence of a time trend during estimation. The dependent variable for all models is $D(EI)_t^{Int}$.

Table 14: Global AEEI Estimates Across Models

There are several things to note about the model results in Figure 8. First, the AMG estimates at the regional level are generally much more stable then the MG estimates. While in some regions such as Australia and New Zealand, Russia, and Western Europe, the MG estimates are in line with the AMG estimates, in almost all other cases they diverge, sometimes substantially. Second, the dynamic and static formulations of th AMG model tend to produce similar estimates though in some cases, such Brazil, Canada, and Japan and South Korea, dynamic models have a wider dispersion in their predictions. Finally, in the specific case of China and India dynamic models seem unstable. For India, dynamic formulations of the MG and AMG model fall off the chart in terms of predictions, though the inclusion of a time trend seems to stabilize the AMG model and produces a range of estimates for the AMG-TD formulation that are more aligned with the static version. In the case of China, the dynamic MG model also creates an substantial outlier, while including a trend in the AMG model also causes it to diverge from the model consensus though to a lesser degree. We should therefore be especially careful when interpreting the final consensus AEEI estimates from these two regions.

Having established that the AMG models tend to deliver superior results to the MG models, Table 15 presents the final consensus AEEI estimates from across all sixteen AMG model formulations. Results are once again obtained by regressing the model estimates on a constant, this time using weighted least squares where the weights are the inverse

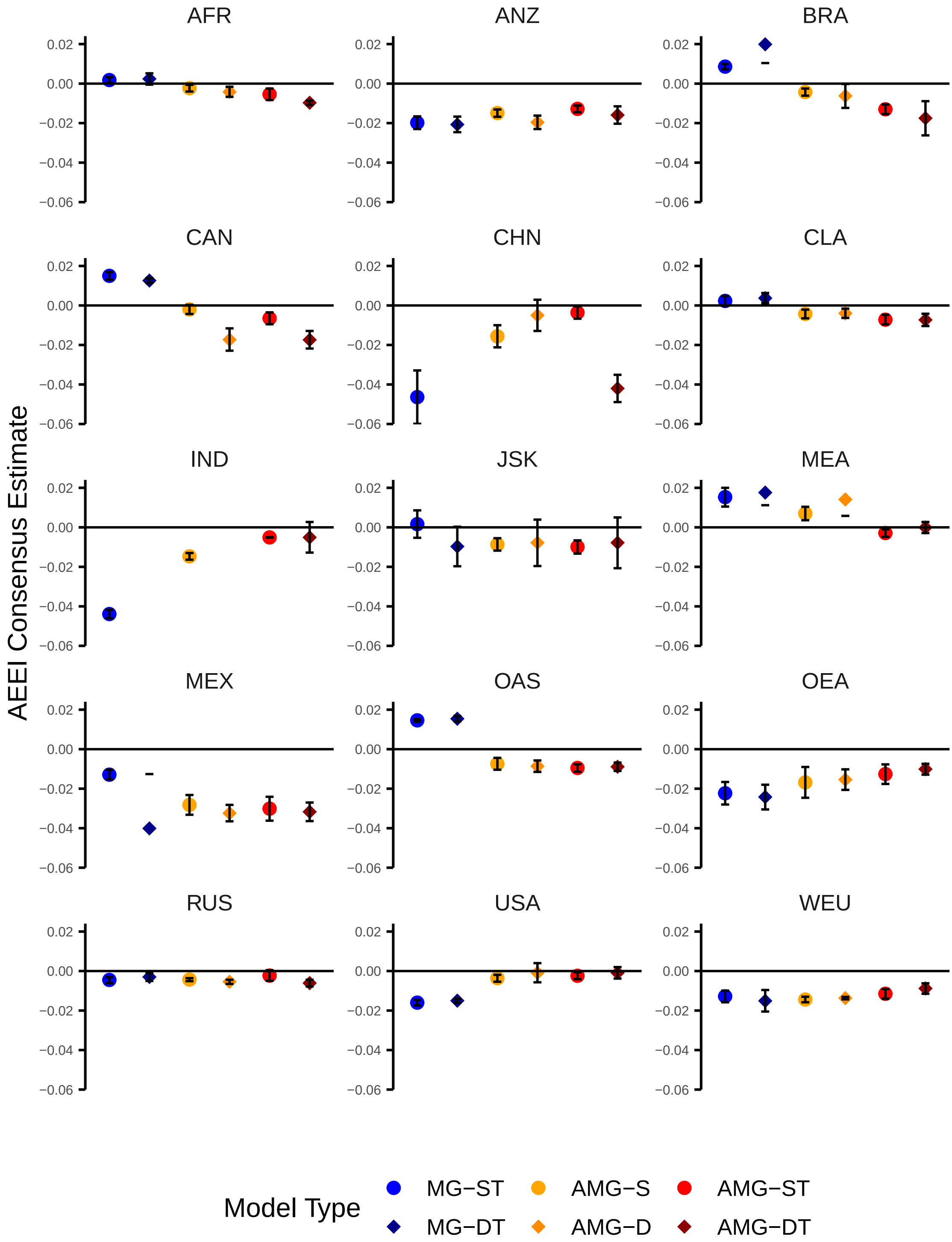

Figure 8: Model Consensus of Regional AEEI Estimates by Model Types

variances to stabilize the results around more confident model predictions. Confidence intervals should be interpreted as representing the strength of the model consensus. Figure 9 shows the same estimates plotted on scatter plot for ease of exposition and analysis.

The results suggest a fairly narrow dispersion of AEEI parameter values, with energy efficiency growth in the range of 1.5% to 0.5% per year across most regions. Two strong outliers are Mexico, with an AEEI of over 3%, and the Middle East, which actually shows *positive* autonomous energy intensity trends indicating a *negative* AEEI. The trend for Mexico is out of line with the results in Jimenez and Mercado (2014), who found that Mexico's trends mirrored those of the rest of the CLA region, though they noted that trends were accelerating at the end of their sample period in 2010. The trends in the Middle East are aligned with the findings in Liddle (2010), who shows that the Middle East has broad divergence in energy intensity both within the region and relative to other regions.

When examining these results, it is important to remember that we are looking at *autonomous* energy efficiency improvement rates, not overall improvement rates. Thus, the estimated AEEI of 0.25% for the United States is lower than the commonly assumed value of 1% discussed in the literature review; however, it is in line with Ekaus and Sue Wing (2007) and Sue Wing (2008) who critique those assumptions and suggest that the real aggregate values are likely to be much lower when structural effects are taken into account. The lower rates of efficiency improvement in the United States and Russia are also in line with the findings from Voigt et al. (2014) who find that these economies experienced lower improvements in energy efficiency overall. The estimated value of 1.09% for China is lower than the estimate of 1.5% found in Timilsina et al. (2021), but as noted before China's estimates have greater uncertainty, and the value of 1.5% falls inside the estimated 90% confidence bound. The overall global value of 0.95% is very much in line with the empirical validation carried out by van der Sluijs et al. (2001), who found a global AEEI of 1%. Perhaps most interestingly, the estimated parameter for Canada is 0.55%, which is almost exactly equal to 0.57% found by Bataille et al. (2006).

Overall, we can say that these findings mirror a number of different AEEI estimates that were obtained for different regions during different time periods and using different techniques. The range of values is in line with the recent expert consensus echoed in Zhang et al. (2024), who use ranges of 0.5% to 3.0% across various regions. This speaks to the

Region	Estimate	Std. Error	90% Lower CI	90% Upper CI
AFR	-0.0043***	.0009	-0.0057	-0.0029
ANZ	-0.0135***	.0008	-0.0148	-0.0122
BRA	-0.008***	0.0014	-0.0103	-0.0057
CAN	-0.0055***	0.0014	-0.0078	-0.0031
CHN	-0.0109***	0.0028	-0.0155	-0.0064
CLA	-0.005***	.0007	-0.0062	-0.0038
IND	-0.0101***	0.0014	-0.0124	-0.0079
JSK	-0.0088***	0.001	-0.0105	-0.0072
MEA	0.002	0.0014	-.0004	0.0043
MEX	-0.0316***	0.0015	-0.0341	-0.0291
OAS	-0.0086***	.0007	-0.0097	-0.0075
OEA	-0.0136***	0.0016	-0.0163	-0.0109
RUS	-0.0044***	.0007	-0.0053	-0.0036
USA	-0.0025***	.0007	-0.0036	-0.0014
WEU	-0.0126***	.0070	-0.0138	-0.0115
World	-0.0095***	.0003	-0.01	-0.0089

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are the weighted average of AEEI estimates across all AMG and AMG-T models, where the weights are the inverse variances. Significance levels and confidence intervals should be interpreted as the indicating the strength of the model consensus.

Table 15: AMG Model Consensus Estimates by Region

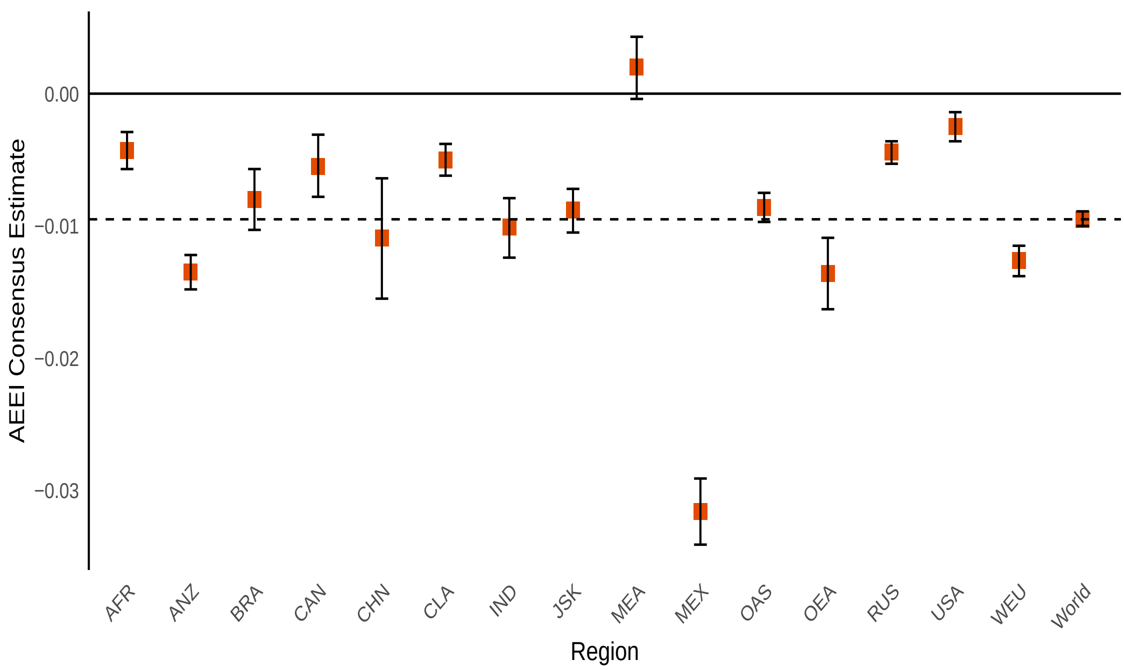

Figure 9: Distribution of AMG Model Consensus

power of the AMG methodology in identifying unobserved latent factors that correlate across countries, which technological progress in the age of globalization surely must be. However, while the results presented here suggest this methodology is generally successful, this study has a number of limitations which I will turn to now.

5.5 Limitations

This study uses a latent factor representation of technological change, and the factors are extracted via cross-sectional time dummies under the assumption that technological progress is correlated across regions. This makes two assumptions - first, that technological progress is indeed a common global process, and second, and that the strength of this process is roughly equal across panel units, enough so that the shape of their technological evolution curves will respond to the common shape of the CDP even if their slope coefficients are heterogeneous. The first assumption is most likely true, but the second assumption will strongly dependent upon the choice of regional sample. This study analyzes energy efficiency across the world as a whole, and studies such as Liddle (2010) and Liddle and Sadorsky (2020) should caution us that divergent trends in certain regions that may introduce noise for those regions that do share strong common trends. Thus, it is worth replicating this study either at the level of the macro-regions as defined in the AD-MERGE 2.0 model or at the level of trade or economic associations such as the EU, ASEAN, or OECD, to elicit stronger underlying trends.

The second challenge in this study comes from the overall aggregation of the data. This is especially problematic for the LMDI decomposition results and for measuring the impact of energy prices. LMDI decomposition requires granularity to better separate structural and efficiency changes, but data of necessary granularity does not exist at this breadth of coverage, thus forcing us to use highly aggregated sectors which may retain many structural shifts within their decomposed series. Likewise, highly aggregated prices of energy commodities, the inference of local price from exchange rates and fuel vectors, the absence of data on electricity prices, and the blending of energy importers and exporters within macro-regions seems to have obscured or muted the impact of price-induced technological change, as cautioned by Liddle and Hasanov (2020) who noted that better dis-aggregation can produce more accurate estimates of price elasticies.

Finally, the CDP is itself an estimated process, and no attempt has been made in this study to account for its covariance with that of the estimated slope coefficient. Depending on whether that covariance is negative or positive, the resulting standard errors on the individual coefficients could either be inflated or excessively optimistic. Given the highly complex interaction of the CDP and the resulting slope coefficients resulting from the two-step nature of the AMG estimator, this problem could be overcoming by treating the estimates of each dummy coefficient in the first stage as normally-distributed measurement errors about a true underlying shock, and using Monte Carlo techniques to simulate multiple runs of the CDP in each model to better assess the true distribution of final estimates. In a similar vein, while the use of multi-model averaging helps overcome issues with local specifications, it doesn't answer the question of what remains the best model for which region, and is possible that averaging has biased the standard errors or is not centered on the optimal estimators. Better model averaging techniques, such as those suggested by Hansen (2007), could help to mitigate these issues.

6 Conclusion

This thesis derived empirical estimates for the Autonomous Energy Efficiency Improvement parameter both globally and for each of the fifteen world regions defined in the AD-MERGE 2.0 Integrated Assessment Model. It built upon established empirical energy efficiency studies and adhered to the best practices recommended by Adeyemi and Hunt (2014) by developing a modeling framework that combined energy price asymmetry with a stochastic exogenous trend. It made this approach more robust by incorporating controls for shifts in the sectoral composition of energy use and generation, thereby isolating technological change from structural influences. Finally, it introduced a novel element by extending this framework into panel studies, employing a latent variable representation of technological progress derived from the common dynamic process in an Augmented Means Groups model. The approach presented here synthesized the research findings of Parker and Liddle (2016), Jin and Jorgensen (2010), and Eberhardt and Teal (2010) and contributed to a unified empirical framework for modeling autonomous energy efficiency in an international setting.

Overall, the first results of this framework suggest that it is a promising avenue to pursue in global energy efficiency studies. The stochastic latent variable representation of energy efficiency generated estimates at both regional and global levels that were superior to those derived from a simple deterministic trend formulation, thereby addressing the critiques by Webster et al. (2008) and Hunt et al. (2003). The parameter estimates derived from the model averages were in line with the consensus on AEEI parameter values in the current theoretical literature, both at a global level and for certain key regions. Crucially, the leveraging of cross-sectional dependence to model technological progress allowed me to utilize information from many regions that would not be available if I were to rely solely on structural time series frameworks, as many countries currently lack the granularity of data and length of time span needed to effectively apply such methods.

Certain limitations will need to be resolved before this approach can be effectively applied in research practice. First, this thesis relied on highly aggregated data across the world as a whole, which may not share the same trends in energy efficiency and, in turn, may distort the estimation of the latent variable representation of technological change. Second, the price elasticities estimated in this thesis were the reverse of those that would be predicted by economic theory, suggesting that more granular analysis would be needed to fully disentangle the impact of energy prices from other effects. Third, no attempt was made to account for the uncertainty of measurement of the common dynamic process itself, and the mean of the differenced process was treated as a known quantity when deriving AEEI values. Finally, in lieu of specifying an optimal model, this thesis relied on a mixed-modeling framework to stabilize parameter estimates. These aspects would need to be improved upon if AEEI values derived in such a framework are to serve as robust estimates for validating theoretical policy models. That said, the framework developed here lays a strong foundation and offers a flexible approach that future researchers could build upon and refine in meaningful ways.

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Appendix

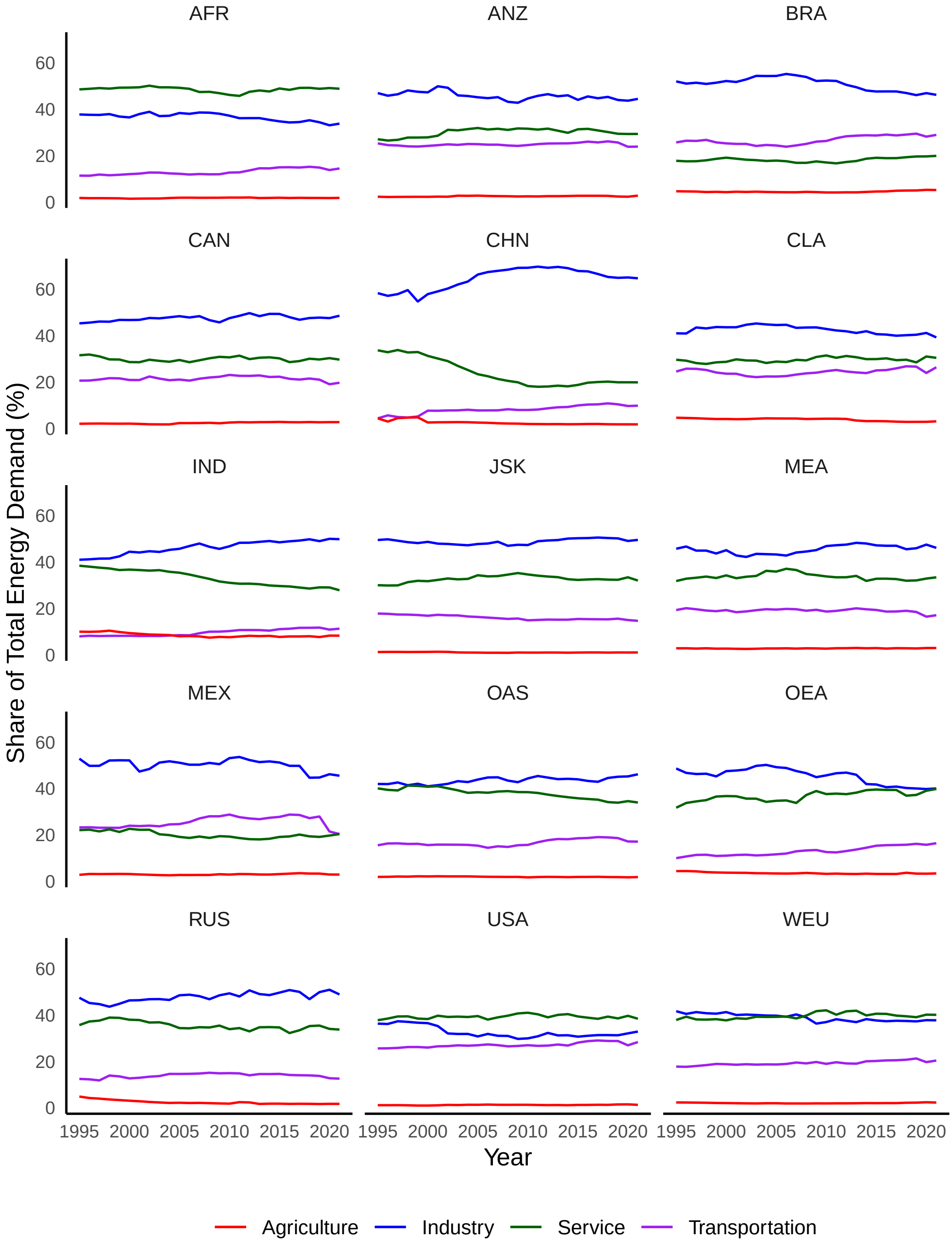

Figure 10: Sector Shares of Energy Demand by Region

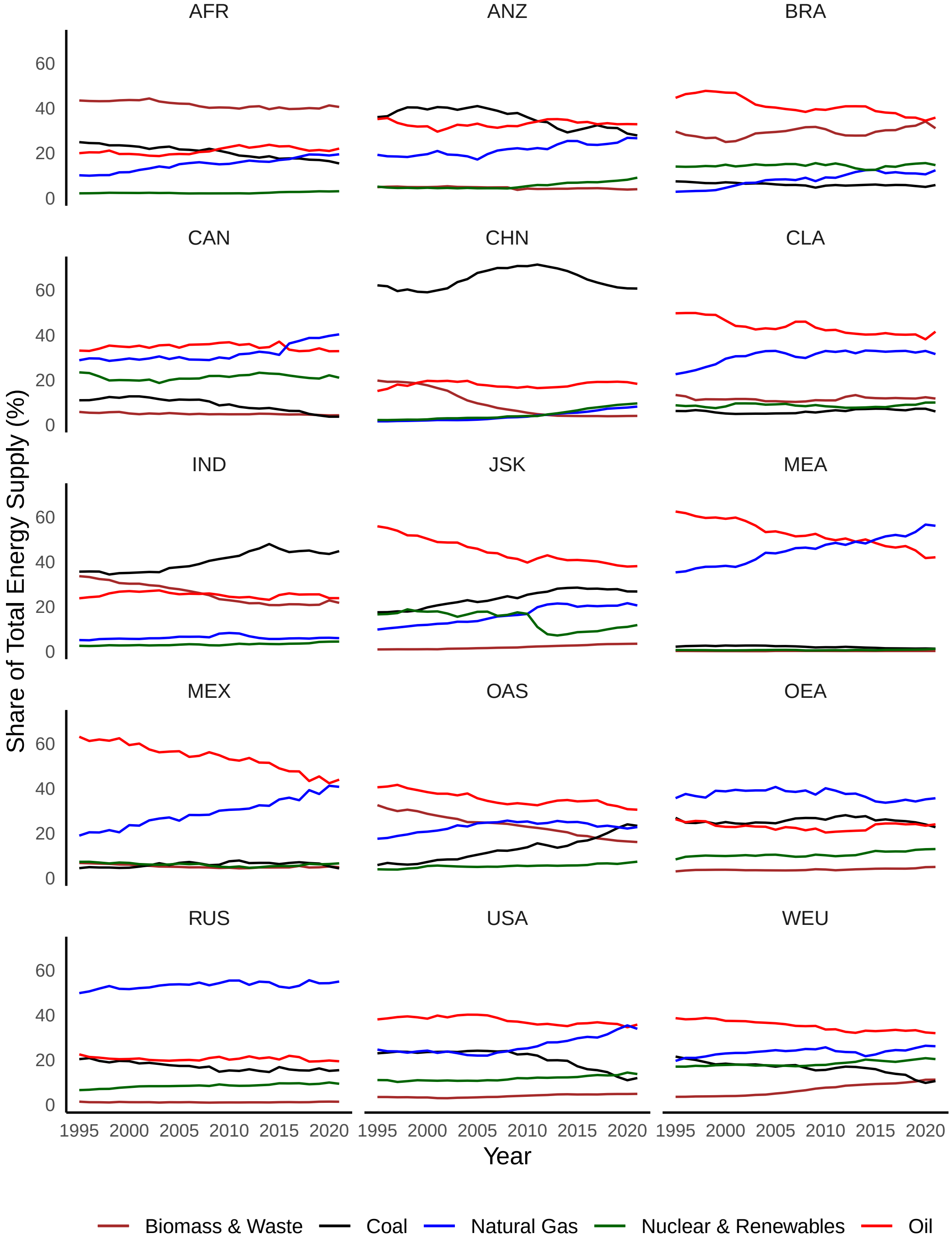

Figure 11: Sector Shares of Energy Supply by Region

Country	Region	Country	Region	Country	Region
Algeria	AFR	Denmark	WEU	Kyrgyzstan	OEA
Argentina	CLA	Dominican Republic	CLA	Latvia	OEA
Armenia	OEA	Egypt	AFR	Lithuania	OEA
Australia	ANZ	Estonia	WEU	Malaysia	OAS
Austria	WEU	Ethiopia	AFR	Mexico	MEX
Azerbaijan	OEA	Finland	WEU	Moldova	OEA
Bangladesh	OAS	France	WEU	Morocco	AFR
Belarus	OEA	Gabon	AFR	Mozambique	AFR
Belgium	WEU	Georgia	OEA	Myanmar	OAS
Bolivia	CLA	Germany	WEU	Netherlands	WEU
Botswana	AFR	Greece	WEU	New Zealand	ANZ
Brazil	BRA	Hungary	WEU	Nigeria	AFR
Bulgaria	OEA	India	IND	Norway	WEU
Cameroon	AFR	Indonesia	OAS	Pakistan	OAS
Canada	CAN	Iran	MEA	Peru	CLA
Chile	CLA	Ireland	WEU	Philippines	OAS
China	CHN	Israel	MEA	Poland	WEU
Colombia	CLA	Italy	WEU	Portugal	WEU
Costa Rica	CLA	Jamaica	CLA	Romania	OEA
Cote d'Ivoire	AFR	Japan	JSK	Russia	RUS
Croatia	OEA	Jordan	MEA	Saudi Arabia	MEA
Cyprus	WEU	Kazakhstan	OEA	Serbia	OEA
Czechia	WEU	Kenya	AFR	Singapore	OAS
Denmark	WEU	Kuwait	MEA	Slovakia	WEU
Dominican Republic	CLA	Kyrgyzstan	OEA	Slovenia	OEA
Egypt	AFR	Latvia	OEA	South Africa	AFR
Estonia	WEU	Lithuania	OEA	South Korea	JSK
Ethiopia	AFR	Malaysia	OAS	Spain	WEU
Finland	WEU	Mexico	MEX	Sri Lanka	OAS
France	WEU	Moldova	OEA	Sweden	WEU
Gabon	AFR	Morocco	AFR	Switzerland	WEU
Georgia	OEA	Mozambique	AFR	Syria	MEA
Germany	WEU	Myanmar	OAS	Tajikistan	OEA
Greece	WEU	Netherlands	WEU	Tanzania	AFR
Hungary	WEU	New Zealand	ANZ	Thailand	OAS
India	IND	Nigeria	AFR	Tunisia	AFR
Indonesia	OAS	Norway	WEU	Turkey	OEA
Iran	MEA	Pakistan	OAS	Uganda	AFR
Ireland	WEU	Peru	CLA	Ukraine	OEA
Israel	MEA	Philippines	OAS	United Arab Emirates	MEA
Italy	WEU	Poland	WEU	United Kingdom	WEU
Jamaica	CLA	Portugal	WEU	United States	USA
Japan	JSK	Romania	OEA	Uruguay	CLA
Jordan	MEA	Russia	RUS	Uzbekistan	OEA
Kazakhstan	OEA	Saudi Arabia	MEA	Vietnam	OAS
Kenya	AFR	Serbia	OEA	Zambia	AFR
Kuwait	MEA	Singapore	OAS		

Table 16: Countries and Corresponding Regions

	Static models				Dynamic models			
Region	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
AFR	0.002	0.0042	-1e-04	0.0011	0.0044	0.006	-0.0016	7e-04
	(0.0051)	(0.0043)	(0.0071)	(0.0058)	(0.0093)	(0.0065)	(0.0125)	(0.0086)
ANZ	-0.0162**	-0.0203***	-0.0251**	-0.0177*	-0.0151	-0.0198*	-0.0269	-0.0208
	(0.0068)	(0.0057)	(0.0105)	(0.0092)	(0.0213)	(0.011)	(0.0304)	(0.0191)
BRA	0.011*	0.0079	0.0075*	0.0082*	0.0366	0.0186	0.0116*	0.0129*
	(0.0064)	(0.0061)	(0.0044)	(0.0045)	(0.0421)	(0.0198)	(0.0066)	(0.0068)
CAN	0.0128*	0.0132*	0.0171**	0.0169**	0.0139	0.014	0.0114	0.0113
	(0.0066)	(0.0068)	(0.0083)	(0.0084)	(0.0109)	(0.0112)	(0.015)	(0.0154)
CHN	-0.0485***	-0.0258	-0.0659***	-0.0453**	0.0164	0.096*	0.0545	0.0919
	(0.0181)	(0.0212)	(0.0233)	(0.0231)	(0.0441)	(0.0547)	(0.0747)	(0.0633)
IND	-0.0406***	-0.0458**	-0.0428***	-0.0464**	-0.1347	-0.2255	-0.145	-0.2253
	(0.0139)	(0.0193)	(0.0151)	(0.0199)	(0.1644)	(0.3064)	(0.1774)	(0.3107)
JSK	0.0088	-0.0017	0.0083	-0.0088	-0.003	-0.0279	-0.0044	-0.0035
	(0.0083)	(0.0092)	(0.0082)	(0.0121)	(0.0367)	(0.0383)	(0.0391)	(0.0594)
MEX	-0.0168	-0.0102	-0.0136*	-0.0108*	-0.0899	-0.0222	-0.0287**	-0.0195*
	(0.0107)	(0.0074)	(0.0071)	(0.0063)	(0.0925)	(0.0183)	(0.0143)	(0.0117)
MEA	0.0205***	0.0201***	0.0102**	0.0102*	0.0248**	0.0241**	0.0108*	0.0109
	(0.0057)	(0.0059)	(0.0051)	(0.0053)	(0.0099)	(0.0105)	(0.0066)	(0.0069)
OAS	0.0139***	0.0143***	0.0156***	0.0147***	0.0141***	0.0142***	0.0175***	0.016**
	(0.0036)	(0.0036)	(0.0043)	(0.0045)	(0.005)	(0.0049)	(0.0064)	(0.0066)
OEA	-0.0308***	-0.0187***	-0.0246***	-0.0151***	-0.0352***	-0.0213***	-0.0225***	-0.018**
	(0.0066)	(0.0058)	(0.0069)	(0.0058)	(0.0107)	(0.0082)	(0.0085)	(0.0078)
CLA	-0.001	4e-04	0.0049	0.0049	5e-04	0.0016	0.0064	0.0065
	(0.0054)	(0.005)	(0.0033)	(0.0033)	(0.0067)	(0.0067)	(0.0039)	(0.0041)
RUS	-0.0063*	-0.006	-0.0035	-0.0024	-0.0049	-0.0051	-0.0017	-2e-04
	(0.0036)	(0.0037)	(0.0033)	(0.0033)	(0.0044)	(0.0046)	(0.0041)	(0.0041)
USA	-0.0176***	-0.017***	-0.0155***	-0.0138***	-0.0162***	-0.0157***	-0.0148**	-0.0133**
	(0.0043)	(0.0042)	(0.0047)	(0.0045)	(0.0063)	(0.0057)	(0.0066)	(0.0058)
WEU	-0.0131***	-0.0174***	-0.0085**	-0.0124**	-0.0152**	-0.0238**	-0.0078	-0.0135*
	(0.0041)	(0.0042)	(0.0041)	(0.0049)	(0.0064)	(0.0095)	(0.0054)	(0.0077)
N	27	27	27	27	26	26	26	26
N / p	6.75	5.40	5.40	4.50	5.20	4.33	4.33	3.71

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are the results of individual regressions. The AEEI is equal to the estimated coefficient on the time trend $\hat{\alpha}$. For dynamic models, the coefficients have have been adjusted via the formula $\hat{\alpha}(1-\hat{\phi})^{-1}$ to derive long-run estimates, where $\hat{\phi}$ is the estimated coefficient of the lagged dependent variable. Standard errors for dynamic models were calculated via the Delta method. N is the sample size per region. N/p is the amount of observations available per model parameter.

Table 17: MG-T Regional AEEI Estimates

	Static models				Dynamic models			
Region	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
AFR	1e-04	-0.0018	-0.0025	-0.0049	-0.0014	-0.0018	-0.0077	-0.0058
	(0.0036)	(0.0031)	(0.0046)	(0.0035)	(0.0055)	(0.004)	(0.0076)	(0.0048)
ANZ	-0.0143***	-0.0127***	-0.018***	-0.0147***	-0.0208**	-0.0168**	-0.0249**	-0.0158***
	(0.0039)	(0.0035)	(0.0049)	(0.0037)	(0.0082)	(0.0068)	(0.0097)	(0.0059)
BRA	-0.0042	-0.0073*	-0.0024	-0.0033	-0.0131	-0.012	-7e-04	8e-04
	(0.0044)	(0.0038)	(0.0034)	(0.0036)	(0.0355)	(0.014)	(0.0055)	(0.0061)
CAN	9e-04	-0.0022	-0.001	-0.0058	-0.0097	-0.0159	-0.0172	-0.0263
	(0.0049)	(0.0051)	(0.006)	(0.0062)	(0.0126)	(0.0149)	(0.018)	(0.0201)
CHN	-0.017**	-0.0074	-0.0238**	-0.0141	-0.0089	0.0067	-0.0158	-0.002
	(0.0078)	(0.0079)	(0.0105)	(0.0091)	(0.0108)	(0.0109)	(0.0147)	(0.0119)
IND	-0.0146*	-0.0121	-0.0172*	-0.0148	-0.063	-0.0805	-0.0714	-0.0847
	(0.0079)	(0.0089)	(0.0101)	(0.0116)	(0.1456)	(0.2253)	(0.2049)	(0.3109)
JSK	-0.003	-0.0101**	-0.0105*	-0.0111**	0.0123	-0.0081	-0.0155	-0.0201
	(0.0045)	(0.0041)	(0.0061)	(0.0052)	(0.0284)	(0.0114)	(0.024)	(0.0266)
MEX	-0.0366***	-0.0281***	-0.026***	-0.0222***	-0.0388***	-0.0331***	-0.031***	-0.0266***
	(0.0046)	(0.0056)	(0.0054)	(0.0054)	(0.0046)	(0.0067)	(0.0058)	(0.0063)
MEA	0.0088	0.0117	0.0022	0.0052	0.0201	0.0252	0.0037	0.0076
	(0.0075)	(0.0078)	(0.0057)	(0.006)	(0.0231)	(0.0237)	(0.0077)	(0.0087)
OAS	-0.0043	-0.005	-0.0081*	-0.0123***	-0.0054	-0.0066	-0.0091	-0.0134***
	(0.0038)	(0.004)	(0.0045)	(0.0044)	(0.0047)	(0.0051)	(0.0056)	(0.0051)
OEA	-0.0245***	-0.0057	-0.0248***	-0.0121*	-0.0242**	-0.0097	-0.0152	-0.0125
	(0.0069)	(0.007)	(0.0062)	(0.0064)	(0.012)	(0.0098)	(0.0098)	(0.0086)
CLA	-0.0071***	-0.006**	-0.0018	-0.0022	-0.0065**	-0.0064*	-0.0011	-0.0019
	(0.0024)	(0.0026)	(0.0024)	(0.0024)	(0.003)	(0.0034)	(0.0024)	(0.0026)
RUS	-0.0046	-0.0034	-0.0054	-0.004	-0.0056	-0.007	-0.0053	-0.0039
	(0.004)	(0.0043)	(0.0035)	(0.0037)	(0.0048)	(0.0059)	(0.0042)	(0.0048)
USA	-0.0024	-0.0052	-0.0013	-0.0056	0.0043	-0.0041	0.004	-0.0076
	(0.0035)	(0.0034)	(0.0043)	(0.0038)	(0.0089)	(0.0079)	(0.0096)	(0.007)
WEU	-0.0132**	-0.0126**	-0.0161***	-0.0157***	-0.0148	-0.0135	-0.0133***	-0.0132**
	(0.0052)	(0.0059)	(0.0038)	(0.0043)	(0.0107)	(0.015)	(0.0049)	(0.0056)
N	27	27	27	27	26	26	26	26
N / p	6.75	5.40	5.40	4.50	5.20	4.33	4.33	3.71

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are the results of individual regressions augmented with the common dynamic process estimated from a pooled regression. The AEEI is derived as the estimated coefficient $\hat{\alpha}$ of the common dynamic process multiplied by the mean of the process in first differences. For dynamic models, the coefficients have have been adjusted via the formula $\hat{\alpha}(1-\hat{\phi})^{-1}$ to derive long-run estimates, where $\hat{\phi}$ is the estimated coefficient of the lagged dependent variable. Standard errors for dynamic models were calculated via the Delta method. N is the sample size per region. N/p is the amount of observations available per model parameter.

Table 18: AMG Regional AEEI Estimates

	Static models				Dynamic models			
Region	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
AFR	-0.0015	-0.0077*	-0.0034	-0.009**	-0.0077	-0.0102*	-0.0106	-0.0103*
	(0.005)	(0.004)	(0.0056)	(0.0045)	(0.009)	(0.0059)	(0.0095)	(0.0061)
ANZ	-0.0123***	-0.0103***	-0.0152***	-0.0135***	-0.0179**	-0.0102***	-0.0223**	-0.0131**
	(0.0039)	(0.0029)	(0.0058)	(0.0043)	(0.0076)	(0.0031)	(0.0112)	(0.0057)
BRA	-0.0149***	-0.016***	-0.0101***	-0.0109***	-0.03	-0.0224**	-0.0095	-0.0083
	(0.0046)	(0.0036)	(0.0037)	(0.0036)	(0.0233)	(0.0106)	(0.0058)	(0.0058)
CAN	-0.0024	-0.0053	-0.0072	-0.0111*	-0.0113	-0.0159	-0.018	-0.0242*
	(0.0049)	(0.0049)	(0.006)	(0.0058)	(0.0113)	(0.0122)	(0.0144)	(0.0146)
CHN	-0.0011	-2e-04	-0.0086	-0.0044	-0.0508	-0.0377*	-0.0469	-0.0325*
	(0.0137)	(0.0126)	(0.0138)	(0.0123)	(0.0348)	(0.022)	(0.03)	(0.0195)
IND	-0.0052	-0.0052	-0.0051	-0.005	-0.0118	-0.0139	-6e-04	0.006
	(0.0085)	(0.0091)	(0.0109)	(0.0121)	(0.0441)	(0.052)	(0.0574)	(0.0759)
JSK	-0.0044	-0.0102**	-0.0143**	-0.0108*	0.0146	-0.0094	-0.0159	-0.0206
	(0.0045)	(0.0042)	(0.0061)	(0.0055)	(0.0355)	(0.012)	(0.0244)	(0.0289)
MEX	-0.0401***	-0.0295***	-0.0284***	-0.0225***	-0.0389***	-0.0329***	-0.0297***	-0.0254***
	(0.0052)	(0.0065)	(0.007)	(0.0067)	(0.0048)	(0.007)	(0.0067)	(0.0067)
MEA	-0.0047	-0.001	-0.005	-8e-04	-0.0017	0.0041	-0.0037	0.001
	(0.0074)	(0.0081)	(0.0064)	(0.0068)	(0.0103)	(0.0132)	(0.0067)	(0.0083)
OAS	-0.0072***	-0.0091***	-0.0091***	-0.0127***	-0.0063*	-0.0084***	-0.0084**	-0.0125***
	(0.0028)	(0.0026)	(0.0033)	(0.0032)	(0.0032)	(0.0032)	(0.0041)	(0.004)
OEA	-0.0169***	-0.006	-0.0186***	-0.0091	-0.0148*	-0.0073	-0.0101	-0.0084
	(0.0055)	(0.0058)	(0.0059)	(0.0059)	(0.0077)	(0.0071)	(0.0082)	(0.0072)
CLA	-0.0103***	-0.0091***	-0.0045*	-0.0047*	-0.0105**	-0.0107**	-0.0037	-0.0044*
	(0.0028)	(0.003)	(0.0025)	(0.0024)	(0.0041)	(0.0046)	(0.0026)	(0.0027)
RUS	-2e-04	0.0011	-0.0057	-0.0043	-0.0039	-0.005	-0.0086	-0.007
	(0.0053)	(0.0054)	(0.0054)	(0.0054)	(0.0064)	(0.0076)	(0.0066)	(0.007)
USA	-8e-04	-0.0038	-3e-04	-0.0046	0.0019	-0.0028	0.0022	-0.005
	(0.0027)	(0.0027)	(0.0036)	(0.0033)	(0.0041)	(0.0038)	(0.0052)	(0.0043)
WEU	-0.0112**	-0.0076	-0.0145***	-0.0129***	-0.01*	-0.0041	-0.0113**	-0.0099
	(0.0044)	(0.0049)	(0.0041)	(0.0049)	(0.0056)	(0.008)	(0.0047)	(0.0066)
N	27	27	27	27	26	26	26	26
N / p	5.40	4.50	4.50	3.86	4.33	3.71	3.71	3.25

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates are the results of individual regressions augmented with the common dynamic process estimated from a pooled regression. The AEEI is derived as the estimated coefficient $\hat{\alpha}$ of the common dynamic process multiplied by the mean of the process in first differences. For dynamic models, the coefficients have have been adjusted via the formula $\hat{\alpha}(1-\hat{\phi})^{-1}$ to derive long-run estimates, where $\hat{\phi}$ is the estimated coefficient of the lagged dependent variable. Standard errors for dynamic models were calculated via the Delta method. N is the sample size per region. N/p is the amount of observations available per model parameter.

Table 19: AMG-T Regional AEEI Estimates