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Three Essays on the Interfuel Substitution and its Dynamics under the Energy Transition

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Abstract

The topic of climate change has dominated public discourse in recent decades, with the adverse effects of rising temperatures, such as extreme weather events and rising sea levels, being widespread. The scientific community agrees that carbon dioxide is one of the primary drivers of climate change. To mitigate carbon emissions while maintaining economic growth, it is essential to harness technological progress. This thesis, consisting of three essays, examines the global energy transition dynamics through fuel switching, focusing on the power sector's shift from carbon-intensive fuels to reliable and lower carbon inputs.

The first essay introduces a new framework for estimating Elasticity of Substitution (ES) values under the influence of biased technological change. The ES helps understand the current state and future trends of energy transitions by measuring how the power mix changes in response to technological advancements and relative input price shifts. Using data on the residual load supplied by non-renewable sources in the US power sector from 1990 to 2019, the study confirms that biased technological progress significantly impacts ES values and dynamics.

The second essay investigates the effects of the Regional Greenhouse Gas Initiative (RGGI), an emission trading system implemented in the Northeastern US, alongside the surge in unconventional natural gas production from the Marcellus shale play on the power generating sector. By scrutinizing the outcomes of both phenomena, such as the carbon intensity of power production, fuel switching, and power prices, the essay underscores the importance of considering commodity prices when evaluating policy impacts. The study reveals that, in addition to policy, the low prices of clean energy substitutes, especially natural gas, are powerful drivers of decarbonization.

The third essay integrates the insights from the first two essays, examining the differences in energy price dynamics and policies worldwide, to estimate ES on a global level. Utilizing a novel dataset of 28 OECD countries, the study employs a dynamic moving-time window approach to

uncover regional and temporal variations in ES values. It discovers a trend of decreasing ES values, indicating a potential slowdown in future interfuel substitution.

Collectively, these essays emphasize the complex interplay between technology, policy, and energy market dynamics in shaping energy transitions. They contribute by providing a novel framework for estimating ES values influenced by changes in technology, input prices, and policies, offering a global comparison of ES dynamics. Additionally, the second essay presents a unique approach to disentangling the effects of co-occurring energy market phenomena, helping understand the differing impacts of policy and energy price shocks on the power sector.

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Abbreviations

ATE Average Treatment Effect

CCGT Combined Cycle Gas Turbine

CD Cobb-Douglas

CDD Cooling Degree Days

CES Constant Elasticity of Substitution

CO2 Carbon-Dioxide

DD Difference-in-Differences

EIA Energy Information Agency

ES Elasticity of Substitution

ETS Emission Trading Scheme

EU ETS European Union Emission Trading Scheme

FE Fixed Effects

FOC First Order Condition

GDP Gross Domestic Product

GHG Greenhouse Gas

GMM Generalized Method of Moments

HES Hicks Elasticity of Substitution

IEA International Energy Association

IFGNLS Iterative Feasible Generalized Non-Linear Least Squares

MES Morishima Elasticity of Substitution

NC Normalization Constant

NLSUR Non-Linear Seemingly Unrelated Regression

RGGI Regional Greenhouse Gas Initiative

RPS Renewable Portfolio Standards

SC Synthetic Control

SDID Synthetic Difference-in-Differences

SEDS State Energy Data System

U.S. United States

WV West Virginia

1 Introduction

1.1 Motivation and Background

Climate change is the biggest imminent threat to our societies in the near future. Its effects range from increased extreme weather events and species extinction to rising sea levels (Cahill et al., 2013, McBean, 2004, Michener et al., 1997). To prevent these effects and stay away from critical tipping points that would lead to an acceleration of rising temperatures, it is imperative to limit global warming to below 2°C (Armstrong McKay et al., 2022, IPCC et al., 2023). Identifying the main driver of climate change, namely Greenhouse Gas (GHG) and specifically CO_2 emissions, the public discourse shifted its focus on mitigating carbon emissions.

It is essential to identify the sources of these emissions to better understand how to effectively reduce carbon emissions. Carbon emissions primarily stem from burning fossil fuels like coal, natural gas, and oil. These inputs differ significantly in their carbon intensities, with coal emitting the highest amount of CO_2 and other GHGs and natural gas being the least carbon-intense of fossil fuels. In the last 30 years, the largest share of CO_2 emissions globally is attributed to power generation at around 34%, followed by the industrial sector at 24% (Lamb et al., 2021).

Despite the power sector having the highest share of global CO_2 emissions, it also has the highest potential for decarbonization due to its ability to directly incorporate zero-carbon electricity such as nuclear power or renewable energy sources. Reducing carbon emissions in other sectors, e.g., transportation, is more challenging because of the sunk capital and existing infrastructure of, e.g., oil-derived fuels (McNally, 2017). The power sector often influences the decarbonization of other sectors, as can be seen with electric vehicles or fuel-cell cars. The potential to electrify our economies, thus, emphasizes the increased importance of how we generate our power (International Energy Agency, 2000, 2002, 2003, 2004, 2009).

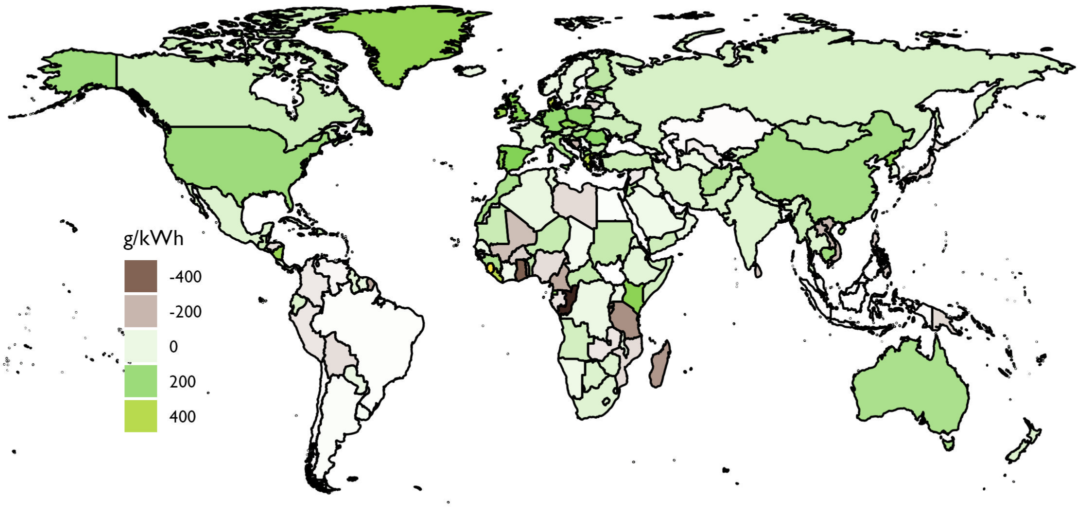


FIGURE 1.1: Carbon intensity reduction in the power sector from 2000 to 2020 (Ember Climate, 2023).

We thus need to analyze the mechanisms that help reduce the carbon intensity of power production. The decrease may be achieved through strategies like fuel switching, as many regions' power sectors still depend on highly polluting coal. Moreover, higher power generation efficiencies may also contribute to emission reduction. Additionally, policies have been introduced to impose a cost on carbon emissions and establish an annual limit on the total amount of carbon released. One of the earliest market mechanisms of this kind is the European Union Emission Trading Scheme (EU ETS), leading the way for similar policies like the RGGI implemented in the Northeastern United States (U.S.) in 2009 (European Parliament, Council of the European Union., 2003).

Decarbonization efforts slightly increased after introducing the Kyoto Protocol in 1997 but started accelerating rapidly with the Paris Agreement in 2015 (United Nations, 1997, 2015). The efforts put into decarbonization depend drastically on a country's socio-economic level, as seen in the power sector in Figure 1.1. Developed economies introduced more sophisticated regulations and policies aimed at mitigating carbon emissions. The Global South, however, is still very dependent on high carbon inputs due to its power demand growth. In some cases, e.g., in Latin America, population growth and a surge in power demand led to increased carbon intensity in the power sector as cheaper fuels such as coal are deployed.

This thesis aims to investigate energy transitions in the context of the increasingly important power sector. Our first essay introduces a novel approach for estimating the Elasticity of Substitution, which measures the change in relative input use in response to variations in relative prices. Our framework accounts for uneven changes in fossil fuel-fired generation efficiencies and allows assessing the changes in ES values over time. The second essay investigates the effects of the RGGI and energy price shocks on the power sector decarbonization in the U.S.. Its goal is to distinguish and isolate the effects of each phenomenon and, hence, provide new insights into the energy transition discussion. The third essay expands its focus to the evolution of the power sector on the international level. It aims to identify regional shifts and differences in relative fuel use in reaction to changes in relative input prices.

Next, we introduce the concept of fuel switching before proceeding with details on each essay, marking the research questions and discussing the methodological contributions to the existing literature.

1.2 Contribution and Methodology

1.2.1 Fundamentals of Fuel Switching

Economies employ a multitude of inputs, which could loosely be divided into capital, human resources, materials, and energy, to support and sustain their activities. Traditionally, macroeconomic literature has focused its analysis on capital and labor inputs, while energy and materials have been included in micro-level models. However, given the rising economic importance of energy and the need for decarbonization, energy has been suggested as a third input by several studies, such as Frieling and Madlener (2016), Kemfert (1998), Papageorgiou et al. (2017) and Zha and Zhou (2014). As decarbonization becomes more critical, governments must emphasize which resources to deploy to support their economic activities while reducing carbon emissions. The growing focus on resource allocation is particularly pertinent in the power generation sector.

This dissertation focuses on the power generation sector, whose relevance is expected to grow in the coming decades due to the ongoing electrification of economies driven by the adoption of low-carbon and clean energy technologies (International Energy Agency, 2000, 2002, 2003, 2004, 2009). According to the classical view, the sector's cost structure consists primarily of capital expenditure and fuel costs, with labor only being a marginal expense (Pindyck, 1979). Apart from this, the long lifetime of power-generating assets, usually 30 or more years, suggests that for the electricity generation sector in its entirety in the long term, energy input costs play a pivotal role in determining the generation utilization based on the supply curve and merit order setting up the profits (Kumar et al., 2015, Rode et al., 2017). Besides influencing the use of the generation capacities, the choice of energy inputs affects carbon emissions from burning fossil fuels. Given the changes in energy input prices stemming from fuel availability, relative input quantities adjust significantly in response to changes in input prices.

Assuming that input energy prices are exogenous to the power sector, determined by the global markets, the sector's operations can be characterized by the absolute and relative consumption of individual inputs, E_i and $\frac{E_i}{E_j}$, respectively, and their absolute and relative prices, p_i and $\frac{p_j}{p_i}$. The relationship between the relative fuel use and relative prices is captured by the concept of the Elasticity of Substitution (ES), which has been introduced by John Hicks (1932), bringing the idea into capital-labor economics. The ES measures the percentage change in relative quantities $\frac{E_i}{E_j}$ in response to a one percent change in their relative price $\frac{p_j}{p_i}$:

$$\sigma_{ij} = \frac{\partial \ln(E_i/E_j)}{\partial \ln(p_j/p_i)} \tag{1.1}$$

If the two inputs are perfect substitutes, then $\sigma = \infty$, in which case the production function takes a linear form. If $\sigma = 1$, (1.2) converges to the Cobb-Douglas case while $\sigma = 0$ indicates strict complementarity and a Leontieff production function. Generally, we consider two goods as substitutes if $\sigma > 1$ and complements if $\sigma < 1$.

Consider a power sector whose demand is given externally by the other sectors. To satisfy the external power demand, the power sector employs a variety of inputs whose quantity depends on the input prices. This situation may be described by the Constant Elasticity of Substitution (CES) production function, which is widely used in power sector analysis, with power output/demand G, input quantities E_i, income shares α_i, and technologies γ_i (Jo, 2020, Jo and Miftakhova, 2022, Kemfert, 1998):

$$G(\mathbf{E}) = \left[\alpha_1 \left(\gamma_1 E_1\right)^{\frac{\sigma-1}{\sigma}} + \alpha_2 \left(\gamma_2 E_2\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1.2}$$

In this context, the concept of ES can be a powerful tool for policymakers, providing valuable insights into the long-term dynamics of input use in the power sector. A higher ES value indicates more fuel switching for a given change in relative input price, increasing the chance of long-term low carbon growth in the power sector (Acemoglu et al., 2012, Klump and de La Grandville, 2000, Papageorgiou et al., 2017). The degree of substitutability between inputs directly characterizes input demand. The relative prices of inputs and input productivity further influence this relationship. Hypothesizing that for profit-maximizing utility companies, the marginal cost of inputs reflects their marginal productivity, the combined First Order Conditions (FOCs) of equation (1.2) illustrate the relationship between relative prices, input productivity, and input demand:

$$\frac{p_i}{p_j} = \frac{\alpha_i}{\alpha_j} \cdot \left(\frac{\gamma_i}{\gamma_j}\right)^{\frac{\sigma-1}{\sigma}} \cdot \left(\frac{E_i}{E_j}\right)^{-\frac{1}{\sigma}} \tag{1.3}$$

This term is similar to the expressions used by Acemoglu et al. (2012), Klump and de La Grandville (2000), Papageorgiou et al. (2017) who found that to support "low carbon growth" in the power sector, the ES between dirty inputs, such as coal, and clean inputs, like natural gas or renewables, must be greater than one. Their studies verify this assumption by scrutinizing three conditions:

- No technical change and σ is greater than one: In this case, an increase in demand for input i results in a smaller decrease in the relative price of i compared to complementarity, improving i's income (market) share (Klump and de La Grandville, 2000).
- Neutral technical change (γ_i and γ_j advance at the same pace) and σ is smaller than one: Under these conditions, a relative increase in demand for i leads to a decrease in i's income (market) share due to significantly lower prices, which may result in an unsustainable growth path (Acemoglu, 2008, Papageorgiou et al., 2017).
- Technical change favors the clean input i over the dirtier input j, and σ is greater than one: If the inputs are complements, increasing the productivity of input i generates more demand for input j, thereby raising j's price and cost share. In the case of substitutability, the increasing productivity of input i instead increases demand for input i, which, combined with its slightly lower prices due to lower marginal productivity, increases its cost (market) share α_i (Acemoglu, 2002).

Based on these findings, Papageorgiou et al. (2017) analyze the ES between clean and dirty inputs and find values significantly above unity, indicating the potential for long-term green growth. However, like many other studies calculating the ES, their analysis overlooks biased technological progress in the estimation procedure. This flaw is critical, as León-Ledesma et al.

(2010a,b) show that misspecifying technological change can lead to significant bias in the ES values estimated, potentially leading to the introduction of non-optimal policies. Many studies assume "neutral" instead of "biased" technological change, which may lead to overestimated ES values. This misinformation may induce policymakers to introduce policies that lack stringency.

Given the relevance of the ES for decarbonization and "green growth", it is imperative to estimate reliable and unbiased ES values to optimally inform policymakers. The following chapter explains the first essay, which adds a new perspective to ES estimates by considering biased technological change in the power sector. The chapter describes the contribution and the changes in the methodology implemented in the first and third essay.

1.2.2 The Influence of Technological Progress

Technological progress significantly influences the estimation of ES values, which measure the shift in input use in response to changes in input prices, providing insights into the substitutability of inputs. Despite a substantial body of literature on computing ES values across countries, industries, and regions, estimates vary considerably and often assume neutral technological change, potentially leading to biased results (Considine, 1989b, Pindyck, 1979, Steinbuks, 2012, Stern, 2008, 2011, 2012).

The first essay challenges this assumption by introducing a novel methodology for estimating ES values that incorporates biased technological change (Klump et al., 2007, León-Ledesma et al., 2010b). Given the continuous changes in generation efficiencies in the power sector, which often vary asymmetrically across inputs, this specification appears more robust. Generation efficiencies usually depend not only on the technology itself but also on the utilization regime of the respective technology. Our study also examines the effects of data aggregation and introduces a moving time window analysis to uncover ES dynamics, testing the assumption of constant ES values.

Based on the shortcomings of existing research, the essay aims to answer a set of interrelated research questions: How do uneven shifts in technology and fuel use affect the Elasticity of Substitution? How does data aggregation affect ES values? Can we detect changes in the ES over time?

Reflecting on the production function introduced in (1.2), the quantities of inputs used in the power sector are determined by economic considerations such as input prices, carbon cost, and generation efficiencies. The "merit order" employed in power markets dispatches plants based on the marginal cost of producing one unit of power, determined by the generation efficiency η_i and the input price p_i. The marginal cost $p_{i,total}$ is calculated by dividing the input cost by the generation efficiency.

Markets select the optimal combination of inputs to meet energy needs based on the varying marginal costs to generate electricity from different inputs. As prices are volatile, $p_{i,total}$ may, in some instances, be higher (lower) than $p_{j,total}$, leading to a higher (lower) demand for input j relative to input i. This reaction is captured by the ES, which measures the response of relative input quantities to changes in relative input prices, ignoring the effect of generation efficiencies. For coal and natural gas, the complex interplay between efficiencies and input prices increasingly favored natural gas due to its price drop and efficiency increase (see Figure 1.2).

FIGURE 1.2: The dynamics of prices and efficiencies (International Energy Agency, 2024a).

Technological bias, such as the improvement in natural gas technology relative to coal technology, has been difficult to account for in ES estimations in the past due to the "impossibility theorem" (Diamond et al., 1978). The "impossibility theorem" states that, under the presence of technological bias of unknown nature, the ES and the individual productivities can not be estimated simultaneously. We thus introduce a novel, multi-equation estimation method that overcomes the "impossibility theorem", developed by Klump et al. (2007), that has been shown to perform well under the presence of technological bias by León-Ledesma et al. (2010b). This method does not only model (1.2) to estimate the ES but also considers (1.3), leading to more precise estimates. Given our ability to incorporate technological change in the estimation procedure, the essay aims to investigate how changes in technology affect ES values over time.

Papers investigating and estimating the ES, e.g., Frieling and Madlener (2016), Jones (1995), Kemfert (1998), typically assume constant ES values throughout the entire observation period. We challenge this assumption, following Arrow et al. (1961), who stated that "the process of economic development itself might shift the over-all [sic!] elasticity of substitution". The ongoing energy transitions lead to shifts in power generation patterns, which, together with the retirement of, e.g., coal capacity, may significantly influence the dynamics of the ES. In the essay, we split the timeframe from 1990 to 2019 into smaller, 22-year windows to analyze the changes and dynamics in the ES over time.

Our study also examines the impact of data aggregation. Existing research, e.g., Fuss (1977), Pindyck (1979), Serletis et al. (2010a), often relies on country-level data, which, in the case of the U.S. implies that the consumption-weighted averages of state-level consumption and prices represent prices and quantities. In the U.S., power distribution may be scrutinized on either the country level or within regional grids (e.g., ERCOT, MISO, PJM, SPP); data aggregation thus may lead to bias estimates since the actual dynamics of power generation depends on balancing the individual grids (EIA, 2012). Our essay analyzes the effects of data aggregation using a dataset that covers the U.S. as a whole and the individual states by calculating the ES on the country level and comparing it to the estimates found using state-level data.

The methodology developed in our research demonstrates that technology significantly affects deployment decisions and, if omitted, overstates the effect of relative input prices on relative input quantities. By considering different levels of data aggregation, we add an additional layer of complexity to the estimation of ES in the power sector, addressing potential biases. Finally, our dynamic time-window analysis reveals previously ignored ES dynamics, offering valuable insights for addressing energy transition challenges. Following the focus on fuel switching, the second essay investigates the effect that changes in policy and input prices have on the power generation mix.

1.2.3 The Effects of Policy and Input Prices

Emission trading systems emerged in the early 2000s, with the EU ETS being the first policy of its kind (Bayer and Aklin, 2020, Marin et al., 2018). The cap-and-trade mechanism at the core of Emission Trading Scheme (ETS) limits total annual emissions for regions and/or industries while implementing a market for emission allowances. The intended effect of such policies relates to increasing the marginal cost of high-carbon electricity. ETS increase the marginal cost of inputs with low generation efficiency and high carbon intensity to a greater extent than cleaner and more efficient alternatives and, thus, may induce fuel switching to lower carbon fuels (Kim and Kim, 2016). Bringing this type of policy to the U.S., the RGGI was implemented by ten states in the Northeastern part of the country in 2009.

Existing studies found that the introduction of the RGGI led to an increase (decrease) in the share of natural gas (coal) in the power mix (Cullen and Mansur, 2017, Johnsen et al., 2019, Kim and Kim, 2016, Knittel et al., 2015, Linn and Muehlenbachs, 2018) while potentially motivating states to outsource their electricity generation to states without carbon policies (Chan and Morrow, 2019, Chen, 2009, Fell and Kaffine, 2018, Lee and Melstrom, 2018). Previous literature aims to scrutinize the efficacy of the RGGI and ETS in general, but little emphasis has been put on co-occurring phenomena that may influence the outcomes of such policies. Moreover, most of these studies focus on individual outcomes, such as power prices, fuel switching, or impacts on Gross Domestic Product (GDP). The only notable exception is Yan (2021), which analyzes various outcomes in the context of implementing the RGGI. This raises important questions about the broader impacts of market changes on policy interventions.

The second essay considers the uptick in unconventional natural gas resource production in the Marcellus shale play from 2009 onwards as a co-occurring phenomenon to the introduction of the RGGI. The decrease in natural gas prices resulting from the increase in unconventional natural gas production significantly impacted the power generation mix in the Northeastern U.S. (Lueken et al., 2016). Influencing the total marginal cost of natural gas generated power, this event may also contribute to reducing carbon emissions through the dynamics shown in Graph 1.2. The higher generation efficiency of natural gas-fired power plants and the reduced cost led to a market situation in which natural gas could suddenly compete with the marginal costs of coal-fired electricity generation, taking a higher share in the power mix (Pacsi et al., 2013). Both phenomena significantly influence the marginal cost of power production, which, given the geographic proximity of the regions, suggests possible interference, which we intend to verify by scrutinizing both interventions separately.

Considering these two events, our study addresses the following key questions: How have both the RGGI and the reduction in natural gas prices impacted the carbon intensity of power generation? Did the Marcellus shale boom significantly contribute to the effects assigned to the RGGI? What are the implications of both phenomena for the power generation mix and economic performance in the Northeastern U.S.?

Understanding these dynamics is crucial for policymakers to design effective climate policies. Our study contributes by using a combination of traditional Difference-in-Differences (DD) frameworks and the Synthetic Control (SC) method. We scrutinize various outcomes to uncover the channels and effects through which both concurrent interventions influenced the power sector (Upton and Snyder, 2017). The study investigates the carbon intensity of power generation, the power generation mix, power demand and prices, and economic performance to provide a nuanced understanding of the underlying dynamics while controlling for exogenous effects by including falsification outcomes (Yan, 2021). By examining both treatments individually, we aim to discover whether some of the effects attributed to the RGGI in existing literature may stem from the decrease in absolute and relative (to coal) gas prices through increased production of unconventional natural gas.

Our study finds that the decrease in natural gas prices due to the uptick in unconventional natural gas production in the Marcellus shale play at least partially contributed to the effects of the RGGI. The generally lower natural gas prices in the U.S. as a result of the fracking boom increase the efficacy of ETS by leveraging the effect certificate prices have on the marginal cost of power production. Additionally, we show that the shale boom led to similar Carbon-Dioxide (CO2) intensity reductions in Marcellus shale play states despite not implementing a cap-and-trade mechanism. Investigating power prices and demand, our study discovers that power prices in the Marcellus states decreased while they increased in RGGI states, leading to a more favorable economic environment. The favorable economic conditions led to a smaller decrease in the GDP per capita in manufacturing in Marcellus states compared to RGGI states, likely to be attributed to lower power prices. By separating the analysis of both co-occurring phenomena, our study is able to identify the effects and channels through which the effects occur, offering a new methodology for the analysis of concurrent interventions. Adding to the existing literature, our study shows how accounting for these concurrent market shocks may influence the efficacy assigned to either of the two phenomena. Given the identified effects that policies and input prices have on fuel switching, the third essay scrutinizes regional differences in ES values induced by diverging policies and resource availability.

1.2.4 International Policies

The third essay investigates the ES on an international level to dynamically assess regional differences in ES values stemming from dissimilar resource availability and policies around the world. Introducing an extensive international dataset covering the power sector of 28 OECD countries, our study scrutinizes the regional differences in resource availability, carbon reduction efforts, and policy interventions. The individual regions differ significantly in terms of the adoption of climate policies. Europe is known to have some of the most stringent climate policies, which contrasts the relatively low efforts that countries in the Asia-Pacific region display. This divergence in local and regional policies motivates us to investigate how countries and regions differ in terms of ES values. We compute country-level ES estimates and compare them to the regional ES that grows in importance given the increased interconnectedness of electricity grids. Given the drastic changes in residual demand due to the increase in adoption of renewable power sources and the switch from coal to natural gas, we conclude our study by implementing a moving time-window analysis that uncovers the dynamics brought to the power sector by policies and shifts in input availability.

International ES comparisons have been a part of academic research since the late 1970s (Pindyck, 1979) to explain and uncover the varying behavior of countries in energy consumption. Studies of this type have again risen in popularity in the 2010s due to the global focus on decarbonization efforts but were limited to smaller sets of 10 to 15 countries or unbalanced panel data (Serletis et al., 2010b, 2011, Steinbuks and Narayanan, 2015).

The paper addresses three research questions: Are there differences in ES values across countries and regions? Do regional ES values change in response to resource availability, policy, and technology? What are the implications of ES values with respect to energy transitions?

To calculate ES, data on fuel consumption and fuel prices are paramount. The limiting factor for ES estimates on an international level has been the availability of consistent and complete fuel price data. Our study relies on fuel consumption and price data from the International Energy Agency (2024a,b). While some of the fuel price data is still incomplete, we were able to attribute missing data points following Sato (2019) and used random forest machine learning algorithms to complete the dataset where necessary. The overall panel spans 28 OECD countries grouped into six regions.

Our study calculates and analyzes the ES for each of the individual 28 OECD countries in the sample. This exercise may help compare differences in decarbonization pathways and inform policymakers about the current state and future path of energy transitions. Higher ES values may support lower carbon growth and, thus, help countries decarbonize their power sectors in the long term. We supplement the country-level analysis by grouping the individual countries into six regions, which allows us to identify how interconnected grids change substitution preferences. Our study concludes by estimating the regional ES, using a 20-year moving time-window procedure analogous to Section 1.2.2 to test whether and in which direction energy transitions affect the ES.

The study's main contribution is the estimation of local and regional ES values that enable us to identify whether policies affect fuel-switching. Estimating the ES values for 28 OECD countries helps reveal regional differences and changes over time in ES values and explore how policies affect ES estimates. We find significant variation in country- and regional-level ES estimates that stem from differences in resource availability and policy adoption. Gaining new insights on regional differences in fuel switching, the study provides a robust foundation for future research. Investigating changes in the ES over time, the study reveals mostly constant ES values, contrasted by a decreasing ES between coal and gas in Northern America. The results highlight the dynamics of policy adoption and resource availability, which both influence fuel-switching decisions.

1.3 Structure of the Thesis

This thesis consists of three independent studies that coincide in their focus on low-carbon fuel switching. Being submitted to different scientific journals, the studies may exhibit similarities in some aspects, e.g., their introductions, concepts, and definitions. As such, the papers should be read and evaluated individually.

The remainder of this thesis is structured as follows. Chapter 2 introduces a new method for estimating ES under biased technological change. It starts by explaining the foundations of the novel approach before estimating ES values that highlight the effects of misspecifying technological change and data aggregation. In the following, the study introduces a moving time-window analysis to capture changes in ES values over time before concluding with a sensitivity analysis that highlights how and why market participants deviate from optimality. Chapter 3 scrutinizes the introduction of the RGGI, an emission trading system, and the rising production of unconventional natural gas resources from the Marcellus shale play in their ability to reduce carbon emissions. The essay explains the two co-occurring phenomena, the analyzed outcomes, and their relevance in evaluating the policy's efficacy. It then introduces the methodology used to create counterfactuals and isolate the effects of both phenomena. The essay concludes by presenting and interpreting the results that reveal the effects of both interventions and channels through which their effects are achieved. Chapter 4 uses the methodology developed in the first chapter by applying it to the international level. It investigates trends in global power markets and estimates ES values on the country- and regional level. Revealing changes in ES values over time, the moving time-window analysis uncovers the dynamics of energy transitions. Chapter 5 concludes this thesis by synthesizing its main findings and indications. The Appendix contains additional details on each essay, such as formulae, graphs, and tables. The Appendices are enumerated from A to C and correspond to Essays 1 to 3, respectively.

2 | Estimating the Interfuel Substitution Under Technological Bias

by Daniel Gatscher, Svetlana Ikonnikova

Decarbonization, radical shifts in the availability of energy resources, and accelerating adoption of energy-efficiency-altering innovations shake energy prices in national and global markets, triggering fuel switching. In this context, an accurate assessment of the Elasticity of Substitution (ES), measuring how the energy mix would change in response to relative prices, becomes particularly critical for budgeting and managing the energy transition. Investigating the reasons for the past disagreements in ES estimates, this study highlights the limitations imposed by the traditional neutral technological change assumption and offers instead a model allowing for *biased* technological change.

Adopting a macroeconomic approach, we develop an econometric procedure featuring a normalized nested Constant Elasticity of Substitution (CES) production function with two or more inputs. Inspired by the evidence of biased technological change in U.S. electricity generation efficiencies from 1990 through 2019, we test our model by estimating the substitution among fossil fuels, including coal, natural gas, and oil products. We show that the technological neutrality assumption leads to overestimated ES values, whereas aggregating data on the national level, instead of using state or regional data, results in lower ES values. To analyze historical sample-based differences, we use a moving time window and examine the evolution of the ES during the past three decades, marking the gradual reduction in the substitutability between natural gas and coal. Finally, taking a closer look at the estimation errors, we compare the optimal (model-based) fuel-switching with the actual dispatch data, offering new insights and ideas for further research.

2.1 Introduction

Climate change has compelled countries around the world to reconsider their energy use, examining possible pathways for the transition to energy sources with lower GHG, especially carbon emissions. To induce the needed shift in the energy mix, governments propose and impose regulations making the consumption of "dirty" fuels with high carbon content more expensive relative to "cleaner" alternatives. The fast-growing International Energy Agency's *Policy Database* contains numerous documents disincentivizing the use of fossil fuels such as coal and oil (and oil-based products) across many sectors and industries, particularly in electricity generation. In this context, it becomes imperative to accurately assess the interfuel Elasticity of Substitution (ES), measuring the shift in the use of one energy resource relative to the other in response to changes in the respective relative energy prices. Used in macroeconomic growth models (Fuss, 1977, Jo, 2020, Kemfert, 1998, Papageorgiou et al., 2017), industry studies (Gilmore et al., 2023, Lilliestam et al., 2021, Victoria et al., 2020), and microeconomic consumption research (Varian, 1992), the ES informs decarbonization policies, supports transition budgeting, and helps manage environmental targets. Although the body of empirical research offering (country and sector-specific) ES estimates is large, the lack of consensus in previous assessments has been calling for further research (Acemoglu et al., 2012, Bacon, 1992, Papageorgiou et al., 2017, Stern, 2012).

Among the key reasons for discrepancies in the ES results is the assumption of neutral or equal change in technological efficiencies across fuels. Technological progress plays a prominent role in the energy transition and decarbonization processes. Advances in existing technologies and innovations supporting emission reductions keep improving energy efficiencies and transforming fuel consumption patterns. However, despite the recognized importance, technological change has not been well apprehended by empirical works focused on the ES due to computational limitations (Hossain and Serletis, 2017). The "impossibility theorem", by Diamond et al. (1978), asserted that in the case of the non-unitary ES, it is impossible to estimate the ES and (unequal) parameters of technological change simultaneously. As a result, empirical ES assessments were forced either to assume neutral technological change or adopt peculiar production function forms (Serletis et al., 2011, Stern, 2012). Such a modeling shortcut has long been criticized in the theoretical literature, warning of the likely biases in the resultant ES estimates (Blackorby and Russell, 1981, Boddy and Gort, 1971, Sato, 1977). Addressing the "impossibility", León-Ledesma et al. (2010b) proposed a novel method that allows for calculating the ES even when the technological change is biased. In the macroeconomic context, they proved to overcome the long-standing problem, offering a promising tool for energy economics research (Klump and de La Grandville, 2000, Klump et al., 2012, Papageorgiou et al., 2017).

The primary purpose of this study is to present a comprehensive methodology for developing interfuel ES assessments in which the change in technological efficiencies across multiple (energy) inputs may be biased. We develop and demonstrate an econometric procedure to analyze the competition between fossil fuels, including coal, natural gas, and oil products, in the U.S. power sector from 1990-2019.

Following León-Ledesma et al. (2010b), we base our ES estimation procedure on the generalized solution for the production profit maximization problem and the corresponding FOCs characterizing it. In contrast to the widely accepted approach employing a single cost-minimizing FOC, the presented model employs all the conditions forming a system of equations sufficient for calculating the ES simultaneously with the technological change parameters. Besides, the solution in its entirety determines the input quantities, along with the optimal output, and hence, overcomes the drawback of the considerable body of literature neglecting the effect of the energy mix change on the output (Stern, 2012, Hossain and Serletis, 2017).

In the macroeconomic study presenting the original approach, the ES procedure was offered for the case of only two inputs: labor and capital. The following energy-oriented studies kept the two-input setup, grouping energy inputs into "dirty" and "clean", when investigating the potential for "green growth" (Jo, 2020, Papageorgiou et al., 2017). We revise the procedure by introducing a class of generalized nested CES production functions to capture more complex production processes or a broader diversity of energy and non-energy inputs. The cases of two, three, and four[1] inputs are used for the ES calculations to gain a better understanding of interfuel substitutability. The nested models reveal how the ES for a given fuel changes when the substitution to one other fuel or a bundle of fuels is considered. That exercise appears especially useful considering the reduction or, in some regions, complete retirement of some types of generation, such as coal.[2]

[1]To test the procedure and examine the ES for other fuels used for the power generation, we ran the model including nuclear generation, providing the results in the Appendix.

[2]Referring to the currently prevailing power market mechanisms, we made a simplifying assumption and considered the analyzed dispatch as the residual load left after renewable and nuclear energy are dispatched. The sensitivity exercises performed in this regard led us to discuss possible further research.

Relaxing the assumption on the nature of technological change helps us avoid the neutral technological change assumption required in the case of the one-equation procedure (Klump et al., 2007, León-Ledesma et al., 2010b, Thompson, 2006) and also permits for cross-sectional along with time series analyses critical in revealing possible estimation biases (Stern, 2012, Considine, 1989a, Jones, 1995, Serletis et al., 2010a). Addressing the past critique, our secondary goal is to examine possible variations in the ES estimates. We compiled a database with state-level statistics on the primary energy[3] used, annual electricity generated, and individual fuel-related expenditures to calculate the benchmark ES values. For comparison, we computed the corresponding ES using: (1) the model assuming a neutral technological change, (2) the data aggregated on a national level, (3) the subset of states employing nuclear generation, and (4) the data from the last two decades only. Cross-value comparison helps reveal ES discrepancies receiving little attention in individual studies.

The results of the last exercise inspired us to expand our study and analyze the ES evolution with the moving time window procedure. Adding to the rich body of research on the interfuel ES (Considine, 1989b, Pindyck, 1979, Steinbuks, 2012, Stern, 2008, 2011, 2012), we focus on the electricity sector to update the past findings. Developments in the energy industry and environmental regulations suggest some structural shifts in the energy markets, echoing those in the power sector energy mix. In this context, our work on the ES evolution is instrumental in tracking how the advances in carbon-reduction-oriented technologies interplay with the price (and cost) shocks altering fossil fuel usage (Berndt, 1990, Chun et al., 2022, Debertin et al., 1990, Markandya et al., 2006, Saunders, 2013, Wing, 2006, Zhu et al., 2021). Offering a CES-alternative to the translog production function-based approaches, we also suggest an alternative view of technological change (Atkinson and Halvorsen, 1976, Bopp and Costello, 1990, Christensen et al., 1975, Christensen and Greene, 1976, Considine, 1989b, Ko and Dahl, 2001). Apart from that, we revisit the question of whether the (economically) optimal fuel-switching behavior assumption is valid given the ongoing energy transition, dramatic shifts in oil and natural gas supply, and environmental regulations. Checking the gap between the model-suggested optimal and the actual individual state fuel choices, we explore the boundaries of the presented tool and raise awareness of the estimate biases important for energy market participants and policymakers navigating decarbonization.

[3] We also collected data on other energy sources, such as nuclear fuel, used for electricity generation and conducted the corresponding ES analysis. However, given the technical limitations in the substitutability, we treat that exercise as a thought experiment, reporting its results in the Appendix.

Our paper is organized as follows. Section 2 reviews the theoretical foundation for the ES, highlighting the role of the biased technological change. Then, we provide the evidence for asymmetric progress in the U.S. power sector energy efficiencies, presenting our data and its exploratory analysis in Section 3. Next, the econometric procedure with all the necessary details is explained in Section 4, followed by our Results in Section 5. Section 6 presents our key insights and suggestions for further research.

2.2 Theoretical Foundations

We start by reviewing the theoretical underpinnings highlighting the two widely accepted definitions of Hicks' and Morishima's ES. Discussing the fundamentals, we emphasize the limitations of the former, being only applicable to the two-input case but widely used in macroeconomics models due to its simplicity and the advantages of the latter, allowing for multiple inputs. Formulating the ES, we turn to the profit maximization problem and its solution, which helps us explain the framework for estimating the ES under asymmetric technological change. In this section, we focus on the theoretical setup, leaving details on the econometric procedure in the Section 2.4.

2.2.1 Definitions of the Elasticity of Substitution

The original ES concept, derived by John Hicks (Hicks, 1932), captured the idea that the price of an input factor of production, such as labor, is determined not only by the factor demand and supply but also by production efficiency and substitutability (and/or complementarity) with other inputs, for instance, capital. So, Hicks' ES has become known as the measure linking the change in the relative factor quantities to the technical rate of substitution (Varian, 1992).[4] To formulate Hicks' ES, consider a producer of some uniform output Y characterized by the twice differentiable production function:[5]

[4]Around the same time, Robinson (1933) came up with a similar but a more tractable formulation of the ES, defining it as the percentage change in the factor ratio and their marginal productivities. Hicks' and Robinson's definitions are shown to be equivalent for two input factor cases Knoblach and Stöckl (2020).

[5]This formalization is general enough and is used in both micro- as well as macroeconomic literature and helps to ensure the existence of the production optimization solution(Fuss, 1977, Kemfert, 1998, Papageorgiou et al., 2017).

$$Y = Y(\mathbf{X}, \mathbf{E}, z) \tag{2.1}$$

With the power sector in mind, we distinguish two major groups of inputs: energy $\mathbf{E} = \{.., E_i, ..\}$ and non-energy $\mathbf{X} = \{.., X_k, ..\}$, adding argument z as an overarching technology factor. Assuming positive dependence between the output and each factor of production, we allow for the same level of supply to be achieved with a variety of $\mathbf{E}$ and $\mathbf{X}$ combinations by analogy with the power sector, where the same level of dispatch can be reached through different generation profiles.

All the combinations of inputs for which the output level is the same form a so-called *isoquant*. Moving along the isoquant, one may measure how much of one factor, e.g., E_i, is needed to compensate for a reduction in another one, say E_j, determining the isoquant's curvature, also known as the marginal rate of substitution:

$$MRS_{ij} = \frac{\partial Y / \partial E_i}{\partial Y / \partial E_j} = \frac{y_i}{y_j} \tag{2.2}$$

The MRS, defined as the ratio of the marginal productivities, lies at the basis of the classical Hicks ES expressed as:

$$\sigma_{ij}^H = \frac{\partial \ln(E_i/E_j)}{\partial \ln(y_j/y_i)}. \tag{2.3}$$

Notably, linking the change in input quantities to the relative factor productivity, σ^H focuses on only one pair of inputs, ignoring possible changes in other inputs or output technology. Criticizing that neglect, other ES concepts have emerged to correct for that and to ensure the dynamics in multiple inputs are captured.

From a producer's perspective, e.g., considering a utility with various generation-type capacities, the choice of optimal input factor quantities heavily depends on the cost and profit implications. Those considerations led to the alternative ES featuring the relative input prices.

Assume that in the short-term, the prices for individual inputs, p_i, and the output, p_Y, are exogenous[6] and that the production costs are separable in terms of non-energy and energy

[6]We refer to the EIA (2012) study and assume that prices of non-energy inputs, including labor and capital, along with the renewable energy generation, are exogenous and have little effect on the interfuel substitutability.

expenses. Then, the total costs are given by:

$$\begin{aligned} TC &= C(\mathbf{X}, \mathbf{E}, \mathbf{p}_X, \mathbf{p}_E) \\ &= C^x(\mathbf{X}, \mathbf{p}_X) + C^e(\mathbf{E}, \mathbf{p}_E) \\ &= C^x(\mathbf{X}, \mathbf{p}_X) + \sum_i p_i \cdot E_i \end{aligned} \tag{2.4}$$

and the producer's optimization problem can be formulated as:

$$\max_{\mathbf{X}, \mathbf{E}} \left[p_Y \cdot Y(\mathbf{X}, \mathbf{E}, z) - \sum_{i:\, \mathbf{E}} p_i \cdot E_i - C^x(\mathbf{X}, \mathbf{p}_X) \right] \tag{2.5}$$

Choosing the input quantities to maximize profit, the producer solves (2.5) and defines demand for each input as a function of input and output prices. Therewith, the optimal output and a relationship between the total cost, energy cost $C^e(Y, \mathbf{p}_E)$, and Y are also uniquely determined and depend on p_i. This framework and its results led Morishima (1967) to the modification of σ^H for the multi-input cases:[7]

$$\sigma_{ij}^M = \frac{\partial \ln(c_i^e(Y, \mathbf{p}_E)/c_j^e(Y, \mathbf{p}_E))}{\partial \ln(p_j/p_i)} = \frac{\partial \ln(E_i/E_j)}{\partial \ln(p_j/p_i)} \tag{2.6}$$

The Morishima Elasticity of Substitution (MES) relates the change in the relative input quantities to a change in the relative input prices p_j/p_i relying on Shepard's Lemma that equates the cost derivative $\frac{\partial C^e(Y, \mathbf{p}_E)}{\partial p_i} = c_i^e$ to the input demands satisfying the cost-minimization condition. Blackorby and Russell (1981) and Blackorby and Russell (1989) proved the equivalency of the different elasticity definitions, including the Hicks' ES, in the case of two inputs and highlighted the advantage of the MES over other definitions, particularly Allen-Uzawa, owing to its inherent asymmetry and usability with the non-Cobb-Douglas (CD) CES production functions.

Traditionally, empirical studies use either σ^H or σ^M to measure the degree of substitutability or complementarity between pairs of inputs, preferring the second one when more than two factors are used. Most econometric procedures used for elasticity estimations are built on the one FOC – cost minimization, examining changes in relative input price ratios ignoring their possible effect on other FOCs determining the profit maximization (Mundlak, 1968). A particular shortcoming of this approach is its inability to handle technological change and, therefore, the application

[7] Here we present the pruned expression for the Morishima elasticity rather than the complete form given by $\sigma_{ij}^M = \frac{p_j \cdot (c_{ij}^e(Y, \mathbf{p}_E) \cdot c_j^e(Y, \mathbf{p}_E) - c_{jj}^e(Y, \mathbf{p}_E) \cdot c_i^e(Y, \mathbf{p}_E))}{c_i^e(Y, \mathbf{p}_E) \cdot c_j^e(Y, \mathbf{p}_E)}$, following Blackorby and Russell (1981).

in time series analysis. Next, we introduce a non-homothetic production function and provide further details on the solution for the profit optimization problem to derive the multiple FOCs required to formulate the interfuel Elasticity of Substitution suitable for estimations of ES with time series data revealing a biased technological change.

2.2.2 Production Function and the ES

In economic literature, the choice of a production function form is often justified by analytical convenience and functional properties and/or by the desire to capture a particular production technique and input-augmenting technological change (Jones, 2005). Standing out in both macro- and microeconomics is a class of generalized Constant Elasticity of Substitution (CES) functions. It is widely accepted and used in production theory, industrial economics, and economic growth theories because of its flexibility in mapping a wide range of input ratios, asymmetry in the direction of technological change, and capability to incorporate multiple (beyond two) input factors (Kemfert, 1998, Frieling and Madlener, 2016, Papageorgiou et al., 2017). As marked by (Sato, 1977) and (León-Ledesma et al., 2011), CES functions are particularly useful as they allow for nesting multiple groups of inputs and for a non-unitary ES. In contrast, alternatives such as Cobb-Douglas and Leontief functions lack the necessary properties (Pindyck, 1979, Considine, 1989b, Jones, 1995, Serletis et al., 2010a).

Embracing a wide range of macro- to microeconomics applications, we denote our output function associating the non-energy input bundle $\mathbf{X}$ with capital K and labor L, for instance, used to service and run the generation facilities. The second input bundle represents a portfolio of energy fuels. Given technological differences, the energy-driven part of the output is nested, generating a separate component in the generalized CES function:

$$Y(\mathbf{X}, \mathbf{E}, z) = z\left\{ \phi_F \left[F(K, L)\right]^{\frac{\kappa-1}{\kappa}} + \phi_G \left[G(\mathbf{E})\right]^{\frac{\kappa-1}{\kappa}} \right\}^{\frac{\kappa}{\kappa-1}} \tag{2.7}$$

$$G(\mathbf{E}) = \left\{\rho_1 \left[G_1(\mathbf{E}_1)\right]^{\frac{\theta-1}{\theta}} + \rho_2 \left[G_2(\mathbf{E}_2)\right]^{\frac{\theta-1}{\theta}} \right\}^{\frac{\theta}{\theta-1}} \tag{2.8}$$

The separability of $\mathbf{X}$ and $\mathbf{E}$ supports further possible nesting of multiple (groups) energy sources and enables us to find:

- the individual input (group) income shares distinguishing, e.g., energy and non-energy ϕ shares, along with importance of different fuel sets captured by ρ_i, and

- the degree of substitutability between the individual factor pairs or groups, calculating the outer elasticity κ measuring the switching between $\mathbf{X}$ and $\mathbf{E}$ and the inner elasticity θ characterizing the competition between $\mathbf{E}_1$ and $\mathbf{E}_2$ energy groups.

Furthermore, with such a representation of production, we can isolate and focus on the interfuel ES analyzing $G(\mathbf{E})$ and the respective costs $C^E(\mathbf{E}, \mathbf{p}_E)$. For illustrative simplicity, we continue with a two-energy-input case and $\mathbf{E} = \{E_1, E_2\}$, posting the derivations for a more general case with multiple nests in the Appendix A1.[8] We simplify (2.8) and redefine the corresponding functions G_i as:

$$G(\mathbf{E}) = \left[\alpha_1 \left(\gamma_1 \cdot E_1\right)^{\frac{\sigma-1}{\sigma}} + \alpha_2 \left(\gamma_2 \cdot E_2\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.9}$$

The function features parameters α_i, interpreted as the fuel-specific income shares, and γ_i, representing input-specific productivity. Distinguishing *individual* productivity parameters, we enhance the production model, allowing asymmetric efficiencies and, through that, in dynamics, a biased technological change as opposed to the symmetric case and technological neutrality implying $\gamma_1 = \gamma_2$.

For two inputs, σ, can be seen as Hicks' or Morishima's elasticity. We refer to it as MES to remind the reader of the possibility of expanding the function through nesting to more than two inputs. The presented expression poses a computational challenge when γ values differ. Adding the productivity parameters increases the number of parameters to estimate and, thus, would require more equations. Further equations would be found if one reviews the solution for the profit maximization problem. Klump et al. (2007) and León-Ledesma et al. (2010b) point out that the FOCs form a system of marginal productivity conditions that can be used to address the issue:

$$\frac{\partial G(\mathbf{E})}{\partial E_i} = G^{\frac{1}{\sigma}} \, \alpha_i \, E_i^{-\frac{1}{\sigma}} \, \gamma_i^{\frac{\sigma-1}{\sigma}} = \frac{p_i}{p_G} \tag{2.10}$$

Combining those conditions to exclude the loosely specified price p_G, we obtain expressions containing the relative price $\frac{p_i}{p_j}$:

$$\frac{\alpha_i}{\alpha_j} \cdot \left(\frac{E_j}{E_i}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{\gamma_i}{\gamma_j}\right)^{\frac{\sigma-1}{\sigma}} = \frac{p_i}{p_j} \tag{2.11}$$

[8] In our approach to modeling production function with multiple nests, we follow Sato (1967).

Together (2.9) and (2.11) provide a sufficient number of equations to estimate elasticity σ while keeping a possibility to analyze technological efficiencies and their change with the $\frac{\gamma_i}{\gamma_j}$ term. Note that an increase in the number of inputs, e.g., when (2.8) is nested, will automatically translate into an increase in the number of FOC equations. Hence, the capability to calculate the elasticities of inner and outer nests and the individual fuel efficiencies, biased or symmetric, will remain.

The defined system of equations, however useful, represents a static situation, whereas to examine technological change and analyze time series data, we need to add a time dimension to the above. We complete our approach by adding time dynamics into our framework, accompanied by the normalization tackling computational stability and interpretability questions raised by De La Grandville (1997), Klump and de La Grandville (2000), and Klump et al. (2007).

2.2.3 Technological Change and the ES

The approach presented so far is static and, hence, is suitable only for cross-section data analysis. To compute the elasticity on the historical E_{it} and input price data and gain the opportunity to explore the effect of technological change on energy use, we rewrite (2.9):

$$G_t = \left[\alpha_{1,t} \left(\Gamma_{1,t} \cdot E_{1,t}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_{2,t} \left(\Gamma_{2,t} \cdot E_{2,t}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.12}$$

Since the technological change measures the shift in efficiencies over some period of time, a base point $\bar{t}$ is needed for comparison. Then, the progression in efficiencies is captured by the so-called *normalized* factor productivities:

$$\Gamma_{i,t} = \frac{\gamma_{i,t}}{\gamma_{i,\bar{t}}} \tag{2.13}$$

Applying normalization, we switch to the *relative* terms and may now track and compare the changes across the fuels, disregarding the measurement units. Substituting the normalized values into the FOC equations, we derive the normalized version of (2.11):

$$\left(\frac{p_{1,t}\, E_{1,t}\, \alpha_{2,t}}{p_{2,t}\, E_{2,t}\, \alpha_{1,t}}\right) \cdot \left(\frac{E_{2,t}}{E_{1,t}}\right)^{\frac{\sigma-1}{\sigma}} = \left(\frac{\Gamma_{1,t}}{\Gamma_{2,t}}\right)^{\frac{\sigma-1}{\sigma}} \tag{2.14}$$

We regroup the expression to isolate the term reflecting the technological change. By definition, the relative change is neutral when the efficiency change for i and j is the same, i.e., $\Gamma_{1,t} = \Gamma_{2,t}$ and the right-hand side of the equation boils down to 1. Yet, it is important to remember that for two substitutable inputs $\sigma > 1$, whereas $0 < \frac{\sigma-1}{\sigma} < 1$ and hence, the right-hand side of (2.14) may take values greater, smaller, or even equal to one even if $\frac{\Gamma_{1,t}}{\Gamma_{2,t}} \neq 1$.[9]

Formulated this way, the obtained equation allows us to simulate a neutral change. Forcing the relative technological change to one, we may test its effect on the elasticity values. Denoting the elasticity in the case of neutrality by σ^n, we rewrite the above condition:

$$\left(\frac{p_{1,t}\, E_{1,t}\, \alpha_{2,t}}{p_{2,t}\, E_{2,t}\, \alpha_{1,t}}\right) \cdot \left(\frac{E_{2,t}}{E_{1,t}}\right)^{\frac{\sigma^n-1}{\sigma^n}} = \left(\frac{\Gamma_{1,t}}{\Gamma_{2,t}}\right)^{\frac{\sigma^n-1}{\sigma^n}} = 1^{\frac{\sigma^n-1}{\sigma^n}} \tag{2.15}$$

Together, expressions (2.14) and (2.15) provide a testable hypothesis for unit or neutral technological change. With the first multiplier, combining prices, quantities, and income shares, being the same in both equalities, the difference between the two equations comes from the right-hand side, given that there is no difference in input data.

For $\frac{\Gamma_{1,t}}{\Gamma_{2,t}}, > 1$, one finds σ to be lower than σ^n, confirming that the neutral technological change assumption may lead to an overestimated ES when the technological change is biased. Hence, in the time series analysis, it is critical to avoid using the neutrality assumption when calculating ES values unless it is supported by empirical evidence. In the following section, we verify that the technological change in the U.S. power sector from 1990 through 2019 was biased, justifying the application of the above-developed approach.

2.3 Data

Climate change and the urgent need to reduce GHG, especially carbon emissions, brought scientists' attention to the world's largest polluters. Among these, the United States of America ranks second IEA (2024) after China. Electricity generation in the U.S. stands second after the country's transportation sector, specifically its associated carbon emissions, calling for close scrutiny of questions of interfuel substitution. Tracking the evolution of fuel efficiencies, along with the fuel switching driven by fuel prices along with other factors, such as changes in the

[9]The closer the value for σ nears ∞, the closer the quotient gets to 1. As the value for σ approaches unity, the quotient becomes closer to zero.

generation fleet, national and state agencies collect comprehensive energy statistics. That data collection helps inform industry leaders, policymakers, and scientists and gives us an opportunity for in-depth ES analysis.

This section reviews the database we compiled to test our methodology and explains the details important to the econometric analysis. In particular, we analyze the nature of technological change, explore state differences related to energy costs, and highlight the dynamics in other variables, laying the foundation for the discussion in our Results section.

2.3.1 Variables for the ES Analysis

The framework presented in the previous section sets the data requirements for estimating the ES and the change in technological efficiencies. We find that for the U.S., the Energy Information Agency (EIA) and its State Energy Data System (SEDS) contain all the information needed to characterize the power generation and perform the ES analysis.

Exploring the databases, however, we note that whereas records on some variables are available from 1960 until the year before the present, on others, for instance, the net power generation, the data are available only from 1990 onward. Hence, to compile a balanced panel, we set the lower bound of the historical period considered to 1990 EIA (2022). Moreover, the granularity or data frequency is not uniform, which forced us to conduct our study on an annual rather than a monthly or quarterly basis. Such a temporal resolution precludes us from making a comprehensive analysis of the shocks brought by the COVID-19 pandemic and the Russia-Ukraine war. So the following discussion and ES estimations are based on 1990-2019 data.

We collect state-level data, including individual fuel consumption E_i, resultant generation Q_i, and expenses associated with each energy input (EIA, 2020). The information available includes fossil and nonfossil energy statistics. But referring to the merit order, according to which renewable and nuclear generation is dispatched first, we limit our model to the residual demand met by coal, natural gas, and oil-based products, $i \in \{C, NG, O\}$, respectively.[10]

[10] Another reason for excluding renewable energy from our analysis is to avoid additional complexity related to the environmental policies and special market mechanisms often applied to renewables. In the Results section, we discuss the possible effect of renewable energy penetration on the calculated elasticities. We perform the ES calculations for nuclear energy. Still, as reported in the Appendix, the resulting values reflect the rigidity in nuclear generation ramping up and down and, hence, present little interest.

Using the net power output $Q_{i,t,s}$, we calculate the final output or G for the respective portfolio of analyzed fuels as:

$$G_{t,s} = \sum_{i=1}^{n} Q_{i,t,s} \tag{2.16}$$

Besides the time dimension, we emphasize the geographical granularity or association of values with individual state s.

Next, we examine the relationship between the primary energy inputs and generation, calculating the effective average technological efficiencies with the annual and state resolution:

$$\gamma_{i,t,s} = \frac{Q_{i,t,s}}{E_{i,t,s}} \tag{2.17}$$

Those values are seemingly easy to calculate and vital for analyzing technological change and inter-fuel substitution. Another critical variable that distinguishes our analysis is the unit input cost. We derive the *effective* input prices $p^e_{i,t,s}$ using individual fuel-associated expenditures reported by the SEDS. The market energy prices might not coincide or reflect the per-unit energy spending, for example, neglecting hedging costs, volume discounts, and other factors. In an attempt to correct for that and to make more accurate ES estimates, we use inflation-adjusted effective input costs.

The effective price exercise helps us find another essential element of the energy cost: payment associated with carbon emissions. Regulations, such as an Emission Trading Scheme (ETS) brought by the RGGI, add extra costs to be considered by utilities in their bidding and generation decisions. To account for that, we adjust the originally calculated $p^e_{i,t,s}$ for 11 states, including Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont,[11] computing the price that will ultimately be used in our econometric analysis:

$$p_{i,t,s}\left[\frac{\$}{MMBtu}\right] = p^e_{i,t,s}\left[\frac{\$}{MMBtu}\right] + c_t\left[\frac{\$}{t_{CO_2}}\right]\cdot\psi_{i,t}\left[\frac{t_{CO_2}}{MMBtu}\right] \tag{2.18}$$

In our calculations, we apply the emission factors ψ provided by EIA (2021a) and emissions certificate cost c_t assigned every three years by the ETS bidding process.

[11] New Jersey has been part of RGGI from 2009 onward but paused its participation from 2012 to 2018; thus, the adjustment for that state is limited to the mentioned years. Virginia has also joined RGGI, yet only starting in 2020, which is beyond our analysis.

The compiled state-level time series database differentiates our work from numerous previous studies primarily focused on nationwide or individual state ES. With the data granularity often marked as the underlying cause of the ES estimate divergence (e.g., see Considine (1989b), Hochman and Timilsina (2017), Jones (1995), Khalid and Jalil (2019), Pindyck (1979)), we have a unique opportunity to investigate how data aggregation or subsetting may translate into the ES differences. A notable study that inspired our analysis, EIA (2012), showed how elasticity values may differ on a regional basis. We update and expand this assessment by analyzing the ES evolution and checking for possible biases related to the technological neutrality assumption.

2.3.2 Exploratory Data Analysis

Constraints on time series-based ES analysis have limited the sector evolution discussions, particularly concerning technological efficiencies. To address this shortage and to understand the implications of technological advances, we look at the dynamics of technical efficiencies and other relevant variables, such as the effective energy costs. In doing so, we verify the necessity for the additional complexity of the proposed methodology.

The U.S. shale revolution untapped abundant natural gas and oil resources, causing major energy price shakeups. In 2008, the fast growth in natural gas supply manifested in a multifold price drop, prices that never fully recovered to previous levels. A surge in production resulted in oil price collapses in 2014 and 2016 and increased price volatility. We depict these dynamics by plotting the U.S. state-consumption-weighted average effective energy costs computed with (2.18) in Figure 2.1.

The distribution of values also reflects energy-price differences and associated supply-cost differentiation associated with infrastructure bottlenecks and other factors.

Radical shifts in the U.S. energy supply, prices, and decarbonization efforts have accelerated fuel switching. The U.S. power generation mix has undergone an unprecedented transformation, as shown in Figure 2.2. Although the combined share of coal- and natural gas-fueled electricity generation has remained fairly constant, at about 65%, the share of natural gas-based generation has been steadily growing, from around 10% to nearly 40% during the past three decades, displacing coal, whose share shrank from around 55% to less than 25%.

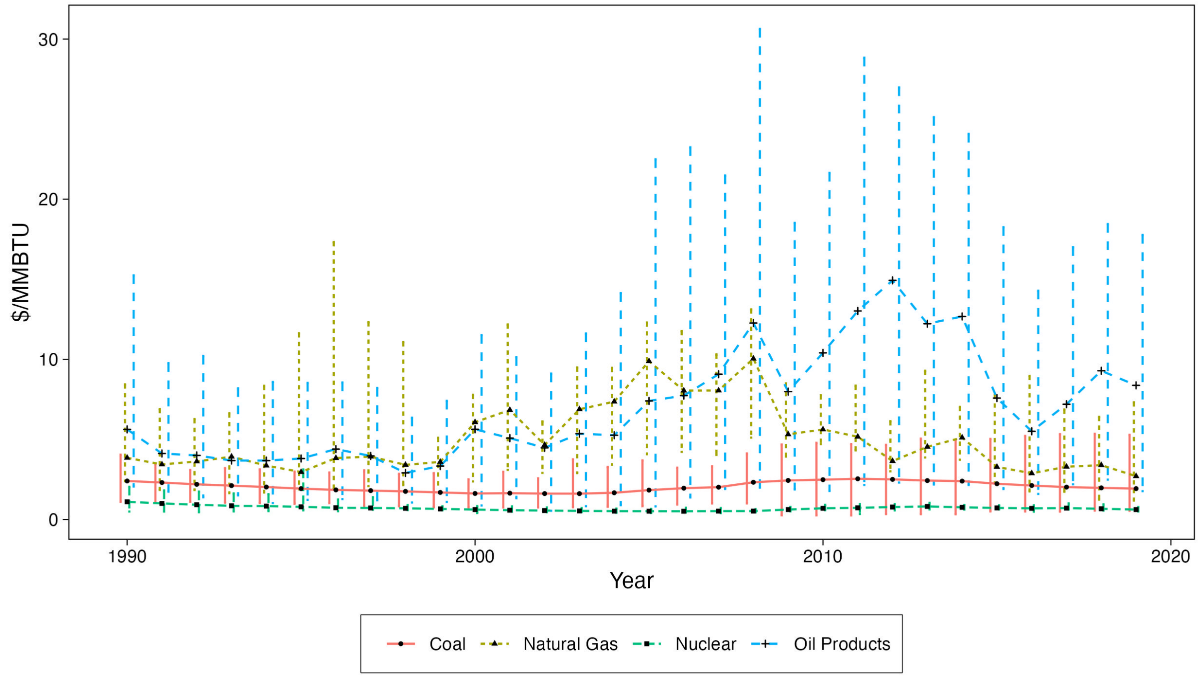


FIGURE 2.1: The U.S. state-consumption-weighted average effective energy costs. Bars mark the highest and lowest values across the states each year (EIA, 2022, 2020).

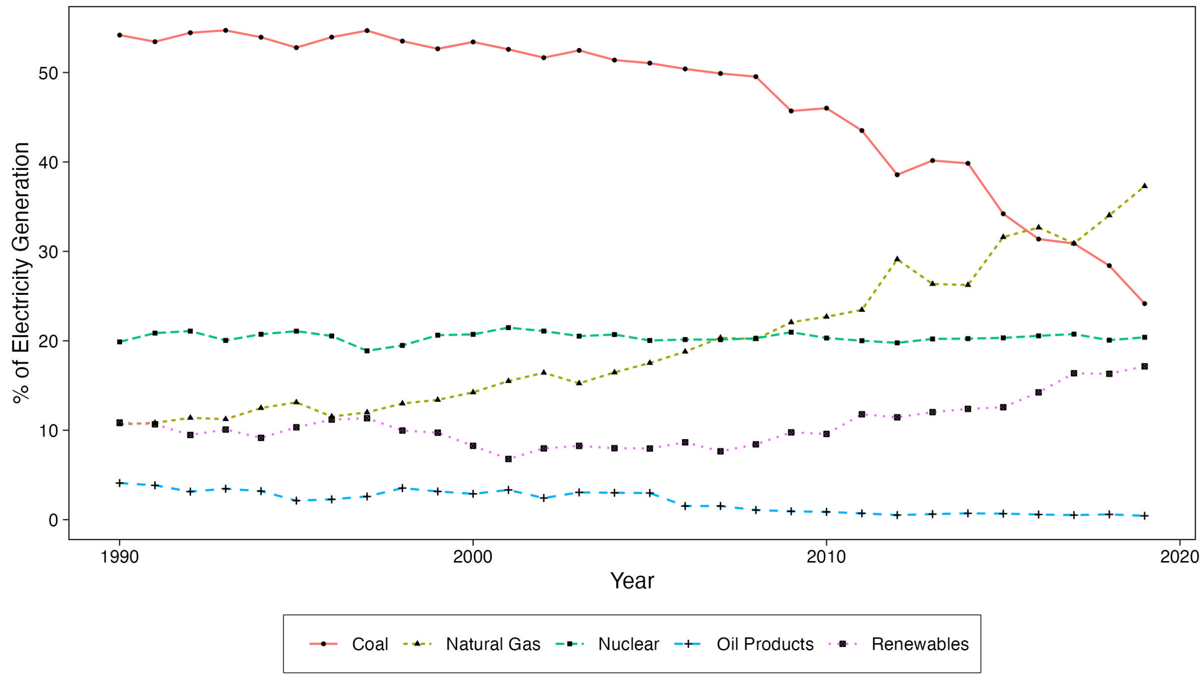


FIGURE 2.2: Relative production shares in the U.S. power sector (EIA, 2022, 2020).

We recognize that changes in the dispatched energy mix might be driven by factors other than energy prices and technological change. But considering the two listed as the most influential, we look at the technical efficiencies next. Plotting the calculated efficiencies in Figure 2.3, we highlight the visible changes in natural gas generation efficiencies. The increasing absolute and relative γ_{NG} values confirm the need to account for the *biased* technological change. The dynamics across $\gamma_{i,t}$ values also suggest an analysis of the ESs evolution.

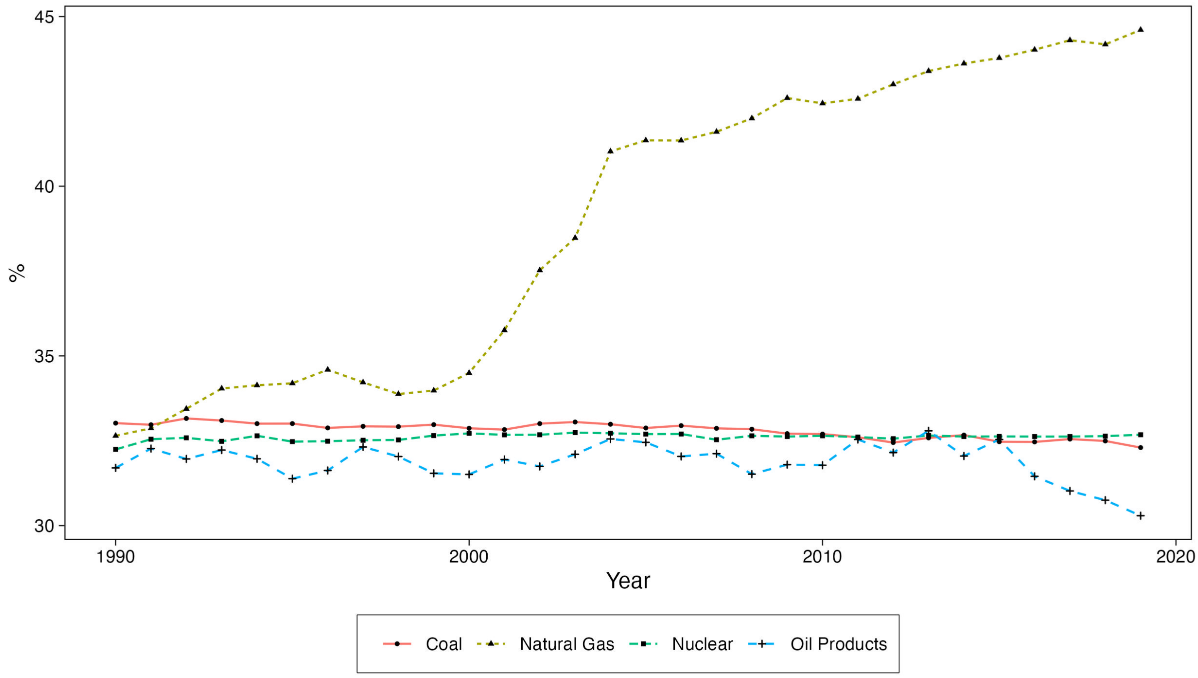
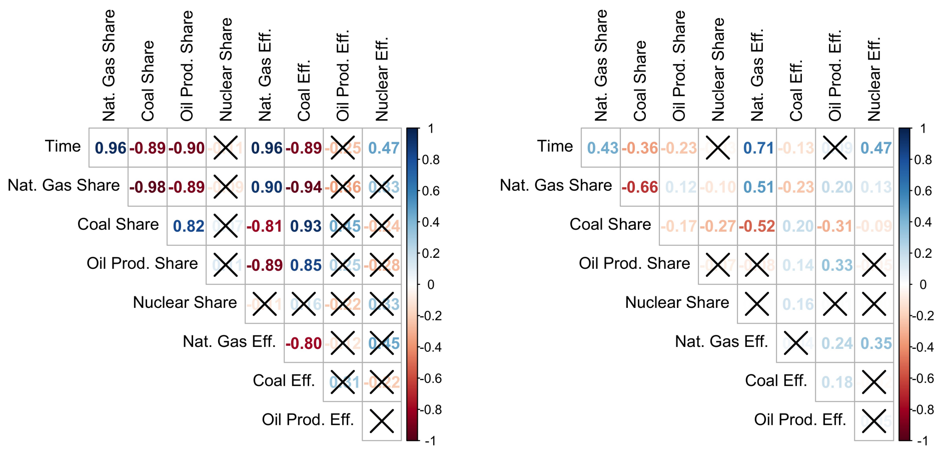


FIGURE 2.3: Dynamics of the electric efficiencies in the U.S. power sector (EIA, 2022, 2020).

Looking into another recognized source of bias in the ES, the divergence in estimates stemming from data aggregation, we examine the correlations in the key variables on the national or aggregate level and state-level data. Results reported in Figure 2.4 reveal that whereas the signs of the correlation stay the same, the strength may significantly vary, implying that the ES values calculated on the aggregate versus state-level data are likely to differ. The presented exercise merely suggests a possible aggregation bias, whereas other arguments may be brought to defend or discard the aggregation. However, considering this result, we calculate the ES varying the data aggregation level.

It is worth mentioning that not all U.S. states have generation capacities using all three fossil fuels, just as not all the states have nuclear power. Ignoring that fact may deepen aggregation-brought biases. To address that issue, we selected the states that do have the fuels identified in the respective model and ES calculations.[12]

[12]Complete information on the states included in the respective model, together with further data analysis insights, can be found in the Appendix A3.



(A) Correlation (Aggregate). (B) Correlation (State).

Figure 2.4: Correlations among the key variables characterizing the U.S. power sector, reporting values with over 1% significance (EIA, 2022, 2020).

2.4 Econometric Estimation

Confirming the necessity for the expanded ES approach that accommodates a technological bias, we now proceed with details on the econometric model. We translate the theoretical derivations into estimation procedure steps, continuing with the two-input model for simplicity, presenting the generalization for three or more inputs in the Appendix A1. We start by expanding the normalization critical for interpreting the results. Then, we take a closer look at the optimality conditions and show how they can also be used to analyze the power sector behavior optimality. To conclude, we briefly discuss the choice of the estimation method.

2.4.1 Normalizing the Production Function

In terms of our study, normalization is a procedure applied to the terms in the production function and the FOC equations to resolve possible dimensionality and interpretability issues. In a nutshell, the output and individual input values are divided by corresponding base values. In Section 2, we have already introduced parameter $\Gamma_{i,t}$, the normalized unitless productivity, to define the technological shifts across the inputs and over time. Here, we apply the normalization to other variables, marking the base values with the subscript zero and FOCs used in the econometric calculations.

Adopting the approach implemented in the multi-sectoral data analysis by Kreuser et al. (2015), we introduce individual state-level Normalization Constants ξ_s and state-specific base values $E_{i,0,s}$ and $G_{0,s}$. Then, following the expressions (2.9) and (2.10), we rewrite the normalized Constant Elasticity of Substitution production function and the associated FOCs:[13]

$$\frac{G_{t,s}}{G_{0,s}} = \xi_s \left[\alpha_{1,s} \left(\frac{E_{1,t,s}}{E_{1,0,s}} \Gamma_{1,t,s} \right)^{\frac{\sigma-1}{\sigma}} + \alpha_{2,s} \left(\frac{E_{2,t,s}}{E_{2,0,s}} \Gamma_{2,t,s} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2.19}$$

$$\frac{\partial G_{t,s}}{\partial E_{i,t,s}} = \left(\frac{\alpha_{i,s} \, G_{0,s}}{E_{i,0,s}} \right) \left(\frac{G_{t,s}}{G_{0,s}} \right)^{\frac{1}{\sigma}} \left(\frac{E_{i,t,s}}{E_{i,0,s}} \right)^{-\frac{1}{\sigma}} (\xi_s \, \Gamma_{i,t,s})^{\frac{\sigma-1}{\sigma}} = \frac{p_{i,t,s}}{p_{Y,t,s}} \tag{2.20}$$

Note that the presented system contains three equations in the two-input case, with $i \in \{1, 2\}$ and (2.20) specified for each input. Used for estimating the elasticity σ, the system in such a formulation also accounts for the fixed effects.

However, term $p_{Y,t,s}$ in the right-hand side of (2.20) is vaguely specified, raising questions about proper measurement. To avoid the related issues, we divide the FOCs by each other to exclude the output price:

$$\frac{p_{1,t,s} \, E_{1,t,s} \, \alpha_{2,s}}{p_{2,t,s} \, E_{2,t,s} \, \alpha_{1,s}} = \left(\frac{E_{2,0,s} \, E_{1,t,s} \, \Gamma_{1,t,s}}{E_{1,0,s} \, E_{2,t,s} \, \Gamma_{2,t,s}} \right)^{\frac{\sigma-1}{\sigma}} \tag{2.21}$$

Recall that our data allow for computing $\gamma_{i,t,s}$ and, thereby, estimating $\Gamma_{i,t,s}$, so the obtained expression does not bring any issues for parameter estimations. In contrast, the above result provides two benefits: the reduced number of equations suggests both improved computational efficiency and greater accuracy.

2.4.2 The Benchmarks for Normalization

With normalization defined, we turn to a discussion of the base values. In general, they could be associated with a specific year, or they could be defined as sample averages. Choice of the base values is dictated by the purposes of the analysis (León-Ledesma et al., 2010b). In search of the most appropriate base, we examine the time series and the distributions for output values, input quantities, prices, and efficiencies. The observed trends and long tails of the distributions suggest the use of the geometric averages for the first three of the listed variables and the median

[13] Assuming that capital and labor expenses do not change significantly, we see them as embedded into the productivity and technology parameters.

time $\bar{t}$ for productivity. Thus, we follow the conventional approach to the base value choice in the time-varying variables and define the normalization bases as:

$$G_{0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, G_{t,s}}{n}\right); \qquad E_{i,0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, E_{i,t,s}}{n}\right);$$
$$p_{i,0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, p_{i,t,s}}{n}\right) \qquad \text{and} \qquad \Gamma_{i,t,s} = \frac{\gamma_{i,t,s}}{\gamma_{i,\bar{t},s}}. \tag{2.22}$$

In contrast, views on the normalization of income shares diverge. We employ the procedure applied in a similar setting by León-Ledesma et al. (2011). According to that study, we specify:

$$\alpha_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s}}{E_{1,0,s}\, p_{1,0,s} \ + \ E_{2,0,s}\, p_{2,0,s}}; \quad \alpha_{2,s} = \frac{E_{2,0,s}\, p_{2,0,s}}{E_{1,0,s}\, p_{1,0,s} \ + \ E_{2,0,s}\, p_{2,0,s}} \tag{2.23}$$

We tested other normalization options, conducting the sensitivity analysis, but we found little effect on the final ES estimations.[14] As a result, we find the above base values acceptable and suitable for the purposes of our analysis.

2.4.3 The Optimality Conditions

Reviewing the FOCs, we realized that our estimations provide grounds for further analysis of the power sector's behavior. Computing the ES, we estimated the production model parameters and calculated the optimal input use and output levels. With that, we obtained a possibility for verifying how close the observed relative fuel use is to the optimal levels determined by First Order Conditions. Performing such a thought experiment, we may obtain insights into the power sector's operational optimality. To pursue this line of investigation, we rewrote (2.21), isolating the term with the relative fuel quantities, and solved it for the optimal ratio of E_1 and E_2:

$$\left(\frac{E_{1,t,s}}{E_{2,t,s}}\right)^{*} = \left(\frac{E_{2,0,s}\,\Gamma_{1,t,s}}{E_{1,0,s}\,\Gamma_{2,t,s}}\right)^{\sigma-1} \left(\frac{p_{2,t,s}\,\alpha_{1,s}}{p_{1,t,s}\,\alpha_{2,s}}\right)^{\sigma} \tag{2.24}$$

This optimal fuel ratio allows us to (1) analyze whether and to what degree a certain fuel is "overused" and (2) track the adjustments in fuel use over time. We define the *misuse* of input i

[14]We present the results in tables in the Appendix A4.

over j relative to the optimal use as:

$$O_{j,t,s} = \frac{\left(\frac{E_{i,t,s}}{E_{j,t,s}}\right)^*}{\frac{E_{i,t,s}}{E_{j,t,s}}} = \frac{E^*_{i,t,s}}{E_{i,t,s}} \cdot \frac{E_{j,t,s}}{E^*_{j,t,s,}}; \tag{2.25}$$

Strictly speaking, the misuse values may lead to erroneous conclusions since expression (2.25) ignores the effect of possible binding constraints. Viewed with caution, however, the results of this experiment may provide some interesting new insights into the delay in reaching optimality and the ability to rely on the FOC.

2.4.4 Estimation Method

To solve the system of equations characterizing the ES and the technological change, we follow the traditional approach and apply logarithms to linearize equations. Then arises the question of a choice of computation method. The applied econometrics literature offers a variety of approaches: for instance, Herrendorf et al. (2015) used the three-stage least squares method, whereas Frieling and Madlener (2016) demonstrated the powerful capabilities of the Generalized Method of Moments (GMM), inspiring our analysis, Klump et al. (2007) and León-Ledesma et al. (2010b) applied Non-Linear Seemingly Unrelated Regressions (NLSURs). The last option presents itself as particularly attractive because of the open source NLSUR-package in *R* software.

However, warned by Luoma and Luoto (2011) of the internal inconsistency of estimators problem, we decided on the Iterative Feasible Generalized Non-Linear Least Squares (IFGNLS) method proposed by Kreuser et al. (2015). Based on a maximum log-likelihood, this approach overcomes the bias toward unity criticized by Luoma and Luoto (2011) and generates results similar to NLSUR when correlated errors are not an issue. Possible drawbacks of the selected method include its higher computational requirements and convergence issues. The latter, however, may also emerge with another method. The NLSUR packages available in *R* and *Stata* help the reproducibility of our results and usability of the model in other applications.

2.5 Results

Applying the developed econometric procedure, we compute the interfuel ES varying the assumption on the nature of technological change, the set of inputs considered, and the data samples. First, we demonstrate our approach with the two- and three-input (nested) models, applied to the aggregate U.S. and state-level data sets. Examining the differences among all estimations, we label the three-input state model as a *benchmark*. Then, we look at the power sector dynamics, analyzing the evolution of the ES and fuel-switching behavior across the states. We conclude with new insights and ideas for further needed research.

2.5.1 State vs. National ES

The ES studies differ in their choice of energy inputs and regional granularity. Our data set is rich enough to support comparative analysis of various model setups and to explore by what methods and how ES values are affected. We start by comparing the results of the two- and three-input models using the country *aggregate* versus *state* data, given in Tables 2.1 and 2.2.

Table 2.1: Two-input substitution elasticities in the U.S. electricity sector (1990-2019).

	NG - C		NG - O		C - O	
	agg	*state*	*agg*	*state*	*agg*	*state*
σ	1.05***	15.90***	2.42***	2.69***	2.12***	2.72***
	(0.08)	(1.95)	(0.21)	(0.05)	(0.36)	(0.10)
N	30	1260	30	1260	30	1260
$R^2(G)$	0.65	0.87	0.98	0.98	0.96	0.98
$R^2(FOC)$	0.08	0.85	0.87	0.86	0.55	0.61

σ - ES; *** p<0.01; (Strd. Error)

First, we mark the statistical significance of all the computed values and satisfactory R^2 for the estimated equations, with the exception of low R^2 for the FOC of the $NG - C$ pair in both the two-input and the three-input models. This issue, however, arises only in the *aggregate* but not in the *state* cases, suggesting better stability and robustness of the latter.[15]

[15] We believe that the low R^2 values are symptomatic of the computational convergence problem associated with the aggregation or the inherent asymmetry of the MES. In our calculations, we set the substitution of coal with natural gas and switching from natural gas to coal to be the same, thus forcing symmetry on the MES. It may not be the case, considering the decarbonization and incentives for coal retirement. Even though our approach allows for asymmetric MES estimations, we leave that computationally complex problem for further research.

TABLE 2.2: Three-input substitution elasticities in the U.S. electricity sector (1990-2019).

	(NG - C) - O		(NG - O) - C		(C - O) - NG	
	agg	*state*	*agg*	*state*	*agg*	*state*
σ	2.10***	2.54***	1.09***	4.95***	1.29***	4.07***
	(0.15)	(0.05)	(0.08)	(0.21)	(0.08)	(0.11)
η	1.16***	4.74***	1.74***	2.93***	2.36***	2.32***
	(0.08)	(0.16)	(0.08)	(0.06)	(0.34)	(0.06)
N	30	1260	30	1260	30	1260
$R^2(G)$	0.84	0.89	0.85	0.89	0.84	0.89
$R^2(FOC\ Nest)$	0.2	0.86	0.84	0.86	0.54	0.61
$R^2(FOC\ Outer)$	0.68	0.47	0.43	0.38	0.62	0.48

σ - outer ES; η - inner nest ES; *** p<0.01; (Strd. Error)

Furthermore, although we find the substitutability across all the fuel combinations to be greater than one, pointing to the elastic response or high sensitivity to changes in fuel costs, the aggregate ES values are consistently lower than the counterpart state values. That suggests that state responses balance out nationally, hiding the severity of fuel changes in some states behind the insensitivity in others. The difference in the estimations is especially large in the coal to natural gas substitution (and $C - O$): a 10% change in the relative costs is expected to cause a 10.5-11.6% change in the aggregate relative fuel use versus a radical more than 40% change projected by the state data. Appearing to be similar, the ES values for the $NG - O$ pair, 2.42 for the aggregate and 2.69 for the state cases, also diverge with the addition of coal: the inner and the outer elasticities move in opposite directions, to 1.74 and 2.93 for $(NG - O) - C$ and to 1.29 versus 4.07 for $(C - O) - NG$, respectively.

The increased gap in the three-input model, state vs. aggregate, estimations, and the direction of the ES values change between the two- and three-input cases led us to the conclusion that the higher the granularity in the inputs and data, the more visible the reactions to the change in the relative fuel cost are. Hence, data disaggregation helps uncover the dynamics concealed otherwise, whereas aggregation is prone to mask it with lower ES values, suggesting milder sensitivity. Monitoring the progress of energy transition, it is critical to detect the signs of structural changes. So, we conclude that even though the two- and three-input approaches may lead to somewhat similar assessment results, nesting, and data disaggregation provide a deeper and more comprehensive view of fuel substitution. In addition, our method helps avoid possible convergence and stability issues. Therefore, we continue our analysis, referring to the three-input state model and its outcome as a *benchmark*.

2.5.2 Possible ES Biases

The effect of data aggregation and input choice led us to investigate other factors that may influence the ES. Following the theoretical discussion, we use our benchmark model to show the bias from the neutral technological change assumption. Calculating the *neutral* ES, we aim to verify the importance of our approach, offering flexibility concerning the nature of technological change. Next, the conclusion that ES accuracy improves with the expanded list of inputs leads us to the analysis of the data sample, including only the states with nuclear generation, the primary base-load substitute for coal, and the key alternative to fossils along with renewables.[16] At present (2024), nuclear generation is used in 28 states, but we focus on 26 that used all 3 fossil fuels in the period considered, referring to the case as NS *26* (Table 2.3). Finally, the trends in energy efficiency and structural shifts in the residual demand inspired our historical bias analysis, for which we apply our benchmark model to the last two decades of data. The reduced sample size causes stability issues, so we stretched the time window to 22 years and name the last case *'97 - '19*.

TABLE 2.3: The three-input ES cross-model comparison.

	η				σ			
	state	*neutral*	NS 26	'97 -'19	*state*	*neutral*	NS 26	'97 -'19
(NG - C) - O	4.74	6.98	3.65	3.17	2.54	2.72	2.61	2.64
(NG - O) - C	2.93	3.37	2.76	2.73	4.95	8.48	3.78	3.05
(C - O) - NG	2.32	2.45	2.49	2.60	4.07	5.67	3.59	2.87

σ - outer ES η - inner nest ES; NS 26 - states with nuclear generation

Looking at the elasticity calculated under the assumption of neutral technological progress, we confirmed the positive bias, finding all the values to be higher than the benchmark results. The difference is exceptionally large for the pairs with natural gas technologies, which have been advancing the most (Fig. 2.3). Thus, a 10% change in coal to natural gas relative cost suggests an almost 70% change in the relative fuel usage under the neutrality assumption versus 47% in

[16]Note that in the course of our study, we analyzed the two-, three-, and four-input models, the latter distinguishing nuclear generation. Yet, to keep the discussion focused on fossil fuel energy, we include the four-input model's results in the Appendix A4.

the benchmark case, accounting for a bias toward natural gas technological change. In contrast, neutral and benchmark values are fairly close for the inner ES of $(C - O)$ and outer ES of $(NG - C) - O$, with coal and oil generation efficiencies barely changing.[17]

Next, we analyzed a sample highlighting the effects of nuclear generation. The U.S. nuclear plants participate in the wholesale power trade, along with natural gas generators, who often set the price for electricity according to the merit of order. Historically, an increase in natural gas prices created incentives for expanding the relatively cheaper nuclear and coal generation, whereas plummeting natural gas prices brought a wave of retirements for both nuclear and coal-fired plants. In line with that, our estimations show lower NS 26 ES values in the pairs particularly affected by the availability of the nuclear option, such as inner $(NG - O)$ and $(NG - C)$. We call this effect "substitution dilution" as the reaction to a change in, e.g., natural gas price, is split between the paired fossil fuel (bundle) and implicitly nuclear. The four-input model, including nuclear to the set of inputs, supports our conclusions (see Appendix A3).

Although the variations in the ES values may result from other sample-specific characteristics, for instance, regulations and demand properties, they emphasize the importance of alternative sources of power generation or changes in residual demand. The past two decades mark the fast growth in renewable energy generation.

To verify its effect, we use a reduced historical sample in our calculations. The ES in columns headed '97 -'19 signifies the change in fuel competition within the past two decades. Inner elasticity changes in the same direction as in the NS 26 case. We attribute that to the similarity in renewables' and nuclear generations' positions in the power supply curve: with low marginal costs, both traditionally precede any fossil fuel. Hence, adding renewables weakens the reaction to the change in natural gas prices, appearing last in the supply curve. At the same time, competition between coal and oil-derived products becomes fiercer. To explain the increased elasticity for oil, we recall that oil products are often used in backup, black-start, or emergency generation, competing with renewable generation combined with battery technologies. Penetration of those technologies exposes fossil fuels to further competition, justifying an increase in the ES.

In sum, we confirm that the neutrality assumption introduces ES bias, but along with that, we conclude that our ES results may reflect population and historical-sample biases. Leaving the

[17]With all the ES values' statistical significance $p < 0.05$ and the standard error not exceeding 10%, we simplify the table view and report only estimated values.

investigation of the former for further research, we focus on the latter to examine the evolution of the ES.

2.5.3 The ES Evolution

We developed a "moving time-window" procedure to analyze how the ES values have changed over time (Figure 2.5). Applying it, we compute the ES for each designated time window, tracking how the calculated values change as the window moves.

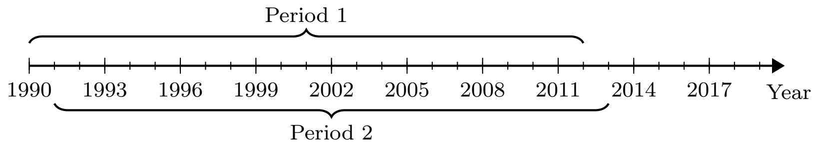


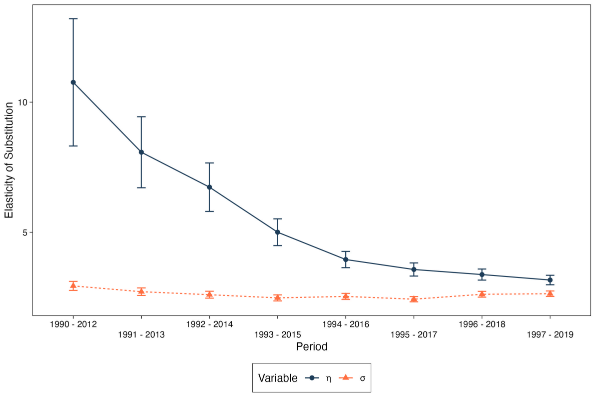
Figure 2.5: Example of a 22-year moving-time window.

We plot the 22-year window results in Figure 2.6. With the notable shrinkage in the 95% confidence intervals indicated by the error bars, the plots show a striking decrease in substitutability between natural gas and coal over time. The corresponding inner and outer ES values drop to a third between the first window of 1990-2012 and the last covering the period of 1997-2019. In contrast, the substitutability with respect to oil products hardly changes.

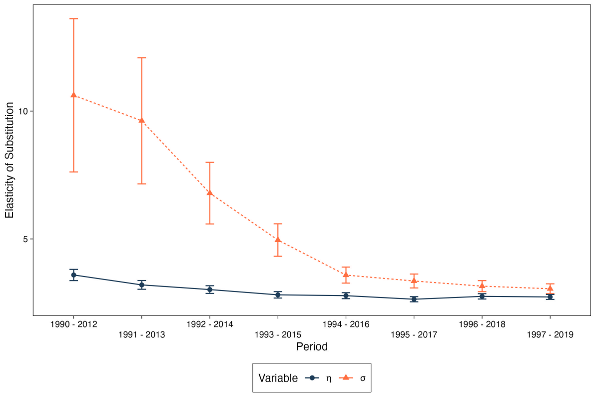
We believe several co-occurring phenomena help to explain the uncovered trends in the ES: the unbundling of natural gas supply that ended in 1992; the Shale Revolution that started in the late 2000s and brought an abundant supply of natural gas and oil to the U.S. market; and the energy transition inducing the retirement of the aged coal-based generation and the penetration of renewable energy in the U.S., accelerating in the 2010s. This historical context suggests that besides the changes in relative energy costs, domestic resource availability and regulations impacted fuel substitutability, especially of natural gas.[18]

Resource availability could explain investments in technology and the deployment of new capacities, allowing for more flexibility in price reactions in the power sector. Adding more efficient, combined-cycle natural gas plants while retiring coal generation and adding back-up and peak-shaving diesel generators would mean increasing reliance on natural gas and limiting gas to coal switching. On the other hand, adopting renewables reduced the demand left for natural gas, pushing the elasticity back to lower numbers. The battle between the two effects, in

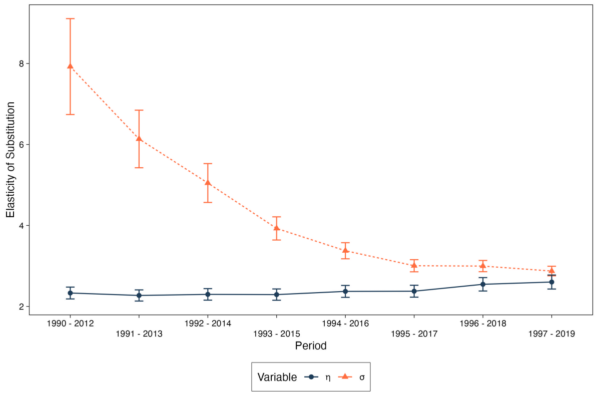
[18] In this context, we also realize the limitations set by the assumption on the ES symmetry. We mark that weakness in the Discussion section, suggesting further research directions to address it.



(A) Inner and outer ES for $(NG-C)-O$.



(B) Inner and outer ES for $(NG-O)-C$.



(C) Inner and outer ES for $(C-O)-NG$.

FIGURE 2.6: The evolution of ES, based on the 22-year moving time-window exercise.

part, explains the high ranges of ES values, but the last two decades indicate convergence and stabilization across all the ES values.

Hence, though the ES can be seen as constant over shorter time windows in times of technological and regulatory turmoil, having a dynamic analysis is crucial to ensure that the estimations represent the sector responsiveness to energy-cost shocks. Industry restructuring, due to the regulatory environment, could change the fuel substitutability dramatically, and hence, power-sector planners and agents must consider the direction of the ES evolution. In view of this, we complete our analysis by investigating the error terms or deviation of the observed ES from the modeled one.

2.5.4 Model vs. Reality

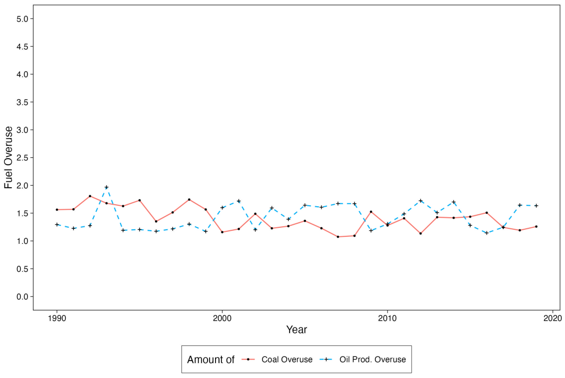
The derived ES relies heavily on the optimality assumption captured by the First Order Conditions. As reported above, the explanatory power of our models for the inner and outer FOC is lower than that for the production function $G(E)$. Lower R^2 values bring us to examine the error term or the difference between what our calibrated model predicts should have been the energy substitution and what was observed in reality. We refer to the methodology in Section 2.4.3 to compare the actual relative use of fuel i over j with the modeled, plotting the weighted average annual *overuse* based on our benchmark model (2.7). In that exercise, we mark the number of states with the *overuse* of a particular fuel to address possible sample biases.

To analyze and interpret the plots, one should realize that the optimality condition holds when the weighted average overuse value equals 1.[19] Looking at the severity of overuse and its spread across the states, we make several observations. First, we see that the relative use of coal over oil-based products is balanced out, with the "overuse" lines fluctuating around 1. The corresponding number of overuse states heavily fluctuates, supporting this argument and showing how, for many states, it takes more than one year to adjust its oil use in response to the oil price shocks.

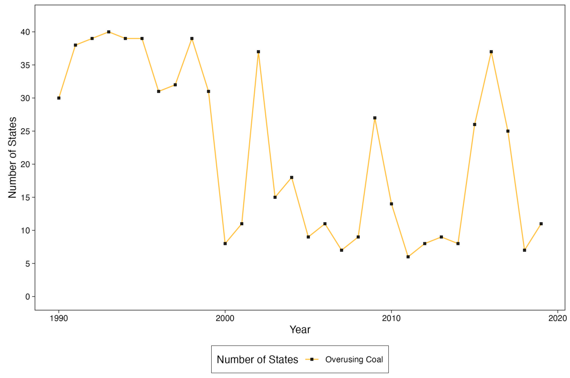
Next, we find that natural gas has been drastically overused between 2000 and 2008 compared to all other inputs. The overuse is especially pronounced in its pairing with coal. We suspect that the pressure on coal use and the need for more natural gas to manage the intermittency of renewables have induced the power sector to expand its reliance on natural gas while the supply was still tight and natural gas prices were high. Later, the availability of shale gas, drop in natural gas prices, and demand shrinkage under the global financial crisis have resulted in adjustments that appear to return to more rational and balanced behavior, bringing the overuse values closer to 1.

Overall, even though the U.S. power sector shows visible deviation from optimality conditions across most of the states during economically unstable times, the sector is prone to return to optimal behavior, as the model dictates, once the shocks are over. This phenomenon implies the validity of our approach but highlights that certain events may induce ES value deviations and fluctuations in the short term.

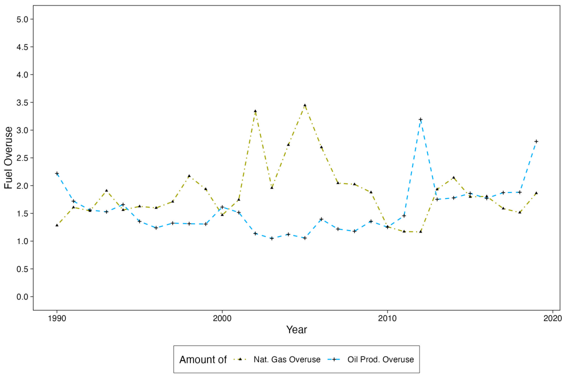
[19] One should, however, be careful with this interpretation, noting that with half of the states overusing one fuel and the other half overusing (by the same amount) the paired fuel, the overuse is equal to 1, and optimality also holds. That is why we analyze the overuse together with the number of overusing states.



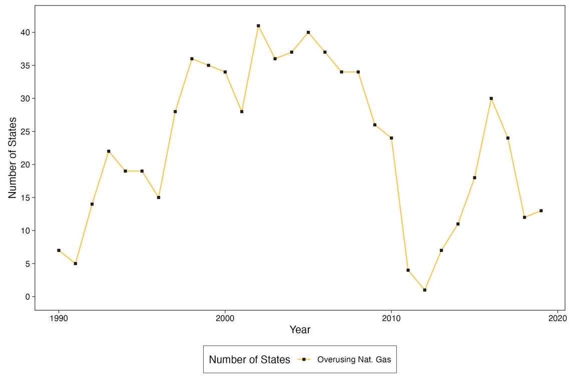
(A) Fuel overuse in $(C - O)$ pair.



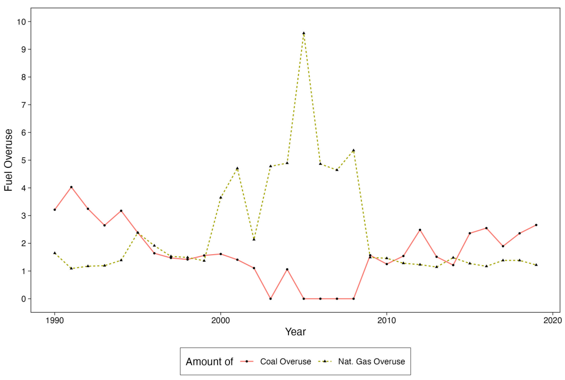
(B) Number of states overusing coal relative to oil products.



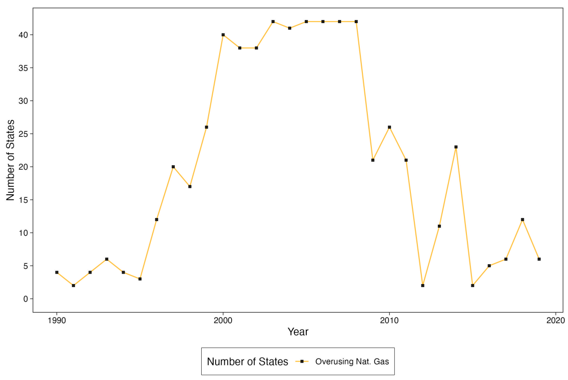
(C) Fuel overuse in $(NG - O)$ pair.



(D) Number of states overusing natural gas relative to oil products.



(E) Fuel overuse in $(NG - C)$ pair.



(F) Number of states overusing natural gas relative to coal.

FIGURE 2.7: Modelled versus actual U.S. power sector interfuel substitution.

2.6 Discussion

Technological innovation is a driving force of decarbonization, supporting the energy-mix transformation and the transition to a low and net zero carbon energy mix. So, it is essential for interfuel substitution, a measure of the energy use responsiveness to the changes in relative fuel costs and a critical indicator of transition progress, to account for and reflect technological change. We present and demonstrate a novel method for estimating ES, allowing for a biased change in efficiencies across energy fuels. In so doing, we confront the key weakness of traditional empirical approaches featuring the assumption of neutral technological change and offer the flexibility needed to capture developments associated with decarbonization.

We confirm that technological change in the U.S. power sector is uneven and biased toward natural gas-fired generation, and we apply our model to estimate ES across fossil fuels. We validate the importance of the biased technological change assumption by showing that results from the neutrality-based model suggest a much higher degree of substitutability between fuels. The degree of ES overestimations caused by the technological neutrality assumption underscores the value of the presented approach.

In the course of conducting our analysis, we also uncovered disparities in the estimated elasticities stemming from data aggregation and production-function specification. Our calculations suggest that disaggregated data enhance the model's ability to capture the variance in fuel substitutability and elicit useful insights into shifts related to energy transition. Employing a nested production function with multiple (more than two) competing fuels helps us develop a further understanding of how a generation portfolio may affect interfuel substitutability. For instance, growth in the first merit order energy sources, such as nuclear power or renewables, reduces the ES for natural gas, the key marginal fuel responding to changes in power demand.

Furthermore, examining our estimations of historical biases, we found a significant difference in the ES values derived from the entire data set and the last two decades of data. That finding inspired us to study ES evolution using a moving time-window procedure. Results showed a gradual reduction in the ES between coal and natural gas, which we attribute to energy-transition processes, namely the penetration of renewable energy and expansion of natural gas generation caused by the abundance of unconventional resources.

Finally, global and U.S. energy market turmoils, caused by financial crises, the shale revolution, and intensified regulatory interference, led us to question the validity of our approach based on optimality conditions. So, we completed our study by examining how well the calibrated model explains real-world observations. To confirm the validity of the profit-maximization assumption and the optimality conditions, we compared the actual versus model-predicted fuel use. We found that even though, in the short term, the energy use may not comply with the optimality conditions, in equilibrium, energy use returns to the levels suggested by the model and aligns with optimality. Another explanation for some of the deviations from optimal fuel use may be the effects of capital allocation, implicitly captured by our model. Additionally, capital efficiency, policy preferences, and the policy-driven support of capacities (e.g., in renewables and/or nuclear power) may have influenced the outcomes. Further research may, thus, also incorporate a measure of capital and capital efficiencies.

In summary, our approach illuminates the complexities within the U.S. power sector and establishes a sturdy platform for further investigations into energy transitions. Yet, drawing from the results of our study, the following topics deserve further research: (1) a nuanced analysis involving diverse data subsamples to scrutinize the impact of nuclear power and the adoption of renewable energy on power-sector elasticities; (2) a more comprehensive investigation using finer-grained data in the moving time-window analysis; (3) the exploration of alternative functional forms in the multi-equation framework, potentially necessitating alterations and adaptations in the application methodology, and (4) an extension of the approach that allows for the calculation of asymmetric ES in the case of panel data. Despite the identified limitations and prospects for refinement, the present work facilitates a more sophisticated comprehension of energy-mix dynamics, offering pathways to enhance predictive models and furnish improved guidance for making policy decisions in an ever-evolving energy landscape.

3 Re-assessing the Impact of the Regional Greenhouse Gas Initiative: The Effect of Low Natural Gas Prices on the U.S. Power Generation

by Daniel Gatscher, Svetlana Ikonnikova

This study re-evaluates the efficacy of the RGGI designed to reduce carbon intensity in the northeastern U.S. power sector. The program's start coincided with the discovery of the Marcellus Shale play and the rapid growth of natural gas production that led to a dramatic drop in regional energy prices. We contribute to the debate on the extent to which each phenomenon, the RGGI and the Marcellus natural gas supply boom, has provoked decarbonization in the power sectors of the affected states.

Using panel data on economic, political, and other relevant characteristics, we aim to isolate the effects of energy prices and carbon policy. We apply a combination of Synthetic Control (SC) and Difference-in-Differences (DD) methods and study the dynamics of CO2 intensity in the RGGI participating states, the Marcellus region, and a placebo "control" group. Our results reveal that besides the RGGI, the reduction in energy prices had a sizable contribution to the observed decarbonization of the power sector in the northeastern U.S.. Moreover, in some non-RGGI states, the drop in energy prices led to an emission drop equivalent to that in the RGGI region. Our findings mark the critical interplay between the energy market dynamics and policy success.

3.1 Introduction

Climate change has emerged as a preeminent topic in the public discourse, compelling governments around the world to develop and implement diverse policies, regulations, and programs aimed at mitigating global warming. A pioneering and most notable initiative in this regard was the EU ETS, a cap-and-trade mechanism established in 2005. Designed to curtail CO_2 emissions, the primary driver of global warming, the program gained widespread acclaim for its efficacy, inducing other regions to adopt analogous initiatives (Bayer and Aklin, 2020, Marin et al., 2018). Among these is the RGGI launched in 2009 in the northeastern United States, which seeks to decrease the emission intensity of the power sector in participating states.

Despite the projected positive outcomes, programs such as the RGGI and EU ETS face criticism, implying that other instruments or market forces might be more efficient or complementary to those employed. For instance, the growth of unconventional resource production in Texas and other U.S. states is cited as an example of how decarbonization can be driven by the availability and affordability of "cleaner" fuels. This is the case for natural gas, which increasingly replaces coal (Pacsi et al., 2013). The discovery and rapid production growth of the Marcellus shale play, adjacent to the RGGI states, raises similar questions: was the coincidental shale boom rather than the ETS the major contributor to the reduction of emissions in the region over the past decade (EIA, 2021b)? Plummeting natural gas prices, both in absolute terms and relative to coal, have been suggested as a primary cause for the shift in the power sector energy mix (Lueken et al., 2016).

The purpose of our study is to synthesize the evidence on decarbonization in the northeastern U.S. power sector and to resolve the debate on the effects of the RGGI and the Marcellus shale gas boom. Considering the competing hypotheses on the drivers for carbon intensity reduction, we suggest an approach for disentangling and evaluating the impacts of co-occurring interventions or so-called *"treatments"*. We apply the developed model to quantify the effects of the RGGI and the drop in natural gas prices on carbon emissions. With the intent to provide a nuanced understanding of the complex relationships between policy instruments and market forces, we offer a tool for more accurate and comprehensive policy analysis and a new perspective on the energy transition.

Focusing on the RGGI, our study contributes to the strand of research analyzing the efficiency of regulatory instruments incentivizing the transition to carbon neutrality (Stephenson et al., 2021). A diversity of approaches have been suggested for the policy analysis, but recent studies highlight two, the Synthetic Control (SC) and the Difference-in-Differences (DD) methods, as the most promising (Abadie and Gardeazabal, 2003, Donald and Lang, 2007, Arkhangelsky et al., 2021). The SC method uses balanced panel data with a long pre-treatment history and a small number of exposed units, in our case, the states, to construct counterfactuals and, thereby, deduct the effect of a considered treatment. DD heavily relies on a substantial number of units, e.g., states, exposed to the treatment to allow for estimating time and unit-specific fixed effects. Due to the data requirements, the two methods are often seen as mutually distinct alternatives for measuring the impact of a particular policy or an intervention (Chen et al., 2022, Kim and Kim, 2016, Sims et al., 1982, Yu et al., 2021). However, Arkhangelsky et al. (2021) suggested that, if data allow, the SC and DD may be combined to improve robustness in results.

Compiling a rich database characterizing the last thirty years of power sector dynamics, individual states' economic performance, and other aspects relevant to decarbonization across the U.S., we gain an opportunity to integrate DD and SC models. In contrast to previous studies, we face the challenge of studying the causal impacts of multiple co-occurring treatments, namely the RGGI and Marcellus boom. By analogy with Arkhangelsky et al. (2021), we aim to develop a procedure that provides robust conclusions and addresses possible unit selection and parameter estimation endogeneity issues.

Past research dedicated to assessing the RGGI, including CERES (2016) and Murray and Maniloff (2015), established that the initiative prompted a shift between coal and natural gas-fired generation (Cullen and Mansur, 2017, Johnsen et al., 2019, Kim and Kim, 2016, Knittel et al., 2015, Linn and Muehlenbachs, 2018). Yet, the studies disagree on the electricity price effect being positive (CERES, 2016) or negative (Stevenson, 2018), especially compared to the non-participating states. Recognizing the fuel price and substitution effects on electricity generation (Bailey, 2020) and marking positive state economy outcomes (Hibbard et al. (2018)), most of the literature remains silent on co-occurring events singling out a particular intervention. Exceptions, such as Yan (2021), while testing a combination of the variables, withdraw from analyzing market (supply) shocks and policy.

Addressing this gap in the literature, we enhance the previous analyses in several ways. First, we include a variety of *outcome* variables besides CO_2 emissions into our analysis to help the accuracy of assessments. Second, following Upton and Snyder (2017) and Rose et al. (2022), we propose a novel approach integrating SC and DD estimations. Studying the two co-occurring interventions, we build counterfactuals while, in parallel, analyzing the before and after differences across the outcome variables. By doing so, we develop more rigorous impact assessments addressing potential biases. Finally, using balanced panel data on the selected states of the continental U.S. covering the period of 1995 to 2019, we provide an update on developments within the RGGI.

In what follows, we start with the details of our database, highlighting the variety of outcome variables employed in the analysis and discussing their importance. In section 3.3, we proceed with the methodology, providing the basics for constructing counterfactuals with SC and applying the DD estimators. Finally, section 3.4 presents the results and the discussion of the complex interactions between policy interventions and market dynamics in the context of decarbonization. In the Conclusion section, we summarize the insights into the ongoing discourse on climate policy effectiveness and suggest an alley for further research.

3.2 Data

Inspired by the conflicting views on the drivers for emission intensity reductions in the northeastern U.S., we start our investigation by identifying the geographical boundaries for the analysis and the variables for quantifying the effects of the RGGI and Marcellus. The statistical procedures for SC and DD require us to select outcome variables and covariates, which may explain their behaviors. *Outcome variables* serve to assess the effects of the RGGI and the Marcellus boom. *Covariates* are used to construct counterfactuals replicating the investigated regions' characteristics before treatment. Apart from these, considering the historical dynamics, we shall identify attributes for normalization and falsification purposes. So, in this section, we introduce a compiled database justifying the selection of variables and dimensions while also introducing the terminology used in the following sections for those unfamiliar with the methods.

Treatment groups The Regional Greenhouse Gas Initiative, the first emission trading system in the United States, was established in 2009 to reduce carbon pollution in the power sector in the participating states. This market-based program regulates CO_2 budgets for fossil fuel power plants in the participating states. Originally, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont joined the RGGI. Yet, soon after signing the cooperative agreement, New Jersey withdrew from the program in 2011 and, therefore, is excluded from our analysis.[20] All the other listed states form *the first treatment group* of our study.[21]

In 2004, when the RGGI was shaping up, the Marcellus unconventional shale gas play was discovered in the northeastern U.S.. A few years later, when the RGGI program was launched, promising environmental improvements and economic gains through the transition to renewable energy, the neighboring Marcellus states took an alternative path. Accelerating the production of natural gas after 2009, the Appalachian region strove to bring financial and environmental benefits by supplying cleaner, in comparison to coal, and more affordable fuel. The Marcellus geologic formation spreads across New York, Ohio, Pennsylvania, Virginia, and West Virginia. Even though shale drilling is primarily located in the territory of Pennsylvania and West Virginia, the proximity to the infrastructure and trading hubs allows adjacent states to benefit from the development. So, we include into *the second treatment group* Ohio, Pennsylvania, Virginia, and West Virginia. We exclude the New York state from the group, considering its moratorium on "fracking" and participation in RGGI. Yet, recognizing that it may experience the influence of both treatment effects, investigate its behavior with extra scrutiny.

Isolating the two treatment groups, we are left with the rest of the U.S. as the "donor pool" from which candidates to generate the counterfactuals shall be selected. Upon further review, we also drop Alaska, Hawaii, and California from the list of remaining states. The first two are removed due to their geographical location outside the contiguous United States and the specifics of their energy mix stemming from their geographical rather than economic position. California is dropped due to its distinct policies and the launch of its own, independent of the RGGI, cap-and-trade program in 2013. The resultant "donor" group of states is also the so-called *placebo* group, given their role in the investigation.

Variables For all the considered states, we collect a balanced panel dataset characterizing power generation in the period from 1995 to 2019. We first identify a group of outcome variables to explore the interventions, the RGGI and the fast growth of Marcellus shale gas supply, which

[20] New Jersey has rejoined the initiative in 2021, which is outside our time range.

[21] We also do not consider Virginia, which faced major headwinds when considering joining the program. Virginia planned to join the RGGI in 2021 but has withdrawn its participation. Similarly, Pennsylvania tried to join the project in 2020 but could not reach a common agreement and, as of 2024, has been in a new round of repealing the RGGI.

we also refer to as *treatments*. Following the discussions on the changes that affordable natural gas and emission-driven policies may bring, we select fourteen variables (see Table 3.1). The key outcome, also extensively analyzed by the previous studies, is carbon intensity. Complementary to it, according to the "merit order curve", are energy efficiencies and the shares of generation by fuel type.

In addition, we include variables characterizing the demand side to control carbon leakage as suggested by studies, e.g., on California's cap-and-trade system (Caron et al., 2015, Lessmann and Kramer, 2024). Along with the electricity demand, we analyze net power imports and capture natural gas supply bottlenecks by scrutinizing the pipeline capacities, all measured in per capita units.

Given that the debates on the causal relationship between energy and economic growth have not been settled, suggesting that it may be bi-directional and changing over time, we use GDP both as an outcome and covariate variable (Belloumi, 2009, Jaiyesimi et al., 2017, Ozturk and Acaravci, 2011). Similarly, we treat energy input prices and generation shares.

Finally, we add to the list of covariates attributes reflecting the political mood of the individual states. The discussion on the role of political will and population preferences in the success and acceptance of a particular policy or market development leads us to the inclusion of political indicators, such as the dominance of democrats (D) or republicans (R) in the State Senate and the State House and the political affiliation of the state governor (Thonig et al., 2021, Tvinnereim and Mehling, 2018).

We summarize the list of variables and provide the data sources in Table 3.1. Focusing on a relatively long historical period, we normalize the variables to support the pre-treatment period analysis and examine the post-treatment dynamics. We do so by adjusting for economic and demographic trends, choosing the GDP deflator and population for that purpose.

At last, we introduce variables used as falsification outcomes to examine confounding effects. Following Upton and Snyder (2017), we take Cooling Degree Days (CDD) and gasoline demand to ensure that there are no drastic changes in climate and general energy consumption patterns. We scrutinize the generation capacity share and generation capacity per capita for conventional inputs as falsification outcomes. If we were to find effects on either of the variables, our results may be significantly biased by capacity constraints. In the next section, we establish how all the variables presented in this section are used in our analysis.

Variable	Type	Unit	Source
Carbon Intensity	Outcome	$\frac{kg_{CO_2}}{kWh_{el}}$	EIA (2023e)
Coal and Gas Efficiencies	Outcome	%	EIA (2023d)
Electricity Prices	Outcome	$\frac{\$}{MMBTU}$	EIA (2023d)
Electricity Demand	Outcome	$\frac{kWh}{Capita}$	EIA (2023d)
Electricity Net Imports	Outcome	$\frac{kWh}{Capita}$	EIA (2023d)
Pipeline Capacities	Outcome	$\frac{cf}{d\,capita}$	EIA (2023b)
Coal and Natural Gas Prices	Outcome/Covariate	$\frac{\$}{MMBTU}$	EIA (2023d)
Generation Share of Coal, Natural Gas, Nuclear, Renewables	Outcome/Covariate	%	EIA (2023a)
Gross Domestic Product	Outcome/Covariate	$\frac{\$\,1000}{Capita}$	BEA (2023)
Gross Domestic Product in Manufacturing	Covariate	$\frac{\$\,1000}{Capita}$	BEA (2023)
Party of the Incumbent Governor	Covariate	*1=D, 0=R*	Klarner (2013)
Share of Democrats in the State Senate	Covariate	%	Klarner (2013)
Capacity of Coal, Natural Gas, Nuclear, Renewables	Falsification	$\frac{KW}{capita}$	EIA (2023a)
Capacity Share of Coal, Natural Gas, Nuclear, Renewables	Falsification	%	EIA (2023a)
CDD	Falsification	*Days*	EIA (2023d)
Gasoline Demand	Falsification	$\frac{Gallons}{Capita\,Day}$	EIA (2023c)
GDP Deflator	Normalization	%	Bank (2023)
Population	Normalization	*Capita*	Bureau (2023)

TABLE 3.1: Sources for the individual variables.

3.3 Methodology

The Regional Greenhouse Gas Initiative (RGGI) and the increasing production of unconventional natural gas resources in the Marcellus region constitute significant interventions. Both the SC method and the DD approach provide hypothetical scenarios assumed to have occurred without any interventions, allowing us to test and verify the mechanisms and rationale behind the shifts in electricity production mix dynamics and changes adopted by states. Each of the methods has shortcomings, with the SC method not allowing for statistical inference and the DD often suffering from biases due to the non-compliance with the "parallel-trends" assumption and endogeneity due to policy adoption not being random. Moreover, they both do not allow for any conclusion with regard to causality. Combining both methods to overcome their imperfections and analyzing a variety of outcome variables, we may assess whether the states participating in the RGGI program have been impacted by the availability of affordable unconventional gas resources and which of the two events, either the RGGI or the influence of cheap unconventional gas resources, holds greater potential in addressing the challenges associated with decarbonization.

First, we introduce a baseline DD estimator that relies on a standard DD framework. As this estimator is likely to suffer from biases through endogeneity (non-random policy adoption), we then develop a two-step framework that creates SC units to create counterfactuals that account for self-selection into policy and second quantifies the Average Treatment Effect (ATE) using the original outcomes and SC units through a DD estimator.

3.3.1 Baseline Difference-In-Differences Estimation

We start by establishing a baseline Difference-in-Differences (DD) model designed to compare the post-treatment behavior of outcomes between treated and untreated states in a conventional DD framework:

$$Y_{it} = \alpha + \delta \cdot D_{Trtmnt} + \gamma_i + \eta_t + \epsilon_{it} \tag{3.1}$$

In this equation, Y_{it} represents the values for the respective outcome variable in state i and year t. The binary variable D_{Trtmnt} serves as a treatment indicator, equaling 1 for treated states after the year 2008 and 0 in all other cases. As such, δ quantifies the treatment effect, while γ_i and η_t are state and year fixed effects. The panel data does not include covariates, as the model aims to capture the difference in outcomes between treated and untreated states in the post-treatment period, yielding the treatment effect δ.

We estimate the baseline treatment effects for each outcome variable Y and each considered intervention separately, using only the respective treatment group and the donor pool. Thus, the sample for the first estimate includes the nine RGGI states and the 33 untreated donor states. In comparison, the second estimate consists of the four Marcellus states and the 33 untreated donor states (the estimates will be presented in the first row of columns RGGI and Marcellus in our results tables). The outcomes only distinguish between treated and untreated units, using the observations of the donor pool as a counterfactual.

We emphasize that the baseline results thus do not account for endogeneity, in this case through self-selection into treatment, and only serve as a reference point for our analysis. Whether to adopt the RGGI policy or provide the legal framework for producing unconventional natural gas resources depends on the state's political preferences, economic condition, and current power generation mix. Blue states with an already low carbon-intense power generation, e.g., Rhode Island, could be more likely to adopt the RGGI policy. In contrast, red states, whose economies critically depend on the export of natural resources, like West Virginia, may be more likely to set a legal framework that allows for fracking. The SC method, in contrast, is able to account for possible issues regarding endogeneity.

The SC method is known for its ability to construct counterfactuals based on pre-treatment characteristics, while the DD method is a powerful tool to quantify the treatment effects. Thus, in the following chapter, we develop an SC method-based DD estimator to create more appropriate counterfactuals that replicate the treated states' pre-treatment characteristics in political and economic indicators and the power generation mix to account for these possible biases.

3.3.2 The Synthetic Control Method

The Synthetic Control (SC) method offers a powerful solution to unraveling the effects of interventions such as the RGGI and the supply shock brought by the Marcellus natural gas. Its ability to construct and investigate counterfactual scenarios *(without treatment)* for treated states is central to our research. The SC method creates a counterfactual for each of our 13 treated units using the untreated donor pool. Each counterfactual is constructed by choosing a weighted combination of the j donor pool units, ensuring similarity between the treated unit and counterfactual across the k *covariates* in the pre-treatment period. As policy adoption is likely endogenous, we chose covariates that may best account for the adoption of policies (economic and political indicators, existing power generation mix, and price levels). We split our panel data into a covariate matrix $X_{k,i,t}$ and an outcome matrix for CO_2 intensity $Y_{i,t}$ with k covariates, i observations and t periods.[22]

In the first step of our combined estimator, we create SC units that work as counterfactuals **for each treated state individually** within the RGGI and Marcellus regions. Using our third, untreated group of states *(donors)* and the second set of variables *(covariates)*, we minimize equation (3.2). Here, (j x 1) vector $\mathbf{W}$ informs us about the importance of each donor while the positive semidefinite and symmetric (k x k) matrix $\mathbf{V}$ captures the relevance of the covariates in creating the counterfactual. Equation (3.2) serves to find the best combination of donors and covariates to replicate the pre-treatment covariate levels of the treated state ((k x 1) vector $\mathbf{X_1}$) using the same covariates from the donor states ((k x j) matrix $\mathbf{X_0}$). It is essential to mention that the time dimension is irrelevant in this context, meaning that for each $n \in \{j\}$ and each treated unit, there are k rows representing the geometric average of the pre-treatment period per covariate.[23] Throughout the paper, we will use the index 1 to denote the vector of a treated state, whereas the index 0 denotes the matrices of the donors.

Mathematically, the problem is formulated as follows:

$$\min\ (\mathbf{X_1} - \mathbf{X_0 W})'\mathbf{V}(\mathbf{X_1} - \mathbf{X_0 W}) \tag{3.2}$$

In this paper, we estimate the values for $\mathbf{V}$, employing a Fixed Effects (FE) model, following Kuosmanen et al. (2021).[24] The approach offers transparency in selecting weights $\mathbf{V}$ which determine the importance of each covariate k in $X_{k,i,t}$ in predicting the *outcome* variable CO_2

[22] i consists of $j = 33$ donors and 13 treated units, t consists of the pre-treatment period T_{pre} from 1995 to 2008 and the post-treatment period T_{post} from 2009 to 2019.

[23] The matrix X is represented by the second group of variables: shares of coal, natural gas, and carbon-neutral electricity production, coal, and natural gas prices, GDP per capita, GDP per capita in the manufacturing sector, the representation of Democrats within the state's legislative bodies, and the political affiliation of the incumbent governor. X_1 and X_0 represent the geometric mean of the respective variable in the pre-treatment period. Notably, both V and W sum to unity.

[24] It is noteworthy that while the *Synth* package developed by Abadie et al. (2010) has been commonly utilized in previous studies, recent research conducted by Klößner et al. (2018) and Kuosmanen et al. (2021) has uncovered numerical instability in the results produced by the *Synth* algorithm.

intensity in the pre-treatment period (Y_{it}^{pre}). In contrast to (3.2), the time dimension does play a role in this context. Here, the subscript i and t denote the state and year while γ_i and η_t are the state and time Fixed Effects. We estimate a FE model to receive the (k x 1) vector $\boldsymbol{\beta}$ with coefficients β_k for each covariate k allowing us to calculate the covariate weights v_k:

$$Y_{it}^{pre} = \alpha + \mathbf{X'_{it}}\boldsymbol{\beta} + \gamma_i + \eta_t + \epsilon_{it} \tag{3.3}$$

$$v_k = \frac{|\beta_k|}{\sum_{j=1}^{K} |\beta_j|} \tag{3.4}$$

$$\mathbf{V} = \text{diag}(v_1, \ldots, v_k) \tag{3.5}$$

Based on the computed covariate weights v_k, we create the diagonal matrix $\mathbf{V}$. Then, an algorithm developed by Kuosmanen et al. (2021) estimates the donor weights $\mathbf{W}$ that minimize equation (3.2).

Next, we generate the *untreated* and de-biased SC unit ($\mathbf{Y_1^U}$), a (t x 1) vector used as a counterfactual. De-biasing adjusts for the state effects γ_i from (3.3), improving the fit of the counterfactual (Ben-Michael et al., 2021, Ferman et al., 2020). $\mathbf{Y_1^U}$ serves to project what would have happened without treatment, combining information from the donor pool's (t x j) outcome matrix ($\mathbf{Y_0}$) (which are assumed not to be influenced by treatment) and (1 x j) state fixed effects vector $\boldsymbol{\gamma_0}$ from (3.3).:

$$\mathbf{Y_1^U} = \mathbf{Y_0 W} + (\gamma_1 - \boldsymbol{\gamma_0}\mathbf{W}) \tag{3.6}$$

We create counterfactuals for the treated states focusing on the CO_2 intensity as the outcome variable (Y). It is regressed on the k covariates X following (3.3).[25] We then calculate $\mathbf{V}$ to substitute into and solve equation (3.2), obtaining $\mathbf{W}$. Combining $\mathbf{W}$ with the state FEs γ_i and donor pool outcome variable matrix $\mathbf{Y_0}$, we compute the de-biased counterfactual values for CO_2 intensity for each treated state following (3.6).

We utilize the CO_2-intensity-derived weights $\mathbf{W}$ for all the remaining outcome variables, employing a simplified FE model to de-bias the outcomes using state fixed effects γ_i. We then

[25] The covariates are the shares of coal, natural gas, and carbon-neutral electricity production, coal, and natural gas prices, GDP per capita, GDP per capita in the manufacturing sector, the representation of Democrats within the state's legislative bodies, and the political affiliation of the incumbent governor.

create the SC units using (3.6).[26]

We estimate $\mathbf{W}$ once, allowing us to compare all outcome variables for state i against one consistent SC unit that serves as the counterfactual. In contrast, Upton and Snyder (2017) estimate distinct $\mathbf{W}$ values for each outcome variable receiving differently composed SC units. Our results demonstrate that our approach does not adversely affect the model fit.

Combined with the actual observed outcomes, the SC units allow us to calculate the ATE. Building on the SC method methodology explained thus far, the following subchapter explains the Difference-in-Differences (DD) framework brought to derive meaningful insights into the effects of these interventions.

3.3.3 SCM-based Difference-In-Differences Estimation

The second part of our combined estimator builds upon the DD framework presented in (3.1) and the counterfactual outcomes created in Section 3.3.2. The estimation econometrically follows (3.1), but changes the underlying dataset. As policy adoption is likely non-random, the donor pool may not be the most appropriate counterfactual; we overcome this limitation by introducing the synthetic control unit outcomes as alternative counterfactuals that account for endogenous policy adoption, assuming that in the pre-treatment period, the underlying covariates, which may influence the decision to implement policies, are similar (Upton and Snyder, 2017).

We do so by pooling the observed outcomes and the SC units per treatment group (RGGI, Marcellus, Donor pool) and outcome variable individually, creating datasets that provide more suitable counterfactuals. These datasets are then employed to estimate (3.1), yielding the ATE.

The estimates of the baseline- and the SC method-based DD model may exhibit similarities, depending on the extent of endogeneity in the decision to implement either policy (RGGI or allowing for hydraulic fracturing). If the estimates between the baseline DD do not differ from the estimates of our SC method-based DD estimator, there is an indication for little to no endogeneity in the decision to adopt the policy. Large differences would suggest the opposite: politics, the economy, and the current power mix play a major role in policy adoption.

[26] As discussed in Chapter 3.2, there is some overlap between the outcome variables and (covariates). Consequently, the second FE model for de-biasing the other outcome variables exclusively employs covariates that do not exhibit this overlap, namely GDP per capita and political indicators. The de-biasing process may result in values falling below 0% or exceeding 100% for variables representing shares. We have manually constrained such values to 0% or 100%, respectively.

We would also like to mention that the values of δ estimated for each treatment group and variable measure the ATE per treatment group over the entire post-treatment period (from 2009 to 2019). As the effects may differ between states, B1 explains the methodology for computing the treatment effects at the state level. The results should coincide with the ATE of our pooled DD model when calculating the group mean.[27] Consequently, these findings will be selectively employed as supplementary information in our analysis as needed.

The statistical methods used allow us to conduct a thorough analysis of the outcome variables. Creating reliable counterfactuals using the SC method, however, relies on the values for $\mathbf{V}$ and $\mathbf{W}$. To ensure the reliability of the results, we implement sensitivity and falsification tests, which will be explained in the following subchapter.

3.3.4 Sensitivity and Falsification Testing

We conduct a series of tests to verify the robustness of our ATE estimates. Our tests scrutinize $\mathbf{V}$ and, consequently, $\mathbf{W}$, generate SC units for the donor pool, establishing a placebo group, and examine falsification outcomes.

We create alternative SC units to address the propensity of the counterfactuals generated by the SC method to exhibit sensitivity to changes in $\mathbf{V}$ and $\mathbf{W}$. Assigning equal weights $\mathbf{V}$ to each covariate, we receive a differently composed $\mathbf{W}$ and, thereby, $\mathbf{Y_1^U}$. This serves (1) to ensure that there is no under- or over-weighting of any individual covariate, and (2) to compare the original pooled ATE against a second pooled ATE using a distinct set of $\mathbf{W}$ values, thereby safeguarding estimates against alternative or unobserved treatments in states within the donor pool.[28] We present these alternative results alongside our SC method-based estimates for comprehensive evaluation.

Next, we investigate the placebo group by generating SC units for each state within the donor pool. Following Abadie et al. (2010), we simulate the "assignment" of treatment to every state within the donor pool.[29] The SC units of this placebo group are expected to coincide with the actual observed values of the donor pool state, indicating the absence of treatment effects. This

[27] This is due to the concurrent application of treatment.

[28] Note that the de-biasing process remains contingent on the individual FE estimated in equation (3.3).

[29] Here, the donor pool encompasses both the untreated states and the specific treated state currently analyzed. Consequently, each donor pool state has thirteen potential SC units to consider (nine states from the RGGI and four from the Marcellus group). To facilitate statistical inference, we compute the average of these SC units.

is based on the assumption that states incorporated into the donor pool remain unaffected from the introduction of the RGGI and the increase in unconventional natural gas from the Marcellus shale play.

Additionally, we explore falsification outcomes, namely Cooling Degree Days (CDD), gasoline consumption, and generation capacity. Assuming that both treatments cannot influence the climate on a larger scale, they should not lead to significant changes in CDD. Moreover, if we were to observe significant changes in CDD after the year 2009, any effects attributed to treatment may possibly stem from the changes in climate. Additionally, we expect gasoline sales per capita and day to remain unaffected by treatment. Deviations from this expectation would suggest a broader change in energy consumption patterns across the states under consideration, rendering our estimates biased. Last, we control for generation capacity per capita and the generation capacity share per input. Changes in those variables for any input may stem from power plant retirements or additions that would directly influence power generation shares, the merit order curve, and thus input and output prices. Controlling for falsification outcomes thus allows us to infer causality, as we may assume that the dynamics discovered in this study actually stem from the analyzed treatments.

Finally, we also include Synthetic Difference-in-Differences (SDID) results based on Arkhangelsky et al. (2021) in Table B2.12 in Appendix B2. Their method does not account for underlying covariates but focuses exclusively on the respective outcome variable and usually provides a lower boundary of estimates when compared to the SC method or DD.

In the following chapter, we evaluate the effects that both treatments have (or do not have) on the power sector, relying on the estimates of the three models.

3.4 Results and Discussion

In this section, we first scrutinize the impacts on CO_2 intensity and its determinants within the power sector, focusing on the electricity generation composition. We examine the influence of low-cost natural gas resources from the Marcellus region on the composition of power generation within both treatment groups, analyzing natural gas prices and potential constraints within the pipeline network. Along with that, we analyze import/export dynamics, market prices, and, consequently, the overall demand for electric power for each region. Finally, we investigate additional factors, including GDP per capita in the manufacturing sector, expected to remain relatively unaffected by the RGGI program and technical efficiencies, which significantly influence carbon emissions.

3.4.1 Carbon Intensity

The primary objective of the Regional Greenhouse Gas Initiative is the reduction of carbon emissions in the power sector. This reduction may be achieved through a lower carbon intensity instead of lower electricity consumption since the latter may indicate decreasing economic activity.

Each column in Table 3.2 includes three estimates for the respective treatment group (RGGI, Marcellus, or the donor pool/placebo group). Based on the conventional DD approach, the first value of each column is the baseline DD estimate. The second estimate comes from pooling the actual observations with their SC units per treatment group in the DD framework, while the third value originates from the pooled SC method-approach with *equally (Eq.)* weighted (in $\mathbf{V}$) covariates as a sensitivity measure.

The RGGI states achieved a marked reduction in carbon intensity, ranging from 20 to 38 $\frac{g}{kWh}$. To provide context, before the implementation of the RGGI program, the average CO_2 intensity in those states stood at 427 $\frac{g}{kWh}$, implying a substantial decrease of 5 to 10% from the original value. The state-level effects illustrate a considerable variation in the treatment effect across the RGGI states, although, in most cases, a trend toward reduced carbon intensity is evident (see Table B2.10).

In contrast, examining the Marcellus region does not reveal any significant effect. However, it is crucial to acknowledge that the effect for the Marcellus region is substantially biased through

TABLE 3.2: Change in carbon intensity $\frac{kg_{CO_2}}{kWh}$

		RGGI	Marcellus	Placebo	Marcellus w/o WV
Baseline DD	ATE	-0.020**	0.007	-	-0.028**
	SE	(0.009)	(0.012)	(-)	(0.013)
	N	1050	925	-	900
Pooled SCM	ATE	-0.038***	0.018*	-0.0004	-0.026***
	SE	(0.010)	(0.009)	(0.004)	(0.007)
	N	450	200	1650	150
Eq. Pooled SCM	ATE	-0.023**	0.010	0.001	-0.012*
	SE	(0.010)	(0.010)	(0.004)	(0.007)
	N	450	200	1650	150
Note:				*p<0.1; **p<0.05; ***p<0.01	

West Virginia (WV).[30] When excluding WV from the analysis, the Marcellus region also displays a notable reduction in carbon intensity, ranging from 12 to 28 $\frac{g}{kWh}$ or 2-4%. For the placebo group, as anticipated, we observe no significant impact (see Table B2.10).

Overall, we find a significant effect of the RGGI program on CO_2 intensity, and a similar effect is observed within the Marcellus states when WV is excluded. In the following, we analyze the mechanisms by which the regions accomplished this reduction.

[30]We will later demonstrate that WV emerges as a general outlier within this group.

3.4.2 Production Shares

Reducing carbon intensity can be attained through a variety of means, including transitioning from higher carbon-intensity fuels, such as coal or oil ($\approx 1100\frac{g}{kWh}$), to lower carbon alternatives like natural gas ($420\frac{g}{kWh}$) or renewables/nuclear power ($0\frac{g}{kWh}$).[31] Consequently, our analysis explores shifts in generation shares and their role in achieving these reductions.

Table 3.3: Change in coal & natural gas Share

		Coal Share:			*Gas Share:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	1.740*	-4.230***	-	4.340***	7.400***	-
	SE	(1.040)	(1.340)	(-)	(1.270)	(1.430)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	-3.260**	-1.970	-1.080**	0.550	7.460***	1.670***
	SE	(1.300)	(1.320)	(0.463)	(1.850)	(1.590)	(0.469)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	-2.820**	-4.160***	-0.309	3.740**	7.980***	-0.075
	SE	(1.350)	(1.350)	(0.464)	(1.860)	(1.480)	(0.464)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

One of the strongest mechanisms contributing to CO_2 reductions in the U.S. is the coal-to-gas substitution driven by changes in relative prices, primarily attributable to the fracking boom experienced in many states. Across the nation, coal is gradually being replaced by natural gas. However, in both treatment groups, a more substantial reduction in coal usage is evident, offset by an increase in natural gas-based power generation compared to untreated states.

The increasing natural gas share in the RGGI region has been investigated in several prior studies.[32] Table 3.3 shows an increase in natural gas-fired power generation by approximately 4%, while coal's generation share decreases by around 3% after the introduction of the RGGI. Notably, we observe the most substantial reductions in CO_2 emissions within the RGGI states,

[31] Given that oil products contribute negligibly to power production in the U.S., they are excluded from our analysis.

[32] Cullen and Mansur (2017), Johnsen et al. (2019), Kim and Kim (2016), Knittel et al. (2015), Linn and Muehlenbachs (2018).

especially Connecticut, Delaware, and Massachusetts, being achieved through a more pronounced coal-to-gas substitution (refer to Table B2.10).[33]

In general, this substitution phenomenon appears to be stronger in the states of the Marcellus Region. We find a reduction of 4% in coal-fired generation, while the share of natural gas increases by 7.5-8%.[34] As expected, the placebo group experiences little to no effect.

Table 3.4: Change in renewable share

		RGGI	Marcellus	Placebo	RGGI w/o ME&VT
Baseline DD	ATE	1.020	-4.220***	-	-3.729***
	SE	(0.918)	(1.070)	(-)	(0.810)
	N	1050	925	-	1000
Pooled SCM	ATE	4.710***	-4.830***	-0.941**	-1.750***
	SE	(1.260)	(0.487)	(0.373)	(0.507)
	N	450	200	1650	350
Eq. Pooled SCM	ATE	2.680**	-5.080***	1.070***	-3.960***
	SE	(1.220)	(0.395)	(0.369)	(0.432)
	N	450	200	1650	350
Note:					*p<0.1; **p<0.05; ***p<0.01

Some studies have reported that implementing the RGGI contributed to an increase in the proportion of renewable power generation (Fell and Kaffine, 2018). Our findings confirm that the RGGI has, to some extent, increased the share of renewable energy sources. However, the state-level results reveal a particular bias due to the influence of Maine and Vermont, both affected by unrelated events (Table B2.10). Maine has adopted stricter policies for renewables through its Renewable Portfolio Standards (RPS). At the same time, Vermont significantly increased its renewable generation share following the retirement of its largest nuclear power station in 2014, previously accounting for over 50% of the state's electricity production. In contrast, we observe that the substantial increase in the natural gas share in the Marcellus states has negatively influenced their transition to renewable energy sources, slowing down their adoption by around 4-5%.

Given that both treatment groups have increased their reliance on natural gas, it raises questions about whether adopting the cap-and-trade system or the availability of cheap natural gas is the

[33] We have considered the possibility that capacity constraints, such as the retirement of coal-fired power plants, may change the generation shares. Our results show no sign of such constraints within the RGGI (Table B2.2). We also do not find any significant changes in the capacity shares (Table B2.3).

[34] When examining the Marcellus region excluding WV (as in Table 3.2), the increase in natural gas production has contributed to a 10.5-13.5% increase in natural gas's generation share while reducing coal's share by 7.5-9.5%.

primary driver behind this transition. Therefore, the following chapter analyzes the natural gas markets.

3.4.3 Price Signals

Both regions are increasingly shifting their power generation from coal to natural gas. Aside from environmental considerations, one of the primary drivers assumed to cause this transition is the change in relative prices, rendering electricity generation with natural gas a more cost-effective alternative compared to coal-fired generation.

In this section, we will analyze the natural gas prices and explore how these are interrelated with the capacities of natural gas pipelines.

TABLE 3.5: Change in the natural gas price in the power sector $\frac{\$}{MMBTU}$

		RGGI	Marcellus	Placebo
Baseline DD	ATE	0.111	-1.310***	-
	SE	(0.157)	(0.226)	(-)
	N	1050	925	-
Pooled SCM	ATE	0.136	-1.140***	-0.018
	SE	(0.125)	(0.190)	(0.077)
	N	450	200	1650
Eq. Pooled SCM	ATE	0.058	-1.250***	0.002
	SE	(0.117)	(0.172)	(0.076)
	N	450	200	1650
Note:		*p<0.1; **p<0.05; ***p<0.01		

Our findings indicate that, on average, the states participating in the Regional Greenhouse Gas Initiative do not experience reduced natural gas prices after 2008 despite their geographical proximity to the Marcellus region. The only exceptions are Delaware, Maryland, New York, and Vermont, with the former three sharing borders with Marcellus states, making the transmission of lower natural gas prices a probable source for the effects (see Table B2.10).

However, the increased production of unconventional gas resources has significantly driven down prices throughout the entire Marcellus region, with our estimates ranging from 1.14 to 1.31 $\frac{\$}{MMBTU}$. Once again, our analysis reveals no impact on the placebo group.[35]

[35] We do find similar outcomes for the natural gas prices in the residential and industrial sectors (see Table B2.4).

Why do the states within the RGGI not benefit from these lower natural gas prices? A possible explanation are constraints within the natural gas pipeline infrastructure. Compared to their untreated peers, RGGI states have expanded their import and export pipeline capacities for natural gas at a slower pace since implementing the cap-and-trade system.

TABLE 3.6: Change in natural gas pipeline capacity $\frac{cf}{d\,capita}$

		Import:			*Export:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	-2055***	497	-	-2230***	2560***	-
	SE	(262)	(396)	(-)	(269)	(435)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	-2309***	1405***	271**	-1908***	3548***	-290**
	SE	(254)	(293)	(134)	(234)	(485)	(138)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	-3276***	1216***	-341**	-2745***	2862***	-54
	SE	(283)	(289)	(135)	(165)	(470)	(138)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

The RGGI states, therefore, may derive comparatively fewer benefits from the lower natural gas prices due to constraints within their network. These constraints could be attributed to spatial limitations, but they may also stem from uncertainties about future developments, given the long-term emissions reduction objectives that challenge the role of natural gas in their energy portfolio.

On the contrary, states within the Marcellus region have shown a notable increase in their import capacities while their export capacities have increased to an even greater extent. This overall expansion in net export capacity indicates an increased level of interconnectivity among these states, facilitating the distribution of surplus natural gas to neighboring regions. Consequently, Marcellus region states are positioned to reap the benefits of lower natural gas prices and distribute them among each other. This is particularly advantageous for states with lower natural gas production, namely Ohio and Virginia. Their geographical proximity allows them to access regionally sourced natural gas at an affordable rate.

Our findings highlight divergent implications associated with the transition to natural gas within the two treatment groups. States engaged in the cap-and-trade system exhibit a noteworthy shift towards natural gas, even though its cost-efficiency does not align with that in the Marcellus region, possibly resulting in higher electricity prices. Furthermore, RGGI states increasingly rely on renewable energy sources, which may introduce challenges related to the intermittency of electricity supply. Consequently, the following chapter will be focused on electricity imports, pricing dynamics, and demand patterns across the regions.

3.4.4 Electricity Market Dynamics

The transition towards cleaner energy sources and the influence of low-cost natural gas from the Marcellus region has triggered a shift in the electricity market. Here, we scrutinize the electricity market dynamics, exploring electricity imports, power demand, and pricing.

The growing reliance on electricity imports is a recurring trend in regions transitioning towards more renewable power production as they face difficulties balancing their grids. Numerous studies have shown that RGGI states, in particular, have progressively "outsourced" their electricity generation.[36] Our results confirm that states within the RGGI framework increased their net electricity imports by approximately 500 $\frac{kWh}{Capita}$ as a consequence of the policy (see Table 3.7).

TABLE 3.7: Change in net electricity imports $\frac{kWh}{Capita}$

		RGGI	Marcellus	Placebo	Marcellus w/o WV
Baseline DD	ATE	220	2445***	-	-333
	SE	(270)	(414)	(-)	(422)
	N	1050	925	-	900
Pooled SCM	ATE	469*	1218*	113	-1015***
	SE	(261)	(636)	(126)	(252)
	N	450	200	1650	150
Eq. Pooled SCM	ATE	588**	2170***	254**	-939***
	SE	(282)	(627)	(126)	(269)
	N	450	200	1650	150
Note:				*p<0.1; **p<0.05; ***p<0.01	

When examining the Marcellus states, there appears to be a similar trend towards surging import dependence, with estimates ranging from 1200 to 2500 $\frac{kWh}{Capita}$. However, it is crucial to note that these findings are significantly influenced by the presence of WV. The state was previously one of the largest electricity exporters due to its cheap coal-fired generation. Over the past decade, WV has substantially reduced its electricity generation and, consequently, its exports,

[36] Chan and Morrow (2019), Chen (2009), Fell and Maniloff (2018), Lee and Melstrom (2018).

thereby introducing bias into the results. Upon excluding WV, we observe that the emergence of unconventional gas resources led to a decrease in net imports by approximately 1000 $\frac{kWh}{Capita}$ in Marcellus states, meaning that they either import less electricity or increased their electricity exports.

Furthermore, our results indicate that RGGI states have experienced an increase in electricity prices by approximately 1.4 to 2.5 $\frac{\$}{MMBTU}$, corresponding to an additional cost of 0.4 to 0.8 cents per kWh. For an average state with a carbon intensity of 280 $\frac{g}{kWh}$ (post-RGGI), the added fee attributed to certificates amounts to around 0.4 cents, meaning that the expenses associated with the cap-and-trade system may be directly passed on to consumers. Any further price may result from the more expensive gas used during peak production, grid enhancements to enable cross-border flows, and/or renewable energy integration. This price may have contributed to a reduction of roughly 600 $\frac{kWh}{capita}$ in power consumption, which could partially explain the lower-than-expected import dependency.

TABLE 3.8: Change in electricity price $\frac{\$}{MMBTU}$ and demand $\frac{kWh}{Capita}$

		Price:			*Demand:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	0.418	-0.255	-	-707***	-12	-
	SE	(0.363)	(0.398)	(-)	(169)	(253)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	1.370***	-1.140***	0.144	-57.40	-235	339***
	SE	(0.494)	(0.329)	(0.133)	(110)	(485)	(86.8)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	2.460***	-0.750**	0.074	-635***	-299*	338***
	SE	(0.501)	(0.329)	(0.135)	(97.4)	(174)	(87.1)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

In comparison, in the Marcellus region, the reduction in natural gas prices has driven down electricity prices by 0.75 to 1.15 $\frac{\$}{MMBTU}$ or 0.25 to 0.4 cents per kWh. However, we did not observe any significant impact on electricity demand in the Marcellus region.[37]

Our findings concur with earlier research, indicating that RGGI states have increased their electricity imports, potentially leading to carbon leakage. These imports may come from nearby Marcellus states, primarily engaged in fossil fuel-based electricity generation. However, the

[37] These price effects are consistent over different types of demand. We study industrial and residential electricity prices in Table B2.5

extent of carbon leakage is expected to diminish as Marcellus states progressively shift from coal towards natural gas.[38] In addition, RGGI states have faced increased electricity prices that may surpass carbon-related expenses, reducing electricity consumption. Conversely, Marcellus states previously reliant on imports are moving towards energy independence, capable of providing their residents with more affordable electricity than before.

3.4.5 Further Considerations

A significant factor contributing to the acceptance of the Regional Greenhouse Gas Initiative has been the argument that the system does not negatively influence economic performance. We thus analyze the GDP per capita within the manufacturing sector.

Notably, the northeastern region of the United States experienced a general decline in manufacturing GDP after the 2008 financial crisis, which may have triggered shifts between economic sectors. Our estimates for the RGGI region range from a reduction of approximately 800 to 1100 $\frac{\$}{Capita}$. In the Marcellus region, the negative effect spans from 500 to 800 $\frac{\$}{Capita}$, respectively. The difference between the smallest and highest values across the groups suggests that the actual economic consequences of the cap-and-trade system could amount to approximately 300 $\frac{\$}{Capita}$. This argument is supported by the fact that the reduction in electricity demand in the RGGI region (see Table 3.8), can be mostly attributed to a demand reduction in the industrial sector (see Table B2.6). We do not find similar outcomes for the Marcellus states.[39]

Next, we observe that the RGGI did not have a negative impact on the efficiency of coal-fired power plants.[40] For natural gas, efficiency decreases by 1.5% to 1.9%. These results align with those estimated by Yan (2021), who examined heat rates as a measure of efficiency.[41]

In contrast, Marcellus states exhibit a 0.64% to 1% lower efficiency in coal-fired power production. This reduction may be attributed to the shift towards natural gas, leading to lower capacity

[38] An intriguing aspect of our study is the observation that carbon leakage is not exclusive to the movement from RGGI to non-RGGI states but also may occur within the RGGI region itself. Remarkably, less carbon-intensive RGGI states, such as Maine and Vermont, are losing ground to fossil-fueled producers like Connecticut and Delaware (see Table B2.10). Moreover, we note that Canada supplies a substantial portion of Vermont's imports, although we lack information on how this electricity is generated.

[39] It is worth noting that this metric exclusively pertains to the manufacturing sector and may not account for the overall economic outcomes. On a related note, another study by Hibbard et al. (2018) found an overall positive economic impact.

[40] However, it's essential to note that these results might be significantly biased due to the states of Maine (+17%), Rhode Island, and Vermont. Rhode Island and Vermont, for instance, do not utilize coal, leading to an efficiency of 0 and potentially distorting the overall findings. State-level estimates range from 0 to -7%.

[41] He found that the heat rate for coal increased by 7.6% (efficiency decrease of approximately 7%). Additionally, he finds a decrease in the heat rate for natural gas at 3.6% (reduction in efficiency by 3.5%).

Table 3.9: Change in GDP per capita in manufacturing $\frac{\$\,1000}{Capita}$

		RGGI	Marcellus	Placebo
Baseline DD	ATE	-0.808***	-0.617***	-
	SE	(0.135)	(0.186)	(-)
	N	1050	925	-
Pooled SCM	ATE	-0.905***	-0.521***	-0.005
	SE	(0.148)	(0.117)	(0.064)
	N	450	200	1650
Eq. Pooled SCM	ATE	-1.090***	-0.784***	-0.005
	SE	(0.170)	(-0.107)	(0.066)
	N	450	200	1650
Note:		*p<0.1; **p<0.05; ***p<0.01		

utilization, which may result in a minor increase in CO_2 emissions from coal-generated electricity. There is no observed effect on natural gas efficiency in the Marcellus region.

Table 3.10: Change in coal and gas electrical efficiency %

		Coal:			*Gas:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	-0.248	-0.638***	-	-1.750	-0.241	-
	SE	(0.483)	(0.152)	(-)	(1.360)	(2.000)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	0.087	-0.724***	0.027	-1.500**	-1.260	0.581
	SE	(0.907)	(0.122)	(0.052)	(0.684)	(1.890)	(0.686)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	-0.059	-1.000***	0.143***	-1.880***	-1.610	-0.068
	SE	(0.908)	(0.130)	(0.052)	(0.663)	(1.390)	(0.688)
	N	450	200	1650	450	200	1650
Note:						*p<0.1; **p<0.05; ***p<0.01	

Examining the falsification outcomes in Table B2.7 in B2 reveals that the treatment did not significantly impact the falsification variables. Additionally, the placebo group, serving as a control for treatment effects, consistently demonstrated insignificant effects throughout the study, supporting the robustness of our methodology in assessing the outcomes of the interventions. Finally, our results indicate a high level of consistency between the effects estimated using the standard DD approach and the two SC method-based models, underscoring the reliability and effectiveness of our approach in estimating treatment effects.

3.5 Conclusion

In this study, we investigate the effects of two co-occurring interventions, that is, the Regional Greenhouse Gas Initiative and the increasing production of unconventional natural gas resources in the Marcellus formation, on various outcome variables. States subject to either of the treatments faced significant changes in their power mix, energy prices, and energy consumption patterns since 2009.

Consistent with prior research, our findings corroborate that implementing the RGGI cap-and-trade system reduced carbon intensity, while the uprise in the production of affordable unconventional gas resources in the Marcellus region led to a comparable outcome. The decline in carbon intensity in both regions may be primarily attributed to the coal-to-gas transition in power generation, which partially impeded the widespread adoption of renewable power sources.

Our results also suggest that changes in generation patterns within the RGGI region may only partially be attributed to the lower natural gas prices stemming from the increased production in the nearby Marcellus region due to lower capacity within the pipeline network. In contrast, we find that lower natural gas prices accelerate the transition from coal to natural gas within the Marcellus region.

In line with existing research, we find evidence of increased electricity imports to the RGGI region following the implementation of the cap-and-trade system, suggesting carbon leakage. This import surge coincides with higher electricity prices and a decrease in electricity demand. The price rise may be due to the direct transfer of emission certificate costs to consumers. Meanwhile, the Marcellus region experienced a reduction in net imports, except for coal-dependent West Virginia, which is paralleled with a decrease in electricity prices of 0.25 to 0.4 cents per kWh without significant effects on electricity demand.

Furthermore, our analysis indicates a decline in GDP within the manufacturing sector across the entire northeastern region of the United States, including both the RGGI and Marcellus groups. The impact within the RGGI region appears to be more pronounced, which, combined with the electricity demand reduction from the industrial sector, suggests that the introduction of the cap-and-trade system indeed has had a negative influence on the economic performance of the region.

In summary, the RGGI appears to be making significant progress toward achieving its carbon reduction objectives. This explains why several states are joining the initiative or establishing their own cap-and-trade systems. However, the question remains whether the policy's negative repercussions, particularly concerning electricity prices and GDP, are an acceptable trade-off, especially given the outcomes achieved in the Marcellus states. After the conclusion of our observation period, two states within the Marcellus region, namely Pennsylvania and Virginia, have decided to join the RGGI. It remains to be seen whether their adoption of the cap-and-trade program will alter their pathway toward a lower carbon future.

4 | Interfuel Elasticities in Flux: Regional Variations and their Evolution

by Daniel Gatscher

This paper investigates the interfuel Elasticity of Substitution (ES) within the power sector across various regions in the OECD, focusing on the period between 1995 and 2020. Employing a novel multi-equation approach to account for biased technological progress, as well as changes in fuel use and prices, our study explores the substitutability of inputs in power markets. We assess how interfuel ES have evolved over time, particularly in the context of policy changes and uneven technological progress in power generation. The study analyzes the ES for the country and regional level to uncover location-specific differences in energy transitions. For a long-run path towards lower carbon fuels, the ES between fuels needs to be greater than unity so that fuel switching can occur. We find that the ES between low-carbon natural gas and coal is above unity for the entire sample with decreasing ES values in some regions. Our findings indicate significant regional variations and demonstrate that ES values fluctuate, highlighting that static models only partially capture the nuanced dynamics of energy transitions. The results emphasize the necessity for energy policies to be tailored to specific regional conditions to effectively support transitions towards less carbon-intensive power generation. Our study contributes to a deeper understanding of the complex interplay between economic considerations and policy in energy transitions, offering valuable insights for policymakers and researchers engaged in shaping a sustainable future.

4.1 Introduction

Throughout the last two decades, discussions about climate change have intensified, demanding effective policy measures to reduce GHG emissions. The emerging public pressure created by climate change discussions motivated governments to ratify international treaties like the Kyoto Protocol and the Paris Agreement. While the countries participating in the treaties agree on the overarching objective of reducing GHG emissions, the specifics regarding how and when these goals will be achieved have remained unclear, leading to diverging policies and energy transition progress across the globe. This discrepancy in policy is also reflected by the relatively slow progress in reducing GHG emissions, with the most notable results in the past decade coinciding with increased public discourse on climate change issues (Fouquet, 2010).

Reducing the most prominent of GHG emissions, CO2, may be achieved through a variety of means, which include, but are not limited to, demand reduction, electrification of sectors, increases in efficiency, or switching from carbon-intense inputs to lower-carbon inputs, referred to as *substitution*. Increasing generation efficiencies and substitution have been taken advantage of to varying extents in the energy transitions of countries, with significant disparities across regions influenced by resource availability, fuel costs, and energy security concerns. The progress of the energy transitions may be tracked by Elasticities of Substitution (ES), informing about the change in relative fuel use as a response to changes in relative prices and thereby measuring the substitutability between fuels.

This paper analyzes the ES in the power sector, which has been growing predominantly and fairly consistently, though not uniformly, across all regions, both in absolute energy terms and relative to other sectors, across 28 OECD countries between 1995 and 2020. The past quarter-century is particularly relevant, as it includes the impact of international climate agreements and technological advancements in power production, providing a comprehensive foundation for understanding changes in interfuel ES. Given the regional differences and ever-changing pace of energy transitions, we compare the levels and dynamics of the ES across regions and identify changes in the ES over time.

Since the introduction of the ES by Hicks (1932), there has been a steady flow of research, calculating Elasticities of Substitution for different sectors, regions, and periods. We base our analysis on this rich body of literature while introducing new dynamics. Based on the drastic acceleration of energy transitions in the last decade, we assume that the ES will be constant for relatively short time intervals (Jo and Miftakhova, 2022). This contrasts existing literature, which considers the ES to be constant throughout the observation period (Christensen et al., 1975, Considine, 1989b, Fuss, 1977, Jones, 1995). Splitting the timeframe into smaller subsets that we shift across time, in which the ES is presumed to be constant, we are able to evaluate its variation over time and, with it, the dynamics of energy transitions.

Estimating reliable ES values can help provide crucial information on the current and future dynamics of energy transitions to policymakers by measuring shifts in relative input use in response to changes in relative input prices. Acemoglu (2002) and Acemoglu et al. (2012, 2023) have shown that the ES may be interpreted as a driver toward a lower carbon future as it directly influences relative input prices in favor of low-carbon inputs, thereby accelerating the substitution dynamics. However, the accelerating effect of relative input prices depends fundamentally on ES values remaining above unity for the respective fuel bundle (Klump and de La Grandville, 2000). We contribute by estimating the Elasticity of Substitution to measure the progress in the energy transition while relying on state-of-the-art estimation methods, as the discussions by Acemoglu et al. (2012) and Klump and de La Grandville (2000) only rely on an analytical approach to analyze changes in generation efficiencies and ES. Similar to our study, Papageorgiou et al. (2017) estimate the ES between clean and dirty inputs in the power sector to be around 2, finding evidence supporting long-term green growth. Their paper, however, ignores biased technological change and thus possibly overestimates the ES.

Our study accounts for dynamic changes in fuel use, technologies, and input prices by implementing a novel multi-equation approach for ES estimation. Given the rapid increase in generation efficiencies of certain technologies, e.g., natural gas Combined Cycle Gas Turbine (CCGT) power plants, the method can account for uneven changes in generation efficiencies, known as *biased technological change*, which significantly influence fuel switching decisions. This approach developed by Klump et al. (2007) and brought to the energy sector by Gatscher and Ikonnikova (2024) has been tested and used in macroeconomic studies (Frieling and Madlener, 2016, Jo, 2020, Kander and Stern, 2014, Klump et al., 2012, León-Ledesma et al., 2011). It overcomes the limitations of assuming neutral technological change by integrating multiple optimality conditions into the analysis.

While our application utilizes the widely employed CES production function, the approach is flexible enough to support a range of different functional forms. In contrast, previous studies calculating the ES for a diverse set of countries and regions like Pindyck (1979), Serletis et al. (2010b, 2011), Steinbuks and Narayanan (2015) rely on static methods based on single equation cost functions limited to neutral technological change.[42]

In the following, we introduce our data and present changes in the power mix over the last two decades. We then develop our econometric model for the calculation of interfuel Elasticities of Substitution (ES) before presenting our results.

4.2 Data

Our study is based on a balanced panel dataset containing 28 countries in the OECD that span six regions from 1995 to 2020. The dataset is unique as it is the most extensive balanced panel used to calculate Elasticities of Substitution on the country and regional level to this moment. Previous studies relied on unbalanced panels or a smaller sample size of a maximum of 15 countries due to data limitations (Serletis et al., 2011, Steinbuks and Narayanan, 2015). Both of these studies scrutinize energy consumption as a whole, making it challenging to identify the impact of individual shocks (such as energy price shocks or policy interventions) on energy transitions. Additionally, higher levels of data aggregation bias results toward lower ES estimates (Gatscher and Ikonnikova, 2024, Papageorgiou et al., 2017).

In contrast, our dataset focuses on the power sector, whose relevance to decarbonization increased in the last decades, given the ongoing electrification of other sectors, e.g., the transport sector (see Figure C1.1, C1). Moreover, the power sector has a substantial potential for decarbonization due to its ability to incorporate zero-carbon power sources, such as nuclear and renewable power (International Energy Agency, 2000). Finally, the power sector's aptitude to switch between fuels *(substitutability)* and respond to advances in technology (in this case, generation efficiencies) make it a common target of climate policies, such as the EU ETS and the RGGI, that influence the ES.

While early 2000s reports from the International Energy Association (IEA) highlighted the need for increased capacity in the rapidly growing (in energy terms) global power sector, with a slight preference for natural gas capacity, later reports emphasized the urgency for countries to accelerate decarbonization by expanding renewable capacity. Apart from capacity concerns,

[42]Neutral technological change means generation efficiencies across fuels are increasing at the same pace.

the IEA also highlights the need for a switch in input consumption, e.g., from high-carbon coal to lower-carbon power sources such as renewables and natural gas. This shift in objectives can be seen in the dynamics of the power mix across regions, which displayed only moderate adjustments from 1995 to 2010 and a drastic switch toward lower carbon-intensity fuels, e.g., natural gas and renewables, from 2010 to 2020 (see Figure 4.1). This dynamic is one of the primary motivators of our analysis, with the increasing use of renewable power and natural gas evident in Northern America and Western Europe. In contrast, the Asia-Pacific region (excluding China) still relies on high-carbon fuels, which may be attributed to the Fukushima incident leading to a temporary shutdown of nuclear power in Japan and Australia's role as one of the globe's biggest coal producers.

The changing power mix is evident in the predominantly decreased carbon intensities within the power sector (refer to Figure 4.2). The most significant decline in carbon intensity is observed in Denmark and Greece. Conversely, there is minimal change in the already mostly decarbonized power sectors of France, Norway, Sweden, and Switzerland, which primarily rely on hydropower and/or nuclear power. Japan is the sole country displaying an actual increase in CO2 intensity, likely attributed once again to the repercussions of the Fukushima incident. Unsurprisingly, European countries consistently exhibit the most notable reduction in carbon intensity, owing to their gradual phasing out of fossil fuels from the power mix.

Apart from the rising popularity of renewables, coal-to-gas substitution is one of the most prevalent mechanisms for reducing carbon intensity in the power sector. This mechanism has also been observed and mentioned by the IEA in their World Energy Outlook from 2010, in which they refer to the time from 2010 to 2035 as the "Golden Age of Gas", as it will have the most extensive demand growth in all of their considered consumption scenarios (International Energy Agency, 2010, 2011). Switching from coal to natural gas may be partially motivated by environmental concerns; however, as profit-driven entities operate most power plants, economic considerations still play a central role in deployment decisions. Combined with the falling prices of natural gas, generation efficiencies, among which natural gas with its CCGT technology saw the most significant increase, contributed to natural gas' rising economic viability. This is because higher generation efficiencies lead to lower fuel demand and, therefore, lower expenditure and lower CO2 emissions for the same amount of power produced. The influence of efficiencies on fuel switching points toward one of the main shortcomings in existing methodologies estimating the ES: the assumption of neutral technological change.

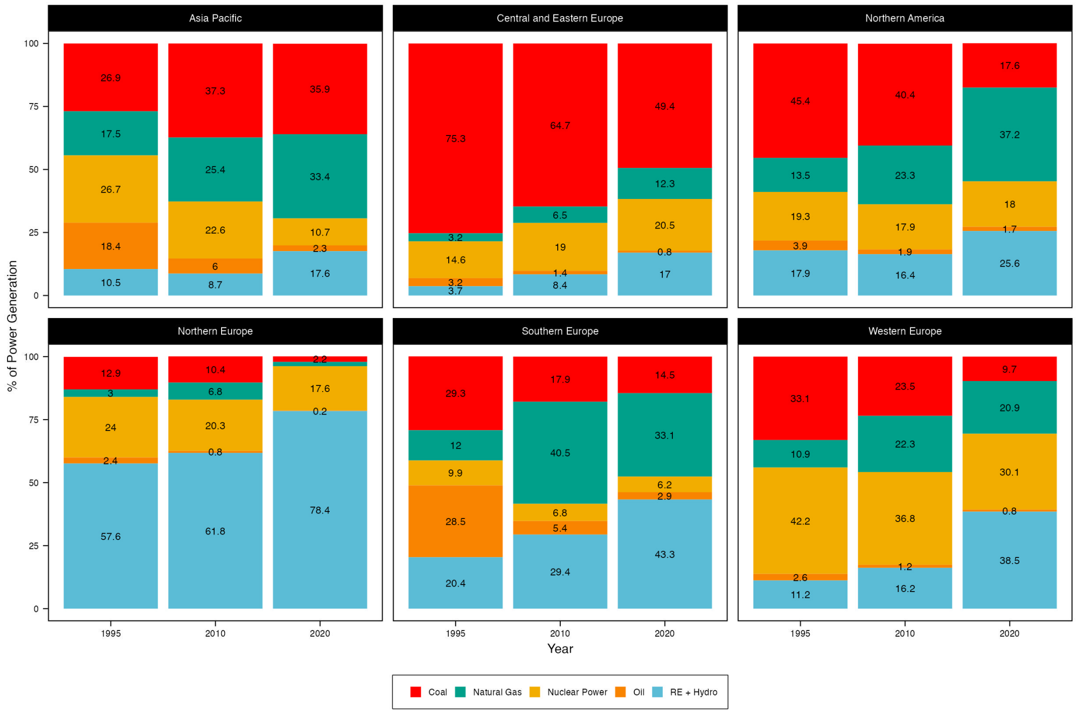


FIGURE 4.1: Composition of the power mix across regions from 1995 to 2020 (International Energy Agency, 2024a).

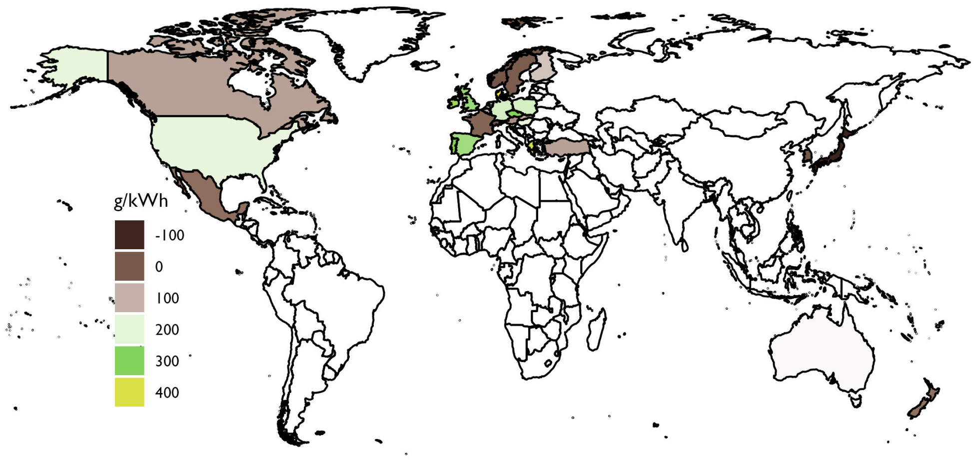
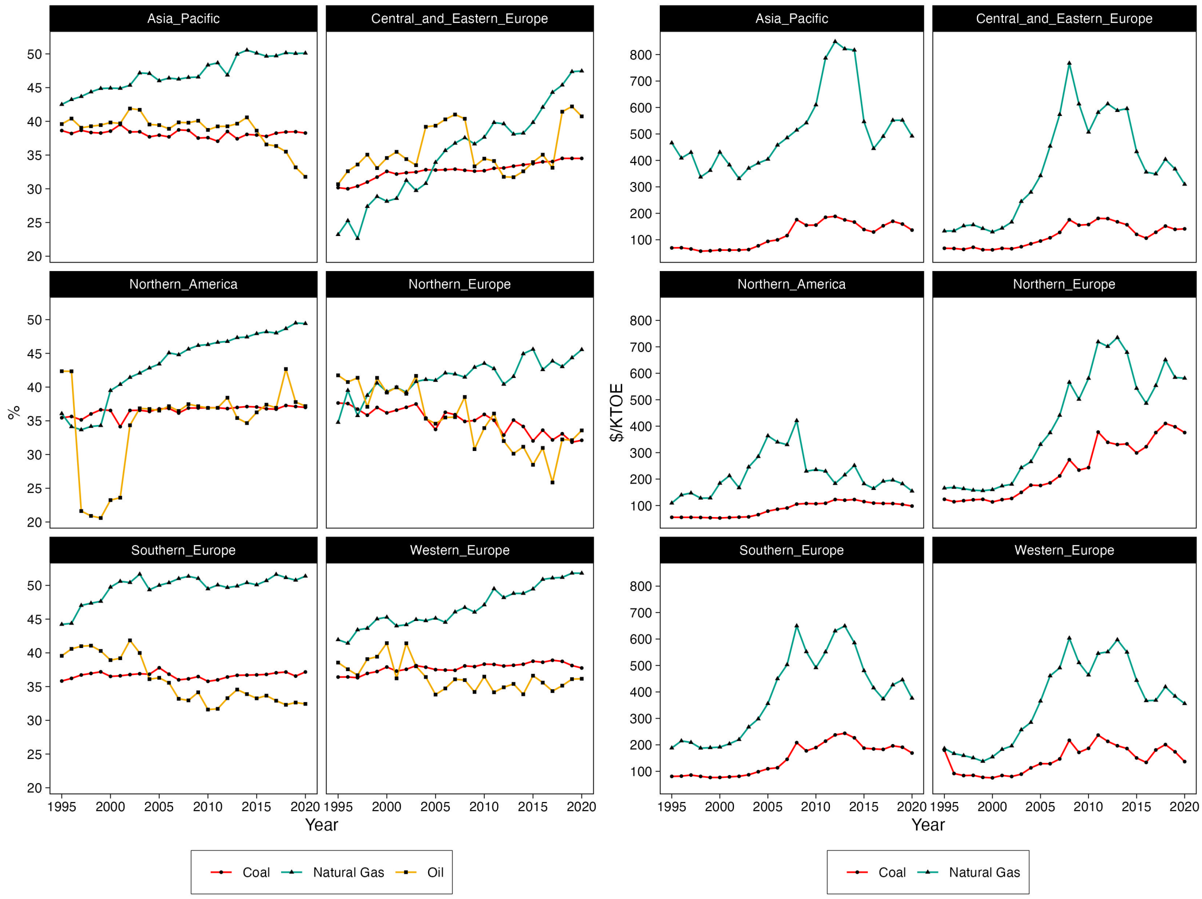


FIGURE 4.2: Carbon intensity reduction from 2000 to 2020 (Ember Climate, 2023).

To quantify the substitution effect with the ES, we gathered balanced country-level data per input i from the IEA on fuel prices p_i, fuel consumption E_i, and power production Q_i from 1995 to 2020 (see Table 4.1).[43] Variables E_i and Q_i enable us to calculate the generation efficiencies

[43] Please note that we do not discount the prices to a base-year, since our methodology relies on the relative prices between fuels, which are insensitive to discount rates. Moreover, we have been missing data points on p_i, which have been imputed using random forest machine learning algorithms based on E_i and Q_i.



(A) Generation efficiencies. (B) Input prices.

FIGURE 4.3: The changes in generation efficiencies and input prices are the two main drivers for coal to natural gas substitution (International Energy Agency, 2024a,b).

η_i (see Equation (4.2)). The resulting generation efficiency values show a drastic increase in natural gas efficiency compared to other inputs, motivating us to challenge the assumption of neutral technological change used in previous studies (see Figure 4.3). To account for biased technological change, updated methodologies are necessary.

Our methodology, shown in Section 4.3, is based on a marginal cost approach, encouraging us to exclude carbon-neutral sources such as renewables, hydropower, and nuclear power. We omit these carbon-neutral inputs due to their intransparent input prices, e.g., subsidies and a marginal cost of zero in the case of renewable- and hydropower. Moreover, nuclear power takes a unique position given its uncommon market mechanisms, like the prioritized dispatch in the merit order and its requirement for a minimum load at all times for security reasons.

We assume that the increasing supply from carbon-neutral sources corresponds to an effective

Table 4.1: Sources of data.

Variable	Variable Symbol	Unit	Source
Power Generation	$Q_{i,t,s}$	$kTOE$	International Energy Agency (2024a)
Input Quantities	$E_{i,t,s}$	$kTOE$	International Energy Agency (2024a)
Input Prices	$p_{i,t,s}$	$\frac{\$}{kTOE}$	International Energy Agency (2024b)
Technical Efficiency	$\gamma_{i,t,s}$	%	Own calculations.

"demand reduction" of fossils, leading to the so-called "residual load". The residual load has a special task in today's power markets, given its function as a backup in times of low renewable power output. In this paper, we are primarily interested in how the growth of carbon-neutral power sources and their implicit influence change the substitution preferences between fossils, especially coal and natural gas.

Based on the collected data, we calculate the value of the total residual power output Y:

$$Y_{t,s} = \sum_{i=1}^{n} Q_{i,t,s} \tag{4.1}$$

Please note that apart from inputs $i \in \{C, NG, O\}$ and the time dimension t, this variable is also specific to country s. Moreover, we compute the average operational efficiency per country and year:

$$\gamma_{i,t,s} = \frac{Q_{i,t,s}}{E_{i,t,s}} \tag{4.2}$$

Finally, we extend the methodology introduced by Gatscher and Ikonnikova (2024) with the average price of the fossil fuel intermediate product p_Y, allowing us to rely entirely on relative prices:

$$p_{Y,t,s} = \frac{\sum_i^I p_{i,t,s}\, E_{i,t,s}}{\sum_i^I Q_{i,t,s}} \tag{4.3}$$

In the following chapter, we show how the gathered data is used in our econometric model to calculate the ES between our fossil fuels, including coal, natural gas, and oil.

4.3 Methodology

The selection of the econometric model in this paper was guided by its ability to accommodate dynamic changes in technology and market conditions, offering a more nuanced understanding of interfuel substitution compared to single equation approaches. In the following, we model the residual power demand Y using a CES production function with three fossil fuel inputs $i \in \{C, NG, O\}$. Based on the model, we derive the commonly used Morishima Elasticity of Substitution (MES), which informs us about the substitutability of two fuels (bundles) in the case of multiple inputs. We start by elaborating on the foundational aspects of the model, such as the framework that accommodates multiple energy inputs and allows for biased technological change. Subsequently, within this framework, we explain the econometric estimation approach employed for determining the ES based on a multi-equation system. Finally, we provide more information on applying our dataset within the framework's context, leading to a dynamic "moving-time-window" analysis.

4.3.1 Model Framework

The Constant Elasticity of Substitution production function is traditionally used in capital-labor-macroeconomics and is limited to two inputs. This limitation has been overcome by Sato (1967), who extended the CES function by replacing individual inputs with another CES function, the so-called nesting. In doing so, the model may be extended to n, or in our case, three inputs. Apart from the nesting, our model differs from standard implementations of the CES by considering the individual productivity γ_i instead of relying on an overarching technology z, which would limit us to the case of neutral technological change. Moreover, we exclude labor in the production function, as we assume the share of labor income to be negligible and not substitutable. By implicitly assuming a fixed ratio between capital and fuel input, we are also able to exclude capital from the production function (Papageorgiou et al., 2017).

We model the residual power demand Y as:

$$Y(\mathbf{E}) = \left\{ \pi_1 \left[\alpha_1 \left(\gamma_1 E_1 \right)^{\frac{\eta-1}{\eta}} + \alpha_2 \left(\gamma_2 E_2 \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1} \frac{\sigma-1}{\sigma}} + \pi_2 \left[\gamma_3 E_3 \right]^{\frac{\sigma-1}{\sigma}} \right\}^{\frac{\sigma}{\sigma-1}} \tag{4.4}$$

In the model, E_i are the input quantities, γ_i the productivity/efficiency for fuel i, and α_i and π_i the income shares of the respective fuel or fuel bundle. Most importantly, the outer elasticity σ

measures the substitutability between the fuel bundle E_1/E_2 and input E_3, whereas the inner elasticity η represents the ES between E_1 and E_2.

Given the residual demand Y and the productivity of the generation fleet per fuel γ_i, the producer chooses the best combination of input quantities E_i, as a response to the (relative) prices p_i to maximize profits:[44]

$$\max_{\mathbf{E}} \left[p_Y \cdot Y(\mathbf{E}, \gamma) - \sum_{i:\,\mathbf{E}} p_i \cdot E_i \right] \tag{4.5}$$

Based on the profit maximization problem, Morishima (1967) and Blackorby and Russell (1981) developed the MES, a n-input generalization of the original Hicks Elasticity of Substitution (HES) which is frequently used for the CES production function, but limited to two inputs (Hicks, 1932). The MES achieves this generalization by holding the output quantity and all input prices constant while letting all inputs adjust to their optimal quantities. The approach sets the cost derivative $\frac{\partial C^e(Y,\mathbf{p}_E)}{\partial p_i} = c_i^e$ equal to the individual input demands under the cost-minimization objective. Using Shepard's Lemma allows us to evaluate the change in the relative input quantities as a response to a change in relative input prices:

$$\sigma_{ij}^M = \frac{\partial \ln(c_i^e(Y, \mathbf{p}_E)/c_j^e(Y, \mathbf{p}_E))}{\partial \ln(p_j/p_i)} = \frac{\partial \ln(E_i/E_j)}{\partial \ln(p_j/p_i)} \tag{4.6}$$

Given its ability to incorporate multiple inputs, the MES is the optimal measure for fuel substitutability in the context of power markets. It considers input demand, input prices, and productivities (efficiencies) to provide information on how relative quantities change, given a change in relative prices. Due to the so-called "impossibility theorem" (Diamond et al., 1978), it used to be unrealizable to calculate the ES while also determining technological progress, thereby limiting the application of the CES production function in the fuel substitution context. In the following, we present our econometric approach that relies on a multi-equation system and normalization procedures to overcome this limitation, following Klump et al. (2007) and León-Ledesma et al. (2010b).

[44] Please note, that given (4.3), the average producer does not make a profit, but breaks even. This is similar to reality, where the fringe producers offer prices equal to their marginal cost.

4.3.2 Econometric Approach

Our econometric model modifies the CES production function by introducing normalization parameters and a set of FOCs. Normalization helps the precise estimation and interpretability of the model by introducing a "common benchmark point", usually sample averages (León-Ledesma et al., 2010b).[45] In addition to the index $i \in \{1, 2, 3\}$, which identifies each fuel type, we use the index t to represent the corresponding year and the index s to denote the specific country involved. As such, $t = 0$ corresponds to the normalized values (see (4.8)). Moreover, we introduce ξ, a normalization constant expected to take a value close to 1. It measures the extent to which sample averages align with the predetermined benchmark point.

$$\log\left(\frac{Y_{t,s}}{Y_{0,s}}\right) = \log(\xi_s) + \frac{\sigma}{\sigma - 1}\log\left\{\begin{array}{l} \pi_{1,s}\left[\alpha_{1,s}\left(\frac{E_{1,t,s}}{E_{1,0,s}}\,\Gamma_{1,t,s}\right)^{\frac{\eta-1}{\eta}} + \alpha_{2,s}\left(\frac{E_{2,t,s}}{E_{2,0,s}}\,\Gamma_{2,t,s}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}\frac{\sigma-1}{\sigma}} + \\ \pi_{2,s}\left[\frac{E_{3,t,s}}{E_{3,0,s}}\,\Gamma_{3,t,s}\right]^{\frac{\sigma-1}{\sigma}} \end{array}\right\} \tag{4.7}$$

Since our variables vary significantly throughout the observation period, we use geometric averages to find the normalization points for the residual power demand Y, input demand E_i, and prices p_i (Herrendorf et al., 2015). The normalized value for the productivity γ_i is calculated in relation to its value at median time $\bar{t}$:

$$Y_{0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, Y_{t,s}}{n}\right); \qquad E_{i,0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, E_{i,t,s}}{n}\right);$$

$$p_{i,0,s} = \exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, p_{i,t,s}}{n}\right) \quad \text{and} \quad \Gamma_{i,t,s} = \frac{\gamma_{i,t,s}}{\gamma_{i,\bar{t},s}}. \tag{4.8}$$

Given the normalized values, we calculate the normalized income shares for the outer function (π_i) and the inner function (α_i):[46]

$$\alpha_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s}}{E_{1,0,s}\, p_{1,0,s} + E_{2,0,s}\, p_{2,0,s}}; \qquad \alpha_{2,s} = 1 - \alpha_{1,s}$$

$$\pi_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s} + E_{2,0,s}\, p_{2,0,s}}{E_{1,0,s}\, p_{1,0,s} + E_{2,0,s}\, p_{2,0,s} + E_{3,0,s}\, p_{3,0,s}}; \quad \pi_{2,s} = 1 - \pi_{1,s} \tag{4.9}$$

[45] Normalization takes place at the country level for all nestings considered.
[46] We provide alternative income share normalization points in Appendix A2.

Moreover, our approach diverges from traditional methods by including one FOC for each input. This procedure coincides with the cost-derivative equalling the factor demand, laying the ground for the MES. To simplify the estimation, we combine the FOCs of inputs 1 and 2 within the inner CES function, while relying on the original FOC for input 3:

$$
\begin{gathered}
\frac{\eta-1}{\eta}\log\left(\frac{E_{2,0,s}\,E_{1,t,s}\,\Gamma_{1,t,s}}{E_{1,0,s}\,E_{2,t,s}\,\Gamma_{2,t,s}}\right) = \log\left(\frac{p_{1,t,s}\,E_{1,t,s}\,\alpha_{2,s}}{p_{2,t,s}\,E_{2,t,s}\,\alpha_{1,s}}\right) \\
\log\left(\frac{p_{3,t,s}}{p_{Y,t,s}}\right) = \log\left(\frac{\alpha_{3,s}\,Y_{0,s}}{E_{3,0,s}}\right) + \frac{1}{\sigma}\log\left(\frac{Y_{t,s}}{Y_{0,s}}\right) - \frac{1}{\sigma}\log\left(\frac{E_{3,t,s}}{E_{3,0,s}}\right) + \frac{\sigma-1}{\sigma}\log\left(\xi_s\,\Gamma_{3,t,s}\right)
\end{gathered}
\tag{4.10}
$$

The combined FOC of inputs 1 and 2 reduces computational complexity and demonstrates the unique relationship between relative prices and relative fuel consumption at the foundation of the Elasticity of Substitution. It also shows how the ES does not only rely on relative prices and input quantities but depends on the relative technological progress $\frac{\Gamma_1}{\Gamma_2}$, demonstrating how omitting technological progress may bias the ES estimates. The econometric model allows us to implement different types of analysis to the dataset, which we present in the following chapter.

4.3.3 Application

We apply the econometric approach to our dataset, which covers 28 OECD countries, in three ways. Our first analysis estimates static country-level ES values. Next, we group countries into six regions, supposing a static and common ES within the group before considering dynamic changes in the regional ES values.

First, we start by performing a static calculation on the country level, covering the entire time-frame from 1995 to 2020. The static ES is calculated for the three different nesting specifications, offering valuable insights. We do so by re-assigning which inputs are part of the inner nesting, with the remaining input being substituted against the bundle within the nest. Comparing the results of the three possible nestings allows us to observe similarities and differences between the nests and helps us better understand the individual countries' power sectors. Due to data limitations and, in some cases, non-use of certain fuels, which would bias our results, we exclude Belgium, Denmark, France, New Zealand, Norway, and Switzerland from the sample.[47]

[47] Norway and New Zealand do not use oil in certain years. Switzerland does not use coal. Belgium and France do not converge, probably due to their reliance on nuclear power. Similarly, Denmark does also not converge.

Second, applying the identical procedure, we group the individual countries into six regions, assuming a common ES per region. The countries are grouped following Table 4.2. Notably, we exclude the same set of countries as in the first model due to data limitations but are able to add Denmark to the Northern European region. The analysis is targeted at identifying a region's ability to substitute. If, for example, Germany has difficulties replacing natural gas-generated electricity with coal-fueled power following an increase in natural gas prices, another country, e.g., the Netherlands, may export its coal-generated electricity to Germany. Similarly, the analysis enables the identification of regional differences that may stem from policy interventions and/or resource availability. Regional differences are becoming more relevant as the global energy landscape transforms, e.g., the United States' transition to become an energy exporter, motivating us to perform a more dynamic analysis.

Table 4.2: Regional scope of the analysis.

		Europe			
Asia Pacific	*Northern America*	*Central/Eastern*	*Northern*	*Southern*	*Western*
Australia	Canada	Czech Republic	(Denmark)	Greece	Austria
Japan	Mexico	Hungary	Finland	Italy	(Belgium)
Korea	US	Poland	(Norway)	Portugal	(France)
(New Zealand)		Slovak Republic	Sweden	Spain	Germany
				Turkiye	Ireland
					Netherlands
					(Switzerland)
					UK

Third, given the acceleration of energy transitions and regional changes in energy production and consumption patterns, we use the regional model to analyze how the ES changes over time. We do so by dividing the timeframe into smaller 20-year windows and tracking how the values change as the window is moved (see 4.4). This procedure offers six observations per region, allowing us to evaluate the changes in the ES and to test the hypotheses of a constant ES on the regional level. Changes in the ES over time may stem from introducing new policies, such as ETSs, or the market entry of relatively cheap energy sources, like Northern America's unconventional natural gas resources. Analyzing if and how these events influence the ES may help researchers choose the correct model specifications (constant or variable ES) in the future and provides valuable insights into the measures selected to increase the ES values that enable low carbon growth.

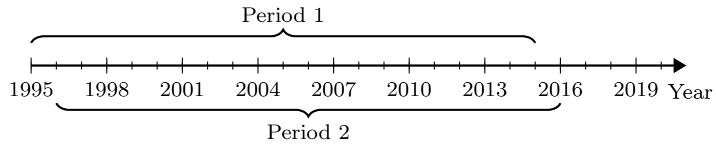


FIGURE 4.4: Example of a 20-year moving-time window.

In the following chapter, we present the results of our analysis of the three different model specifications.

4.4 Results and Discussion

We compute the ES for the three different model specifications by applying the econometric procedure to our sample. First, we calculate the country level ES for the three nesting variants. Next, considering the similarities across countries within the same region, we develop a regional ES for six OECD regions. Last, we examine the change of the ES for the (Coal - NG) - Oil nesting over time to analyze how the acceleration of the energy transition may be quantified.

4.4.1 Country-level Estimates

Usually, the ES differs between fuels and fuel bundles, meaning that oil, e.g., might be a good substitute for input i but could act as a complement for input j. Therefore, analyzing all three possible nestings offers valuable insights into power sector dynamics globally.

The MES indicates substitutability between inputs for ES values above one, while values below one indicate complementarity; that is, both fuels are essential within the country's power sector. In the case of values above one, higher values point to better substitutability, whereas in the case of values below one, lower values denote more substantial complementarity. In the context of Klump and de La Grandville (2000) and Acemoglu et al. (2012), ES values above unity related to natural gas would support long-run low carbon transitions towards natural gas. Interestingly, our results indicate substitutability in most cases, with the only notable outliers hinting at complementarity being Germany, Japan, Korea, and Mexico.

The first column of Table 4.3 shows the countries' names grouped by region; columns two to four display the three nestings' outcomes. Please note that some nestings for certain countries do not contain values, which may be explained by computational complexities inside the model. Values of zero indicate insignificant results (p>10%); the remaining values are significant to the 1% level if not stated otherwise.

Our ES results, such as 6.77 for coal-gas substitution in Australia, thus indicate high substitutability. Returning to (4.6), the value suggests that a 1% increase in the relative price of coal to natural gas leads to an increase of 6.77% in relative natural gas to coal consumption. Given the strong response of the power sector to this change in relative prices, the Australian power sector can easily substitute coal-fired power production with natural-gas-fueled electricity generation.

It is also important to note that, ideally, the results among the nestings are consistent for each country to ensure the internal validity of the results. The Slovak Republic is a prime example of this behavior: the ES between coal and natural gas is measured at 1.2, while the ES between the (Coal - Oil) bundle and natural gas stands at around 1.06, and the ES between the (Natural Gas - Oil) bundle and coal is 1.13. Given the relatively low use of oil in the Slovak Republic, the last two values are mainly driven by the coal-to-natural-gas relationship and, thus, consistent with the other nestings. Moreover, the results indicate that the consumption adjustment for, e.g., coal and natural gas, in response to a relative price change is more than five times stronger in Australia (6.77) compared to the Slovak Republic (1.2).

We find relatively high substitutability in Northern and Southern Europe, while the substitutability in Northern America seems to be comparably low. Moreover, complementarity is only present in Asian countries, as well as Mexico and Germany. These countries, facing complementarity, are known for their solid industrial and manufacturing sectors; thus, relatively high power demand should ideally be met at a comparatively low cost. This fact is particularly concerning since, in the case of complementarity, low-carbon energy transitions are more challenging. The low ES values for Germany, Japan, Korea, and Mexico thus emphasize the need for tailored energy policy to support decarbonization, depending on the needs of the country, to maintain ES values above unity.

Currently, Germany is attempting to reduce its carbon emissions in the power sector by participating in the EU ETS. Policies, like the EU ETS, and resource availability affect substitution dynamics across a variety of countries, prompting us to consider regional ES variations, which we investigate in the following chapter.

4.4.2 Region-level Estimates

The ES on the regional level is becoming more relevant given the increasing importance of regional policy, balancing regional grids through the use of renewables and, with it, cross-border power trading. Our results indicate that most regions can overcome the "problem" of complementarity once we consider them in a group.

We observe consistent estimates across the nestings for all regions, pointing to the internal validity of our approach. Nevertheless, we want to emphasize the (Coal - NG) - Oil model, which best represents modern power grids. Coal is exclusively dispatched as a base load, given

Table 4.3: Country level ES.

	(Coal - NG) - Oil		(Coal - Oil) - NG		(NG - Oil) - Coal	
State	Inner (η)	Outer (σ)	Inner (η)	Outer (σ)	Inner (η)	Outer (σ)
Asia Pacific						
Australia	6.77	2.84	1.83	1.78	–	–
Japan	0.32	2.97	0	1.34	–	–
Korea	–	–	1.85	6.37	9.8	0.55
Eastern Europe						
Czech Republic	1.51	3.32	3.32	2.23	2.97	1.64
Hungary	–	–	4.01	0	–	–
Poland	–	–	–	–	3.78	2.11
Slovak Republic	1.2	1.99*	0	1.06	1.44	1.13
Northern America						
Canada	1.07	1.54	1.06	1.22	–	–
Mexico	–	–	–	–	29.81**	0.83
United States	1.28	2.47	2.66**	1.27	1.48	1.49
Northern Europe						
Finland	4.09	1.79	2.16	3.84	1.5	6.11*
Sweden	1.49	2.58	3.61	1.94	–	–
Southern Europe						
Greece	–	–	1.18	0	17.13	2.34
Italy	3.29	1.89	1.23	3.99	–	–
Portugal	3.63	0	–	–	6.58	1.74
Spain	–	–	1.98	0	–	–
Turkiye	–	–	2.28	0	–	–
Western Europe						
Austria	1.81	2.19	2.75	1.75	2.2	1.89
Germany	0.9	1.92	2.54	0.92	–	–
Ireland	1.34	5.57	–	–	5.24	1.25
Netherlands	2.42	1.36	1.25	0	–	–
United Kingdom	5.71	4.06	–	–	5.34	6.25

Note: All values significant to the 1% except *p<0.1; **p<0.05; 0 = insignificant

its traditionally low marginal cost and relatively slow response to changes in load. On the contrary, oil-fueled plants are mainly used as emergency peak-load products. Natural gas may be used for both base and peak load. Given the dramatic reduction in natural gas prices since 2008, which helped natural gas compete with coal-fired generation even as a base load, and our interest in coal-gas substitution, the nesting appears to be the most relevant.

Our results indicate coal-gas substitution to be around 2 to 7.5, with the extremely high ES in Central/Eastern Europe standing out. Given relative price changes, these results suggest that it is comparatively easy for Central/Eastern European countries to switch from one fuel to another. In contrast, Northern America has the lowest coal-gas ES. Overall, the response of relative inputs consumption in response to relative price changes is 16 times higher in Eastern Europe compared to Northern America. The finding may be explained by factors like, e.g., the competitive energy landscape, in which only the most economical power plants survive, leading to a comparatively low spare capacity that would allow for fuel-switching in Northern America. Alternatively, the effect may stem from the low range of relative price changes, given the relatively similar level of coal and natural gas prices in the U.S.. A small absolute price change in either of the two goods would lead to a significant percentage change in relative prices, which, given that the relative price change functions as a divisor, could neutralize major adjustments in relative input quantities. Looking at the relatively small variance in input prices in the United States, the relative price effect seems to be the driving force behind the low values (see 4.3b). Our findings indicate that policymakers in Northern America may want to introduce policies to increase the ES between coal and natural gas by, e.g., implementing emission trading systems, such as in Europe, to ensure long-run growth in relatively low-carbon natural gas-fueled generation.

Table 4.4: Region level ES.

	(Coal - NG) - Oil		(Coal - Oil) - NG		(NG - Oil) - Coal	
Region	Inner (η)	Outer (σ)	Inner (η)	Outer (σ)	Inner (η)	Outer (σ)
Asia Pacific	4.14	3.88	5.31	3.96	–	–
Eastern Europe	18.07*	6.37	4.46	22**	–	–
Northern America	1.14	3.91	2.22	3.96	3.1	0.99
Northern Europe	2.13	2.63	2.55	2.65	–	–
Southern Europe	7.36	5.56	5.92	6.82	6.21	4.08
Western Europe	3.43	3.88	8.03	4.12	4.52	4.06

Note: All values significant to the 1% except *p<0.1; **p<0.05; 0 = insignificant

Moreover, oil-powered generation appears to carry out its task, namely substitution, in times of extremely high power consumption. On average, it has the highest ES values related to either input or bundle. The fuel is a substitute in all nestings and regions, making it suitable for "shaving off" peak load.

In summary, our findings indicate ES values concerning natural gas to be above unity, supporting a lower carbon energy transition with the help of natural gas. There is a lot of potential for substituting coal with natural gas, with the only case close to complementarity being Northern America. This indicates that the Northern American power sector, in some cases, still treats coal as an essential input that has to be in the power mix to satisfy demand. Given that natural gas is a substitute for coal in most regions, we aim to determine whether this situation has been different or will change in the future. In the following chapter, we divide the timeframe into smaller windows that we move across time to determine whether there have been changes in the ES over time.

4.4.3 Dynamic Region-level Estimates

Traditional literature on the ES, especially in the CES framework, suggests elasticities to be constant over long periods. Considering the acceleration of energy transitions and the increased retirement rate of coal capacity, this assumption may be questioned. We analyze the ES dynamics for the (Coal - NG) - Oil nesting over time. The nesting is especially relevant when related to the "Golden Age of Natural Gas" and the substitution of coal-fired generation with renewables and natural gas due to decarbonization efforts (International Energy Agency, 2010, 2011). We follow the framework presented in Figure 4.4.

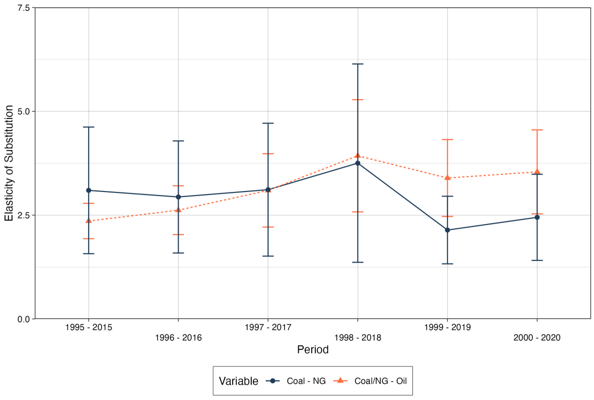
Our results show that while in some regions, such as Northern and Western Europe, ES appear to be relatively constant, there are significant regional differences in ES trends. Constant ES values between coal and gas indicate that the energy transition is still underway at a steady rate and that there is no acceleration/deceleration to be expected. With ES values above unity, this development supports long-run decarbonization of the power sector in these regions, as fuel switching may favor lower-carbon natural gas in the long term.

Conversely, coal/gas substitution is decreasing significantly in Southern Europe, coming from a value of around 10 to a value of around 3.5. Similar developments can be seen in Northern America, where the ES between coal and gas decreased from 3.75 to 1.25. This decrease in Northern America is problematic, as lower ES values make the transition from coal and oil to natural gas more complex. Northern America may thus want to try to increase the ES again by introducing policies, such as carbon prices, that could possibly help intensify fuel switching values in the future.

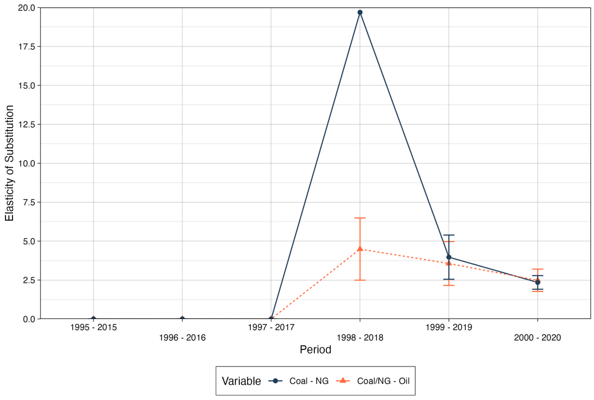
In Central/Eastern Europe, our model did not converge for the first periods but showed a significant decline through the later time windows. With this trend also observable in Southern Europe and Northern America, we interpret this as a sign that the substitution between coal and gas became more challenging. It is difficult to conclude whether this development is positive or negative in the short term. It could stem from the fact that a lot of coal has already been substituted by natural gas; the energy transitions achieved their goals and are now slowing down. The effect may also be influenced by higher substitution away from coal due to the implicit impact of renewable power integration that partially substitutes coal-powered generation. The decreasing values also suggest that energy transitions may have achieved a temporary limit, in which natural gas plants cannot effectively replace the remaining coal in the energy systems. Policies are needed to re-accelerate the transition away from coal. Relating to Table 4.4, Northern America may have reached the point where the substitutability transitions to complementarity.

Remarkably, we find that there is a positive trend for oil-related substitution. The ES between oil and the coal/gas bundle is increasing in almost all regions. This trend may indicate the rising importance of local oil-powered generation in times of increasingly intermittent power production through renewables as a backup tool or in emergencies.

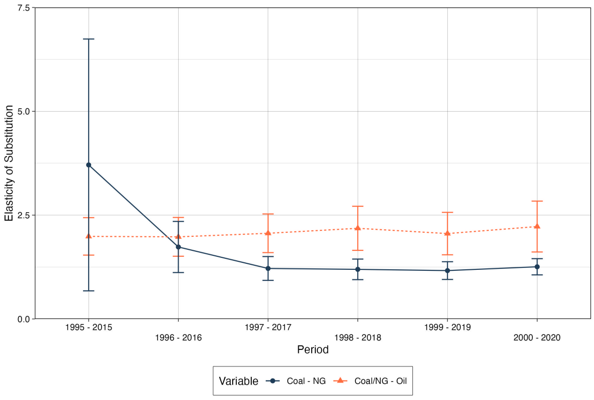
In summary, we find that the assumption of constant ES holds through the entire observation period in some regions. However, it is essential to mention that relying on a static framework for calculating ES poses significant risks, as can be seen in the cases of coal/gas substitution in Central/Eastern Europe, Northern America, and Southern Europe. Mis-specifying the nature of the ES and the omission of biased technological change may significantly influence the applicability and validity of the results.



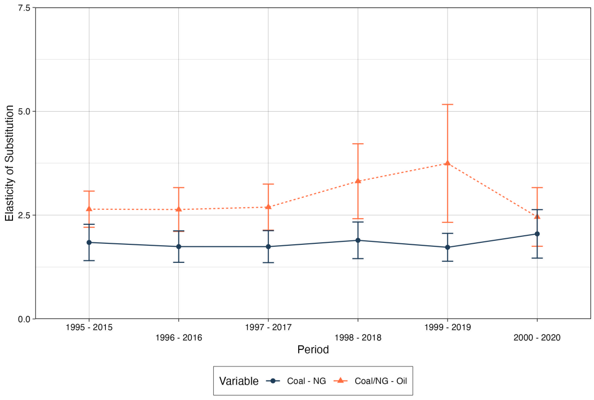
(A) Inner and outer ES for Asia Pacific.



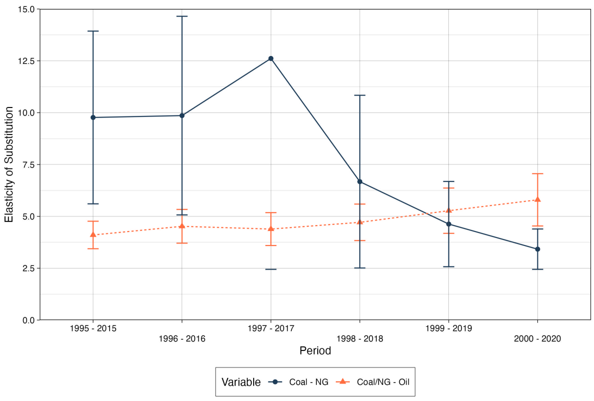
(B) Inner and outer ES for Central/Eastern Europe.



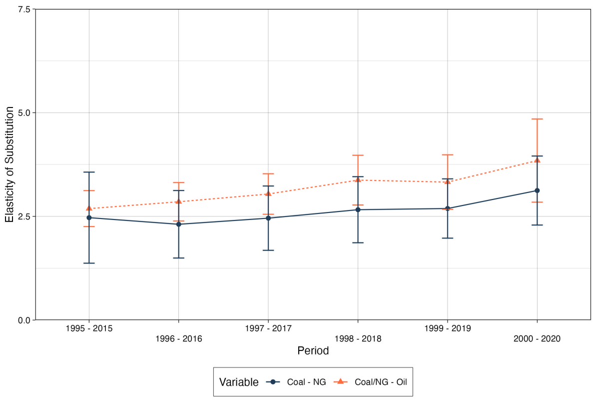
(C) Inner and outer ES for Northern America.



(D) Inner and outer ES for Northern Europe.



(E) Inner and outer ES for Southern Europe.



(F) Inner and outer ES for Western Europe.

FIGURE 4.5: The evolution of ES, based on the $(C - NG) - O$ 20-year moving time-window exercise.

4.5 Conclusion

In concluding this comprehensive study on interfuel elasticities of substitution across various regions and their evolution over time, it is imperative to highlight the findings and their broader implications on energy policy and economic modeling. Our analysis, covering 28 OECD countries across six regions from 1995 to 2020, underscores interfuel substitution's nuanced and dynamic nature in response to evolving economic and technological landscapes.

The calculated interfuel Elasticity of Substitution provides evidence of considerable regional variations and shifts over the entire period. Our novel multi-equation approach, which accommodates changes in fuel usage, technologies, and input prices, reveals that the elasticity is not static but fluctuates across time and regions. This finding challenges the traditional assumption of constant ES and underscores the importance of adopting flexible models that reflect the temporal dynamics in energy markets.

Moreover, the study's application of a multi-equation methodology has successfully captured the biased technological changes influencing fuel-switching decisions, a critical aspect often oversimplified in previous models. By integrating these factors into our analysis, our study enhances the accuracy of ES estimates. It provides a more realistic depiction of the energy sector's responsiveness to economic and technological signals.

Our findings also have significant implications for policy-making and energy modeling. Values of the ES for natural gas-related bundles are usually above unity but, in some cases, declining. This finding indicates a negative development, as long-run carbon reduction of the residual load may be unachievable in some regions. The regional differences observed suggest that energy policies must be tailored to specific regional dynamics to effectively support the transition towards less carbon-intensive energy systems. For instance, some regions' high substitutability between coal and natural gas indicates potential pathways for reducing carbon emissions through strategic fuel switching, supported by appropriate policy incentives. Based on our findings, we recommend policymakers focus on designing targeted subsidies and tax incentives that leverage the specific interfuel elasticities identified in this study to accelerate the transition towards less carbon-intensive energy sources.

In conclusion, this study contributes to a deeper understanding of the complex interplay between economic factors and energy transitions. It highlights the critical role of adaptable econometric models in capturing the essence of these transitions. It provides a robust foundation for future research and policy formulation to achieve sustainable energy systems. This work extends the academic discourse on interfuel elasticities and offers practical insights for policymakers striving to balance economic growth with environmental sustainability.

5 Conclusion

This dissertation aims to comprehensively analyze the complex interplay between interfuel substitution, carbon pricing, price shocks, and energy policy. By examining these factors, this study seeks to deepen our understanding of how regional energy policies, market forces, and technological advancements shape energy transitions and environmental outcomes. The Elasticity of Substitution (ES) serves as a valuable tool for quantifying and analyzing the dynamics of energy transitions. Carbon pricing and price shocks, such as the surge in unconventional natural gas production, exert significant influence on market participants' decisions to switch from high-carbon inputs to lower-carbon alternatives. Given the global differences in resource availability, it is essential to assess regional differences in ES values and dynamics to evaluate the necessity and impacts of energy policy.

The first essay in this work presents a novel methodology for estimating ES under biased technological progress. Our study reveals that technological progress has favored natural gas-fired power generation in the past two decades. By estimating ES values, we show that neglecting this bias in technological change leads to significantly overestimated ES values, indicating that some of the substitution attributed to changes in relative prices is actually due to technological progress. Overestimated ES values would make energy transitions appear more robust than they are. As ES may inform policymakers about the current state of energy transitions, this finding highlights the importance of our multi-equation framework. It may help us understand the significance of selecting the correct model specifications. Furthermore, our analysis demonstrates that disaggregated data improves the model's ability to capture variance in fuel substitution and provides better insights into the underlying dynamics of interfuel substitution. We test different nesting specifications and find that substitution primarily occurs between coal and natural gas, while oil-fueled power generation serves as a backup. By separating our sample into smaller time windows that we shift across time, our study suggests that estimates may also suffer from significant bias when considering historical data. While the assumption of a constant Elasticity of Substitution may hold in the short term, our results show that the ES significantly changes over time. The declining ES between coal and natural gas is a concerning indicator of a slow-down in the U.S.' energy transitions. Lastly, comparing the model-suggested relative fuel use to real-world observations, we conclude that market participants may deviate from optimality conditions in the short term but return to optimal behavior in the long run. One of the shocks leading to this phenomenon is the fracking boom that inspired the second essay.

The second essay in this work investigates the impact of the Regional Greenhouse Gas Initiative (RGGI) and the surging production of unconventional natural gas in the Marcellus shale on CO_2 emissions and energy market dynamics. We consider both events occurring in 2009 as concurrent treatments, aiming to determine whether the increase in natural gas production affected the adjacent states subject to the RGGI. The analysis considers various outcomes to untangle the channels and effects of both treatments on power generation and consumption. While different in their cause, both treatments significantly reduced the CO_2 intensity of power production. The reduction has been achieved by a shift from coal-fired generation to natural gas-fueled power generation in both regions. This switch has been more intense in states subject to the increasing natural gas production. In contrast, the RGGI led to a more substantial adoption of renewable power. At the same time, the drastic coal-to-gas shift in the Marcellus shale play region slowed the adoption of renewables. To test the hypothesis that the surging production of unconventional gas influenced the outcomes of the RGGI, we scrutinized natural gas prices. This approach helps us to identify the driver behind the coal-to-gas transition. Our findings contradict our initial expectations. The decrease in natural gas prices resulting from the increased supply in the Marcellus shale region did not translate to the adjacent RGGI states, suggesting that the coal-to-gas substitution in the RGGI region is driven by the Emission Trading Scheme (ETS). Our analysis of natural gas pipeline capacities reveals that limited pipeline capacity hinders the transmission of price signals from the Marcellus region to the RGGI states. In addition, our study shows that adopting the RGGI led to increased power imports. At the same time, the lower cost of natural gas encouraged the export of electricity in Marcellus shale play states. Potentially resulting from the increased costs of importing power and obtaining emissions certificates, we find higher power prices in the RGGI states, significantly reducing power consumption. This decline in demand is primarily due to industrial consumers, who, along with the decrease in GDP per capita in the manufacturing sector, indicate severe negative economic consequences of the policy. On the other hand, the lower natural gas prices reduced power prices for Marcellus shale states without affecting power demand or GDP. Both treatments have substantially reduced CO2 emissions in the power sector. Our study indicates that the effectiveness of the RGGI has not been affected by the lower natural gas prices in the Marcellus shale region. By examining various outcomes, the study offers an in-depth understanding of the dynamics of the ETS and price shocks. This information may be useful for policymakers in establishing the appropriate legislative framework to facilitate energy transitions, considering the availability of local resources.

The third essay concludes by scrutinizing the ES on an international scale. Our compiled dataset consists of 28 OECD countries, allowing us to explore global patterns of interfuel ES and their evolution over time. By calculating the ES values at the country level for three different nestings, our results reveal that economies with a strong manufacturing sector may face challenges in achieving long-term decarbonization. These economies exhibit complementarity rather than substitutability, making energy transitions contingent on technological progress. However, most economies exhibit strong tendencies toward substitutability, enabling them to phase out coal in the long run. We estimate regional ES values by grouping individual countries into six regions, taking into account network effects such as the interconnectedness of the electricity grid and commodity trading. The impact of such network effects is reflected in the significantly higher ES estimates that now indicate substitutability across all regions. By employing the moving time-window analysis of the first essay, we confirm that the elasticity of substitution is not static, varying significantly across regions and periods. This variability is influenced by changing economic conditions, technological advancements, and policy interventions. The study emphasizes the critical role of adaptable econometric models in accurately capturing the complex interactions in energy markets. It provides a robust foundation for future research and policy formulation to achieve sustainable energy systems.

Together, these studies contribute to a deeper understanding of the multifaceted nature of energy transitions. They demonstrate the pivotal role of policy interventions, market forces, and technological innovation in shaping the future of energy systems. The insights gained from this research offer valuable guidance for policymakers and stakeholders striving to balance economic growth with environmental sustainability. As the energy landscape continues to evolve, the findings of this thesis underscore the necessity of flexible and region-specific approaches to effectively navigate the challenges and opportunities of the energy transition.

Appendix

A1 Extension to the n-Input Case

Since the the method only allows for up to two inputs, we refer to León-Ledesma et al. (2011) who extend the model based on Sato (1967) to four inputs. We use this model to include all conventional fuels (coal, gas, petroleum and nuclear) in energy production. This results in the following equation:

$$\frac{G_{t,s}}{G_{0,s}} = \xi_s \left\{ \begin{array}{l} \pi_{1,s} \left[\alpha_{1,s} \left(\frac{E_{1,t,s}}{E_{1,0,s}} \Gamma_{1,t,s} \right)^{\frac{\eta-1}{\eta}} + \alpha_{2,s} \left(\frac{E_{2,t,s}}{E_{2,0,s}} \Gamma_{2,t,s} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1} \frac{\sigma-1}{\sigma}} + \\ \pi_{2,s} \left[\beta_{1,s} \left(\frac{E_{3,t,s}}{E_{3,0,s}} \Gamma_{3,t,s} \right)^{\frac{\zeta-1}{\zeta}} + \beta_{2,s} \left(\frac{E_{4,t,s}}{E_{4,0,s}} \Gamma_{4,t,s} \right)^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1} \frac{\sigma-1}{\sigma}} \end{array} \right\}^{\frac{\sigma}{\sigma-1}} \tag{A1.1}$$

where $G_{t,s}$ is the output quantity, $G_{0,s}$ is normalized output, ξ_s is the Normalization Constant (NC), $\alpha_{i,s}$ are the income shares for the first nest, $\beta_{i,s}$ are the income shares for the second nest, and $\pi_{i,s}$ are the income shares between the nests, $E_{i,t,s}$ are the input quantities, $E_{i,0,s}$ are their normalization, $\Gamma_{i,t,s}$ is the normalized productivity measure, η is the elasticity of substitution of the first nest, ζ is the elasticity of substitution of the second nest and σ is the elasticity of substitution between the nests.

Already combining the FOCs for inputs 1 & 2 in (A1.2) and inputs 3 & 4 in (A1.3) concludes the four input model:

$$\frac{p_{1,t,s}\, E_{1,t,s}\, \alpha_{2,s}}{p_{2,t,s}\, E_{2,t,s}\, \alpha_{1,s}} = \left(\frac{E_{2,0,s}\, E_{1,t,s}\, \Gamma_{1,t,s}}{E_{1,0,s}\, E_{2,t,s}\, \Gamma_{2,t,s}} \right)^{\frac{\eta-1}{\eta}} \tag{A1.2}$$

$$\frac{p_{3,t,s}\, E_{3,t,s}\, \beta_{2,s}}{p_{4,t,s}\, E_{4,t,s}\, \beta_{1,s}} = \left(\frac{E_{4,0,s}\, E_{3,t,s}\, \Gamma_{3,t,s}}{E_{3,0,s}\, E_{4,t,s}\, \Gamma_{4,t,s}} \right)^{\frac{\zeta-1}{\zeta}} \tag{A1.3}$$

where $p_{i,t}$ are input prices.

Last, as seen in many papers that analyze the electricity sector, like Serletis et al. (2010a), we also try to model fossil fueled power production (3 inputs).

$$\frac{G_{t,s}}{G_{0,s}} = \xi_s \left\{ \begin{array}{l} \pi_{1,s} \left[\alpha_{1,s} \left(\frac{E_{1,t,s}}{E_{1,0,s}} \Gamma_{1,t,s} \right)^{\frac{\eta-1}{\eta}} + \alpha_{2,s} \left(\frac{E_{2,t,s}}{E_{2,0,s}} \Gamma_{2,t,s} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1} \frac{\sigma-1}{\sigma}} + \\ \pi_{2,s} \left[\frac{E_{3,t,s}}{E_{3,0,s}} \Gamma_{3,t,s} \right]^{\frac{\sigma-1}{\sigma}} \end{array} \right\}^{\frac{\sigma}{\sigma-1}} \tag{A1.4}$$

where in contrast to (A1.1) the value of σ is now the elasticity of substitution between input three and the first nest.

The FOCs for inputs 1 & 2 is exactly the same as (A1.2). For input 3 however, we need a similar adjustment as mentioned for the other FOCs:

$$\frac{p_{3,t,s}\, E_{3,0,s}\, \pi_{1,s}\, \alpha_{2,s}}{p_{2,t,s}\, E_{2,0,s}\, \pi_{2,s}} = \frac{\frac{E_{2,t,s}}{E_{2,0,s}}^{\frac{1}{\eta}}}{\frac{E_{3,t,s}}{E_{3,0,s}}^{\frac{1}{\sigma}}} \frac{\Gamma_{3,t,s}^{\frac{\sigma-1}{\sigma}}}{\Gamma_{2,t,s}^{\frac{\eta-1}{\eta}}} \frac{1}{\left(\alpha_{1,s} \left(\frac{E_{1,t,s}}{E_{1,0,s}} \Gamma_{1,t,s} \right)^{\frac{\eta-1}{\eta}} + \alpha_{2,s} \left(\frac{E_{2,t,s}}{E_{2,0,s}} \Gamma_{2,t,s} \right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\sigma-\eta}{\sigma(\eta-1)}}} \tag{A1.5}$$

The Point of Normalization for n-Inputs

$$\begin{aligned}
& For\, both\, cases: \\
& \alpha_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s}}; \quad \alpha_{2,s} = \frac{E_{2,0,s}\, p_{2,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s}} \\
& For\, the\, three\, input\, case: \\
& \pi_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s} \;+\; E_{3,0,s}\, p_{3,0,s}} \\
& \pi_{2,s} = \frac{E_{3,0,s}\, p_{3,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s} \;+\; E_{3,0,s}\, p_{3,0,s}} \\
& For\, the\, four\, input\, case: \\
& \beta_{1,s} = \frac{E_{3,0,s}\, p_{3,0,s}}{E_{3,0,s}\, p_{3,0,s} \;+\; E_{4,0,s}\, p_{4,0,s}}; \quad \beta_{2,s} = \frac{E_{4,0,s}\, p_{4,0,s}}{E_{3,0,s}\, p_{3,0,s} \;+\; E_{4,0,s}\, p_{4,0,s}} \\
& \pi_{1,s} = \frac{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s} \;+\; E_{3,0,s}\, p_{3,0,s} \;+\; E_{4,0,s}\, p_{4,0,s}} \\
& \pi_{2,s} = \frac{E_{3,0,s}\, p_{3,0,s} \;+\; E_{4,0,s}\, p_{4,0,s}}{E_{1,0,s}\, p_{1,0,s} \;+\; E_{2,0,s}\, p_{2,0,s} \;+\; E_{3,0,s}\, p_{3,0,s} \;+\; E_{4,0,s}\, p_{4,0,s}}
\end{aligned} \tag{A1.6}$$

A2 Alternative Income Share Normalization

Alternative income shares at any point of time can be defined as:

$$
\begin{aligned}
&For\, all\, cases:\\
&\alpha_{1,t,s} = \frac{E_{1,t,s}\; p_{1,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s}}; \quad \alpha_{2,t,s} = \frac{E_{2,t,s}\; p_{2,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s}}\\
&For\, the\, three\, input\, case:\\
&\pi_{1,t,s} = \frac{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s} \;+\; E_{3,t,s}\; p_{3,t,s}}\\
&\pi_{2,t,s} = \frac{E_{3,t,s}\; p_{3,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s} \;+\; E_{3,t,s}\; p_{3,t,s}}\\
&For\, the\, four\, input\, case:\\
&\beta_{1,t,s} = \frac{E_{3,t,s}\; p_{3,t,s}}{E_{3,t,s}\; p_{3,t,s} \;+\; E_{4,t,s}\; p_{4,t,s}}; \quad \beta_{2,t,s} = \frac{E_{4,t,s}\; p_{4,t,s}}{E_{3,t,s}\; p_{3,t,s} \;+\; E_{4,t,s}\; p_{4,t,s}}\\
&\pi_{1,t,s} = \frac{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s} \;+\; E_{3,t,s}\; p_{3,t,s} \;+\; E_{4,t,s}\; p_{4,t,s}}\\
&\pi_{2,t,s} = \frac{E_{3,t,s}\; p_{3,t,s} \;+\; E_{4,t,s}\; p_{4,t,s}}{E_{1,t,s}\; p_{1,t,s} \;+\; E_{2,t,s}\; p_{2,t,s} \;+\; E_{3,t,s}\; p_{3,t,s} \;+\; E_{4,t,s}\; p_{4,t,s}}
\end{aligned}
\tag{A2.1}
$$

Based on the values from (2.23), León-Ledesma et al. (2010b) and Klump et al. (2007) advocate the usage of the average income shares for the normalization points. This is because in capital-labor income shares are usually constant, so that the mean best represents the behaviour of the sample over time. We call this normalization point $S = 0$

$$
\begin{aligned}
\alpha_{i,s} &= \frac{\sum_{t_{min}}^{t_{max}} \alpha_{i,t,s}}{n}; \quad \sum_{i=1}^{2} \alpha_{i,s} = 1\\
\beta_{i,s} &= \frac{\sum_{t_{min}}^{t_{max}} \beta_{i,t,s}}{n}; \quad \sum_{i=1}^{2} \beta_{i,s} = 1\\
\pi_{i,s} &= \frac{\sum_{t_{min}}^{t_{max}} \pi_{i,t,s}}{n}; \quad \sum_{i=1}^{2} \pi_{i,s} = 1
\end{aligned}
\tag{A2.2}
$$

A second choice for the normalization of income shares may be geometric averages. Herrendorf et al. (2015) argue that this procedure allows for values further away from the point of normalization due to the exponential behaviour of factor shares. This normalization will be defined as $S = 1$

$$\begin{aligned}
\alpha_{i,s} &= exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, \alpha_{i,t,s}}{n}\right); \quad \sum_{i=1}^{2} \alpha_{i,s} \neq 1 \\
\beta_{i,s} &= exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, \beta_{i,t,s}}{n}\right); \quad \sum_{i=1}^{2} \beta_{i,s} \neq 1 \\
\pi_{i,s} &= exp\left(\frac{\sum_{t_{min}}^{t_{max}} ln\, \pi_{i,t,s}}{n}\right); \quad \sum_{i=1}^{2} \pi_{i,s} \neq 1
\end{aligned} \tag{A2.3}$$

A3 Graphs & Figures

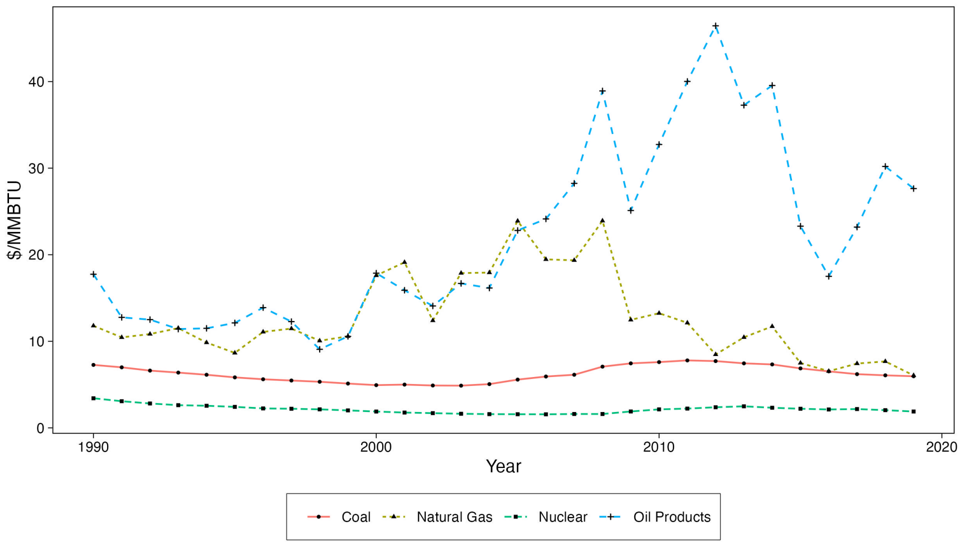


Figure A3.1: Electricity generation cost per fuel (EIA, 2020, 2022).

Commencing in 2008, producing electricity through natural gas emerged as a cost-competitive alternative to coal-based generation. Nuclear power maintains its position as the most cost-effective producer, whereas petroleum, despite its higher expense, persists in its utilization as a producer during peak demand periods.

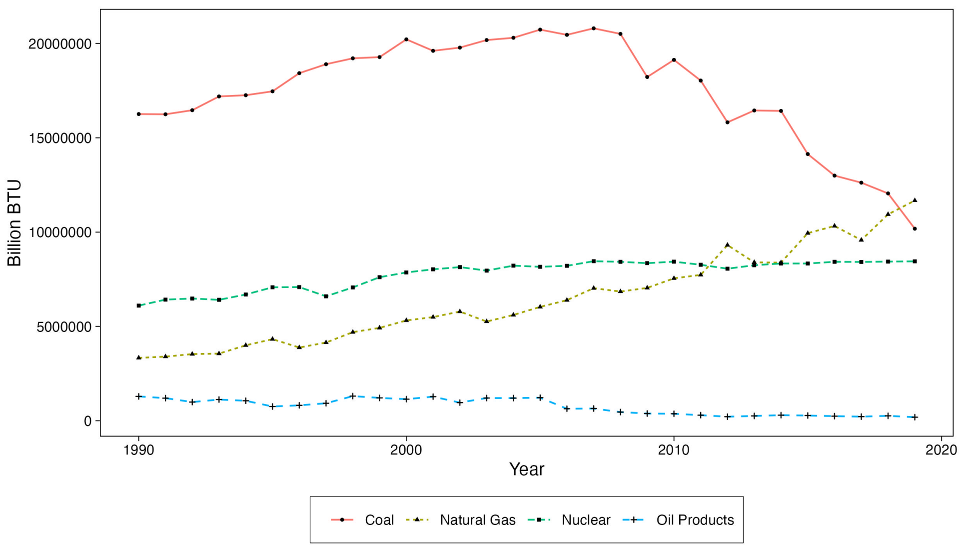


Figure A3.2: Total input quantity per fuel (EIA, 2022).

A noticeable decline in coal utilization emerged in the late 2000s in the electric power sector. Conversely, there has been a consistent and marked upsurge in the consumption of natural gas, particularly following a surge in adoption around 2008, coinciding with the moment when electricity generation via natural gas attained cost competitiveness (refer to Fig. A3.1). However, the upsurge in natural gas consumption registers a smaller magnitude than the decline in coal usage. This discrepancy can be attributed to natural gas's inherently superior generation efficiency characteristic.

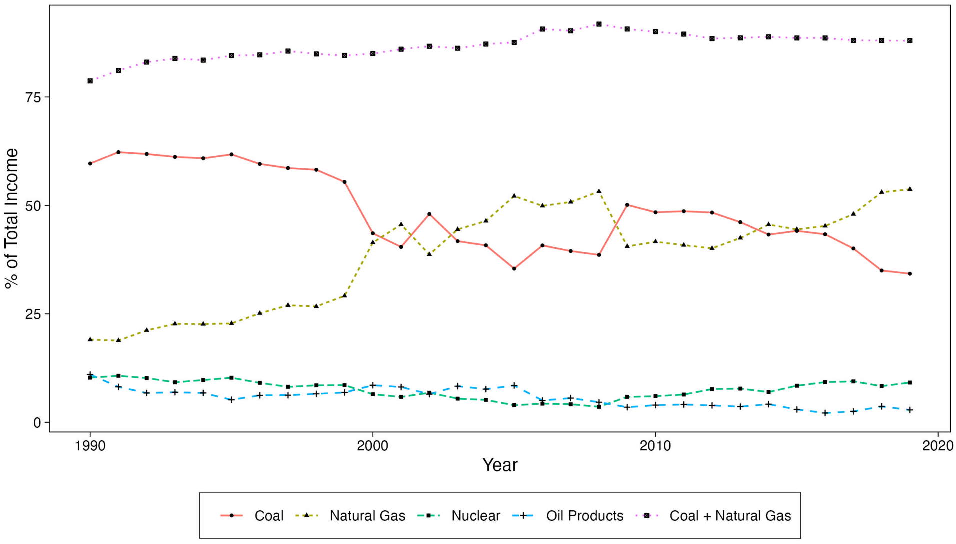
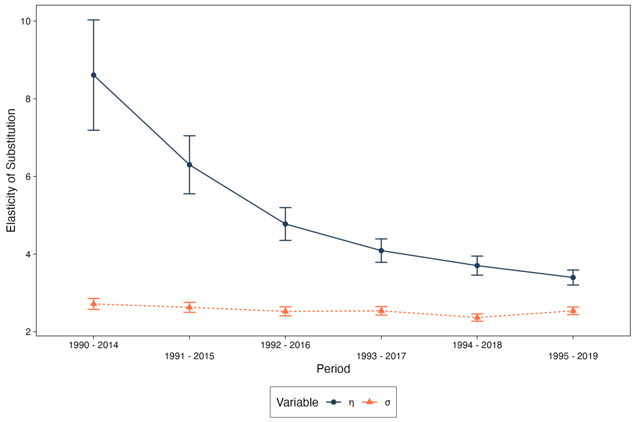


Figure A3.3: Income share per fuel (EIA, 2020, 2022).

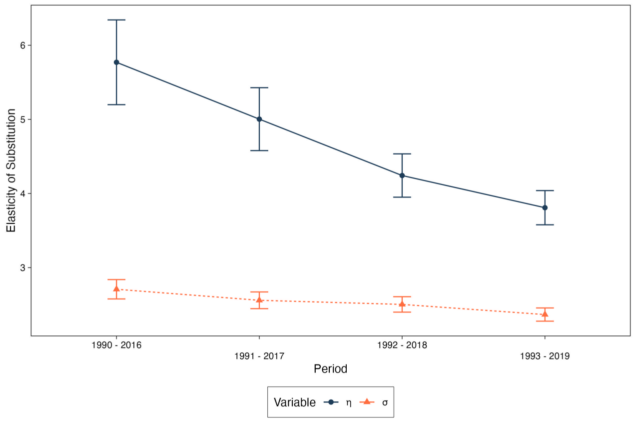
From the late 1990s onward, natural gas experienced a consistent rise in its market share within the energy income spectrum. Predominantly, this escalation stems from the decline observed in coal's share. An evident substitution effect becomes apparent upon analyzing the cumulative income shares of coal and natural gas, exhibiting constancy over this period. Concurrently, the proportion of income attributed to petroleum-fired generation exhibited a gradual and steady decrease.

MSN	Statename	state	NS26	MSN	Statename	state	NS26
AK	Alaska	✓	✗	MT	Montana	✓	✗
AL	Alabama	✓	✓	NC	North Carolina	✓	✓
AR	Arkansas	✓	✓	ND	North Dakota	✗	✗
AZ	Arizona	✓	✓	NE	Nebraska	✓	✓
CA	California	✗	✗	NH	New Hampshire	✗	✗
CO	Colorado	✓	✗	NJ	New Jersey	✓	✓
CT	Connecticut	✓	✗	NM	New Mexico	✓	✗
DC	District of Columbia	✗	✗	NV	Nevada	✓	✗
DE	Delaware	✓	✗	NY	New York	✓	✓
FL	Florida	✓	✓	OH	Ohio	✓	✓
GA	Georgia	✓	✓	OK	Oklahoma	✓	✗
HI	Hawaii	✗	✗	OR	Oregon	✓	✗
IA	Iowa	✓	✓	PA	Pennsylvania	✓	✓
ID	Idaho	✗	✗	RI	Rhode Island	✗	✗
IL	Illinois	✓	✓	SC	South Carolina	✓	✓
IN	Indiana	✓	✗	SD	South Dakota	✓	✗
KS	Kansas	✓	✓	TN	Tennessee	✓	✓
KY	Kentucky	✓	✗	TX	Texas	✓	✓
LA	Louisiana	✓	✓	UT	Utah	✓	✗
MA	Massachusetts	✗	✗	VA	Virginia	✓	✓
MD	Maryland	✓	✓	VT	Vermont	✗	✗
ME	Maine	✓	✗	WA	Washington	✓	✓
MI	Michigan	✓	✓	WI	Wisconsin	✓	✓
MN	Minnesota	✓	✓	WV	West Virginia	✓	✗
MO	Missouri	✓	✓	WY	Wyoming	✓	✗
MS	Mississippi	✓	✓	US	United States	√̸	√̸
-	Intermediate	21	14	-	Total (w/o US)	42	26

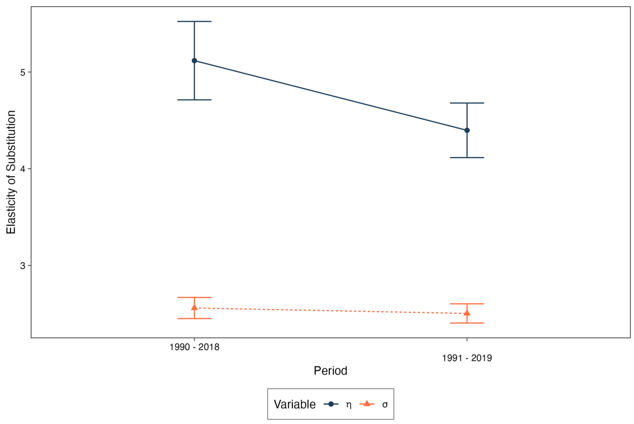
FIGURE A3.4: States per model.



(A) 24-Year Window for $(G - C) - O$.



(B) 26-Year Window for $(G - C) - O$.



(C) 28-Year Window for $(G - C) - O$.

FIGURE A3.5: Reducing the window size leads to the ES trending to the mean values for the $(G-C)-O$ model.

A4 Tables

TABLE A4.1: Two-input ES in the US electricity sector (1990-2019), S = 2, N = 42, common NC

	Model:		
	NG - C	NG - O	C - O
σ	4.82***	2.52***	2.57***
	(0.18)	(0.04)	(0.08)
ξ	0.93***	0.94***	0.99***
	(0.004)	(0.01)	(0.002)
N	1260	1260	1260
$R^2(G)$	0.76	0.96	0.98
$R^2(FOC's)$	0.87	0.85	0.61

σ - outer ES; ξ - NC; *** p<0.01; (Strd. Error)

TABLE A4.2: Three-input ES in the US electricity sector (1990-2019), S = 2, N = 42, common NC

	Model:		
	(NG - C) - O	(NG - O) - C	(C - O) - NG
σ	2.19***	4.67***	3.18***
	(0.04)	(0.21)	(0.08)
η	4.13***	2.57***	2.34***
	(0.14)	(0.04)	(0.07)
ξ	0.92***	0.92***	0.92***
	(0.004)	(0.004)	(0.004)
N	1260	1260	1260
$R^2(G)$	0.67	0.66	0.63
$R^2(FOC(Nest))$	0.86	0.86	0.61
$R^2(FOC(Outer))$	0.47	0.39	0.49

σ - outer ES; η - inner nest ES; ξ - NC; *** p<0.01; (Strd. Error)

TABLE A4.3: Three-input ES in the US electricity sector (1990-2019), S = 1, N = 42, individual NC

	Dependent variable:		
	(NG - C) - O	(NG - O) - C	(C - O) - NG
σ	2.44***	5.73***	4.11***
	(0.04)	(0.30)	(0.11)
η	4.85***	2.90***	2.28***
	(0.16)	(0.05)	(0.06)
N	1260	1260	1260
$R^2(G)$	0.9	0.89	0.89
$R^2(FOC(Nest))$	0.87	0.86	0.61
$R^2(FOC(Outer))$	0.48	0.39	0.48

σ - outer ES; η - inner nest ES; *** p<0.01; (Strd. Error)

TABLE A4.4: Two-input ES in the US electricity sector (1990-2019), S = 2, N = 26, individual NC

	Model:					
	NG - C	NG - O	C - O	O - N	NG - N	C - N
σ	3.48***	2.65***	2.45***	2.34***	15.00***	13.20***
	(0.10)	(0.05)	(0.09)	(0.09)	(3.82)	(3.18)
N	780	780	780	780	780	780
$R^2(G)$	0.9	0.99	0.98	-0.43	0.18	0.54
$R^2(FOC)$	0.85	0.87	0.66	0.62	0.77	0.72

σ - outer ES; *** p<0.01; (Strd. Error)

TABLE A4.5: Four-input ES in the US electricity sector (1990-2019),
S = 2, N = 26, individual NC

	Model:	
	(NG - O) - (C - N)	(C - O) - (NG - N)
σ	4.33***	3.60***
	(0.38)	(0.29)
η	2.66***	2.61***
	(0.06)	(0.10)
ζ	5.94***	5.88***
	(0.64)	(0.54)
N	780	780
$R^2(G)$	0.78	0.78
$R^2(FOC(Nest1))$	0.87	0.66
$R^2(FOC(Nest2))$	0.72	0.77

σ - outer ES; η - nest1 ES; ζ - nest2 ES; *** p<0.01; (Strd. Error)

TABLE A4.6: Four-input ES in the US electricity sector (1990-2019),
S = 2, N = 26, common NC

	Model:		
	(NG - C) - (O - N)	(NG - O) - (C - N)	(C - O) - (NG - N)
σ	1.62***	2.90***	2.22***
	(0.29)	(0.20)	(0.12)
η	3.59***	2.65***	2.56***
	(0.11)	(0.06)	(0.09)
ζ	2.38***	5.87***	5.35***
	(0.08)	(0.63)	(0.45)
ξ	0.94***	0.94***	0.95***
	(0.003)	(0.004)	(0.004)
N	780	780	780
$R^2(G)$	0.65	0.65	0.66
$R^2(FOC(Nest1))$	0.85	0.87	0.66
$R^2(FOC(Nest2))$	0.62	0.72	0.77

σ - outer ES; η - nest1 ES; ζ - nest2 ES; ξ - NC; *** p<0.01; (Strd. Error)

TABLE A4.7: Three-input ES in the US electricity sector (1990-2019), S = 2, N = 42, individual NC, neutral technology

	Model:		
	(NG - C) - O	(NG - O) - C	(C - O) - NG
σ	2.72***	8.48***	5.67***
	(0.06)	(0.68)	(0.24)
η	6.98***	3.37***	2.45***
	(0.38)	(0.08)	(0.07)
N	1260	1260	1260
$R^2(G)$	0.88	0.89	0.89
$R^2(FOC(Nest))$	0.87	0.87	0.63
$R^2(FOC(Outer))$	0.51	0.43	0.52

σ - outer ES; η - inner nest ES; *** p<0.01; (Strd. Error)

TABLE A4.8: Three-input ES in the US electricity sector (1990-2019), S = 2, N = 26, individual NC, neutral technology

	Model:		
	(NG - C) - O	(NG - O) - C	(C - O) - NG
σ	2.55***	6.49***	5.11***
	(0.07)	(0.42)	(0.22)
η	5.87***	3.10***	2.37***
	(0.30)	(0.07)	(0.08)
N	780	780	780
$R^2(G)$	0.91	0.91	0.91
$R^2(FOC(Nest))$	0.85	0.88	0.65
$R^2(FOC(Outer))$	0.61	0.47	0.6

σ - outer ES; η - inner nest ES; *** p<0.01; (Strd. Error)

Table A4.9: Three-input ES in the US electricity sector (1990-2019), S = 2, aggregate US, neutral technology

	Model:		
	(NG - C) - O	(NG - O) - C	(C - O) - NG
σ	2.23***	1.55***	1.77***
	(0.18)	(0.18)	(0.17)
η	1.66***	2.08***	2.40***
	(0.18)	(0.13)	(0.33)
ξ	0.98***	0.98***	0.98***
	(0.003)	(0.003)	(0.003)
N	30	30	30
$R^2(G)$	0.98	0.96	0.98
$R^2(FOC(Nest))$	0.35	0.83	0.53
$R^2(FOC(Outer))$	0.72	0.5	0.72

σ - outer ES; η - inner nest ES; ξ - NC; *** p<0.01; (Strd. Error)

B1 State-level Treatment Effects

To address potential confounding factors stemming from other state-level events, we have undertaken an additional step in our analysis by calculating treatment effects at the state level. In this endeavor, we draw inspiration from the approach proposed by Upton and Snyder (2017), leveraging their DD estimator to facilitate the computation of state-level effects that can augment the interpretation of our findings. The model formulates as:

$$Y_{it} = \alpha + \delta \cdot D_{Trtmnt} + \gamma \cdot D_{TrtmentUnt} + \eta \cdot D_{PreTrtmnt} + \epsilon_{it} \tag{B1.1}$$

In this equation, Y_{it} represents the values for the outcome variables, while the binary variable D_{Trtmnt} serves as an indicator for treatment, taking the value of 1 for treated states after 2008 and 0 otherwise. Consequently, δ quantifies the treatment effect. Additionally, $D_{TrtmentUnt}$ denotes the original outcomes, and $D_{PreTrtmnt}$ designates the pre-treatment periods, with γ and η representing their respective effects. In our analysis, we focus solely on the values of δ as they will complement and enrich the interpretation of our results.

B2 Additional Tables

Table B2.1: Change in nuclear share

		RGGI	Marcellus	Placebo
Baseline DD	ATE	0.751	1.020*	-
	SE	(0.903)	(0.559)	(-)
	N	1050	925	-
Pooled SCM	ATE	-0.597	0.876*	-0.433**
	SE	(1.610)	(0.461)	(0.188)
	N	450	200	1650
Eq. Pooled SCM	ATE	-0.546	1.150**	-0.814***
	SE	(1.610)	(0.449)	(0.188)
	N	450	200	1650
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table B2.2: Change in coal & natural gas capacity per capita $\frac{KW}{capita}$

		Coal Capacity:			*Gas Capacity:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	0.120***	-0.178***	-	-0.036	0.023	-
	SE	(0.024)	(0.035)	(-)	(0.042)	(0.057)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	0.039*	-0.052*	-0.029**	0.001	-0.018	0.079***
	SE	(0.020)	(0.030)	(0.012)	(0.042)	(0.034)	(0.020)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	0.018	-0.168***	0.026**	0.021	-0.006	-0.019
	SE	(0.020)	(0.031)	(0.012)	(0.045)	(0.037)	(0.020)
	N	450	200	1650	450	200	1650
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table B2.3: Change in coal & natural gas capacity shares

		Coal Capacity Share:			*Gas Capacity Share:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	6.540***	-1.450	-	4.010***	5.040***	-
	SE	(0.754)	(1.060)	(-)	(0.956)	(1.110)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	0.469	2.800***	-0.572	3.530**	2.470**	0.634*
	SE	(0.660)	(0.929)	(0.371)	(1.380)	(1.220)	(0.370)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	1.780**	0.208	-0.814**	5.520***	3.320***	-0.734**
	SE	(0.726)	(0.836)	(0.369)	(1.360)	(1.140)	(0.369)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

Table B2.4: Change in natural gas prices $\frac{\$}{MMBTU}$

		Industrial Sector:			*Residential Sector:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	1.150***	-0.402**	-	0.347**	-1.000***	-
	SE	(0.144)	(0.181)	(-)	(0.149)	(0.190)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	1.200***	-0.218	-0.002	0.025	-0.862***	0.059
	SE	(0.175)	(0.180)	(0.060)	(0.180)	(0.162)	(0.065)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	1.080***	-0.378**	0.065	0.451***	-0.813***	-0.059
	SE	(0.176)	(0.177)	(0.060)	(0.172)	(0.158)	(0.362)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

Table B2.5: Change in electricity prices $\frac{\$}{MMBTU}$

		Industrial sector:			*Residential sector:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	0.393	0.521	-	0.193	0.028	-
	SE	(0.372)	(0.403)	(-)	(0.415)	(0.449)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	1.020**	-0.598*	0.020	1.320**	-0.589*	0.144
	SE	(0.498)	(0.337)	(0.135)	(0.583)	(0.322)	(0.151)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	2.270***	-0.495	0.327**	2.050***	-0.038	-0.256*
	SE	(0.511)	(0.338)	(0.136)	(0.583)	(0.332)	(0.153)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

Table B2.6: Change in electricity demand in the industrial sector $\frac{kWh}{Capita}$

		RGGI	Marcellus	Placebo
Baseline DD	ATE	-496***	-177	-
	SE	(122)	(178)	(-)
	N	1050	925	-
Pooled SCM	ATE	-277***	-176	129**
	SE	(85.6)	(174)	(60.6)
	N	450	200	1650
Eq. Pooled SCM	ATE	-484***	-101	241***
	SE	(84.9)	(130)	(60.9)
	N	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE B2.7: Change in CDD and gasoline demand $\frac{Gallons}{Capita\ Day}$

		CDD:			*Gasoline:*		
		RGGI	Marcellus	Placebo	RGGI	Marcellus	Placebo
Baseline DD	ATE	13.700	32.400	-	0.017	-0.048**	-
	SE	(17.000)	(24.600)	(-)	(0.015)	(0.020)	(-)
	N	1050	925	-	1050	925	-
Pooled SCM	ATE	-49.300***	25.400	-14.300*	0.029	-0.015	0.027***
	SE	(16.900)	(15.500)	(8.390)	(0.018)	(0.026)	(0.006)
	N	450	200	1650	450	200	1650
Eq. Pooled SCM	ATE	4.090	43.700***	-2.870	-0.008	-0.009	0.002
	SE	(14.500)	(15.400)	(8.320)	(0.018)	(0.026)	(0.006)
	N	450	200	1650	450	200	1650

Note: *p<0.1; **p<0.05; ***p<0.01

Donor	Treated Unit													Donor Appearance
	Connecticut	Delaware	Massa chusetts	Maryland	Maine	New Hampshire	New York	Rhode Island	Vermont	Ohio	Penn sylvania	Virginia	West Virginia	
Alabama	0.00%	0.00%	0.00%	9.28%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.85%	2
Florida	0.00%	38.28%	17.77%	15.87%	50.21%	3.57%	42.19%	0.00%	0.00%	0.00%	0.00%	15.26%	0.00%	7
Georgia	0.00%	0.00%	0.00%	29.53%	13.91%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	25.94%	0.00%	3
Idaho	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	9.86%	2.47%	89.47%	0.00%	0.00%	0.00%	0.00%	3
Indiana	0.00%	35.32%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	46.34%	0.00%	0.00%	0.00%	2
Kentucky	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	15.06%	1
Louisiana	47.44%	0.00%	51.37%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
Michigan	1.37%	0.00%	0.00%	0.00%	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
Minnesota	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.18%	5.20%	40.12%	1.33%	0.00%	4
Mississippi	0.00%	0.00%	14.49%	0.00%	0.00%	0.22%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
North Carolina	5.13%	7.19%	0.00%	0.00%	13.94%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3
North Dakota	0.00%	0.00%	0.00%	7.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	30.98%	2
New Mexico	0.00%	1.77%	0.00%	10.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	39.15%	3
Nevada	0.00%	17.44%	0.00%	0.00%	0.00%	0.00%	3.34%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
Oklahoma	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	48.77%	0.00%	0.00%	0.00%	0.00%	0.00%	1
Oregon	0.00%	0.00%	0.00%	0.00%	1.50%	10.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
South Carolina	46.06%	0.00%	0.00%	0.00%	0.00%	75.35%	0.00%	0.00%	0.00%	16.32%	38.78%	25.55%	0.00%	5
South Dakota	0.00%	0.00%	0.00%	27.96%	0.00%	10.70%	0.00%	0.00%	0.00%	0.00%	4.55%	25.28%	0.00%	4
Texas	0.00%	0.00%	16.37%	0.00%	0.00%	0.00%	16.87%	48.76%	0.00%	0.00%	0.01%	1.07%	0.00%	5
Utah	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	30.78%	16.55%	5.57%	0.00%	3
Washington	0.00%	0.00%	0.00%	0.00%	20.44%	0.00%	27.74%	0.00%	9.07%	0.00%	0.00%	0.00%	0.00%	3
Wyoming	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.28%	1.36%	0.00%	0.00%	11.96%	3
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	

Table B2.8: Weight matrix

Donor	Treated Unit													Donor Appearance
	Connecticut	Delaware	Massa chusetts	Maryland	Maine	New Hampshire	New York	Rhode Island	Vermont	Ohio	Penn sylvania	Virginia	West Virginia	
Alabama	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.19%	1
Arkansas	0.00%	0.00%	0.00%	38.66%	0.00%	0.00%	0.00%	0.00%	38.09%	0.00%	0.00%	0.00%	49.44%	3
Colorado	0.00%	33.53%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1
Florida	0.00%	0.00%	0.00%	0.00%	20.06%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	18.11%	0.00%	2
Georgia	0.00%	0.00%	0.00%	12.04%	2.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	9.72%	0.00%	3
Idaho	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	50.93%	0.00%	0.00%	0.00%	0.00%	1
Illinois	61.57%	0.00%	0.00%	0.00%	0.00%	7.83%	22.54%	0.00%	0.00%	0.00%	0.00%	13.64%	0.00%	4
Indiana	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	31.36%	6.76%	0.00%	0.00%	2
Kentucky	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%	18.55%	2
Louisiana	20.99%	0.00%	81.80%	0.00%	0.00%	0.00%	0.00%	48.30%	0.00%	0.00%	0.00%	0.00%	0.00%	3
Michigan	0.00%	0.00%	0.00%	0.00%	0.00%	19.16%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1
Minnesota	0.00%	0.00%	3.87%	28.18%	0.00%	0.00%	0.00%	0.00%	3.23%	17.34%	31.83%	29.17%	0.00%	6
Mississippi	0.00%	0.00%	0.00%	0.00%	36.43%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1
North Carolina	0.00%	42.43%	0.00%	0.00%	6.17%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2
North Dakota	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	20.82%	1
Nevada	0.00%	13.25%	14.33%	21.12%	0.00%	0.00%	55.84%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4
Oklahoma	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	46.31%	0.00%	0.00%	0.00%	0.00%	0.00%	1
Oregon	0.00%	0.00%	0.00%	0.00%	15.07%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1
South Carolina	0.00%	0.00%	0.00%	0.00%	2.01%	2.26%	0.00%	0.00%	0.00%	13.52%	24.45%	0.00%	0.00%	4
South Dakota	0.00%	0.00%	0.00%	0.00%	0.00%	56.99%	0.00%	0.00%	0.00%	0.00%	22.26%	26.59%	0.00%	3
Texas	17.44%	0.00%	0.00%	0.00%	0.00%	2.42%	9.57%	5.39%	0.00%	0.00%	5.81%	2.77%	0.00%	6
Utah	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	30.04%	8.87%	0.00%	0.00%	2
Washington	0.00%	3.96%	0.00%	0.00%	18.04%	11.34%	12.05%	0.00%	7.74%	0.00%	0.00%	0.00%	0.00%	5
Wyoming	0.00%	6.84%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.74%	0.00%	0.00%	0.00%	2
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	

TABLE B2.9: Weight matrix equal **V**

Variable	Treated Unit													T-Test	
	Connecticut	Delaware	Massa chusetts	Maryland	Maine	New Hampshire	New York	Rhode Island	Vermont	Ohio	Penn sylvania	Virginia	West Virginia	RGGI	Marcellus
CO2 Intensity	-0.0826 (0.0764)	-0.1561 (0.0006)	-0.0901 (0.0003)	0.0226 (0.4483)	-0.0232 (0.4414)	-0.0557 (0.021)	-0.0684 (0.0001)	0.1428 (0)	-0.0303 (0.0013)	-0.0301 (0.3124)	-0.0181 (0.4731)	-0.0308 (0.216)	0.1492 (0)	-0.0379 (0.2132)	0.0176 (0.7164)
Coal Generation Share	-2.3874 (0.2557)	-22.5653 (0.0011)	-5.7749 (0.0495)	3.3021 (0.4376)	0.583 (0.5472)	-1.7182 (0.4813)	-2.4243 (0.1308)	1.521 (0.0215)	0.0893 (0.0133)	-7.6574 (0.0892)	-7.0068 (0.0587)	-8.0703 (0.0306)	14.8597 (0)	-3.2639 (0.2394)	-1.9687 (0.749)
Natural Gas Generation Share	14.3642 (0.0002)	28.2769 (0)	11.264 (0.0058)	-8.1702 (0.0189)	-26.3189 (0.0075)	2.0028 (0.6569)	-6.692 (0.0123)	-5.0687 (0.0026)	-4.7046 (0.0006)	7.2317 (0.0554)	12.1309 (0.0001)	12.4873 (0.0042)	-2.026 (0.0237)	0.5504 (0.9191)	7.456 (0.1146)
Nuclear Generation Share	5.1144 (0.3101)	0 (NaN)	5.3613 (0)	10.662 (0)	-1.9524 (0.6291)	1.7191 (0.5662)	7.2658 (0)	0 (NaN)	-33.5426 (0.0019)	2.8607 (0.0001)	1.6262 (0.0914)	-0.8978 (0.5176)	-0.0842 (0)	-0.5969 (0.8938)	0.8762 (0.376)
Renewable Generation Share	-0.4456 (0.0844)	-0.6445 (0.1466)	0.7887 (0.3197)	-3.5911 (0.0092)	18.5175 (0.0002)	0.6489 (0.5311)	3.1467 (0.0095)	-12.1171 (0)	36.0711 (0.0001)	-2.856 (0)	-5.4265 (0)	-3.0539 (0.0011)	-7.9615 (0)	4.7083 (0.3494)	-4.8245 (0.0275)
Coal Capacity per Capita	0.1318 (0.0021)	-0.1893 (0.0657)	-0.019 (0.6018)	0.2322 (0.0001)	0.0002 (0.988)	0.1463 (0.0053)	0.0359 (0.1375)	0.0096 (0.0847)	0 (NaN)	-0.0736 (0.4814)	-0.0752 (0.3308)	0.009 (0.88)	-0.0675 (0.645)	0.0386 (0.3656)	-0.0518 (0.0841)
Natural Gas Capacity per Capita	0.2615 (0.1241)	0.6895 (0.0014)	-0.0051 (0.9782)	-0.4654 (0.0011)	-0.2604 (0.1662)	0.0398 (0.8429)	-0.0539 (0.5811)	0.1252 (0.4947)	-0.3183 (0)	0.0211 (0.8768)	0.1421 (0.3866)	0.0197 (0.8973)	-0.2557 (0.0382)	0.0014 (0.9903)	-0.0182 (0.8427)
Coal Capacity Share	0.0894 (0.9197)	-5.1452 (0.1409)	-2.7743 (0.1409)	9.6581 (0)	2.4935 (0.0519)	-0.4333 (0.7816)	-0.2379 (0.8188)	0.5741 (0.0238)	0 (NaN)	-2.7944 (0.5044)	0.8554 (0.7816)	-2.09 (0.3864)	15.2453 (0)	0.4694 (0.738)	2.8041 (0.5541)
Natural Gas Capacity Share	12.3323 (0.0019)	23.5473 (0.0001)	8.1191 (0.0229)	-5.5331 (0.1731)	-10.3489 (0.1391)	5.2487 (0.3396)	2.8553 (0.3997)	1.6516 (0.2914)	-6.1317 (0)	6.0805 (0.1599)	4.4639 (0.3106)	2.3617 (0.5575)	-3.0188 (0.0277)	3.5267 (0.3411)	2.4718 (0.3009)
Natural Gas Price	1.0874 (0.4008)	-1.0169 (0.4173)	0.6266 (0.6127)	-0.2331 (0.855)	0.1167 (0.9218)	2.2625 (0.1002)	-0.4783 (0.6861)	0.1595 (0.8935)	-1.3001 (0.2755)	-1.2911 (0.2642)	-1.2737 (0.3401)	-0.3224 (0.7935)	-1.6616 (0.1641)	0.136 (0.7188)	-1.1372 (0.0284)
Pipeline Export Capacity per Capita	-2262.204 (0)	-1015.0447 (0.0001)	-5973.9968 (0)	1205.8871 (0.0012)	659.8258 (0.0011)	-166.1041 (0.432)	-450.9007 (0.1871)	-9007.8187 (0)	-163.6615 (0)	2320.5573 (0.0876)	7280.0089 (0)	1386.4246 (0.0013)	3205.4231 (0.0205)	-1908.2242 (0.1305)	3548.1035 (0.0718)
Pipeline Import Capacity per Capita	-6121.8837 (0)	-2717.5711 (0)	-9453.0677 (0)	368.8421 (0.4568)	-1295.5253 (0.0001)	-608.3052 (0.0272)	1219.6189 (0.0097)	-1869.3528 (0)	-305.3009 (0.0002)	2294.5523 (0.0195)	1400.0889 (0.0005)	621.7801 (0.1358)	1303.6263 (0.1494)	-2309.1717 (0.0773)	1405.0119 (0.0264)
Natural Gas Price Industry	0.7216 (0.5841)	3.9536 (0.0057)	0.2358 (0.8795)	0.9005 (0.5042)	0.1315 (0.9339)	2.0738 (0.1671)	-0.6611 (0.6154)	2.7839 (0.0823)	0.6507 (0.6161)	-0.9616 (0.4395)	1.4447 (0.2491)	-0.4152 (0.7284)	-0.9411 (0.4385)	1.1989 (0.0389)	-0.2183 (0.7266)
Natural Gas Price Residential	-1.5888 (0.2062)	0.9184 (0.5484)	-1.2611 (0.3604)	-1.5009 (0.2923)	0.4155 (0.7906)	1.3822 (0.3319)	-2.159 (0.1011)	0.3062 (0.808)	3.7128 (0.0163)	-0.3999 (0.7525)	-0.6698 (0.5954)	-1.8284 (0.1929)	-0.5496 (0.6672)	0.025 (0.9688)	-0.8619 (0.0779)
Electricity Net Imports per Capita	-3777.8978 (0)	-962.6699 (0.1729)	458.6393 (0.2137)	440.3908 (0.3218)	3156.3105 (0.0027)	676.7666 (0.3853)	817.3943 (0.0001)	-664.7293 (0.1741)	4078.937 (0.0008)	-1891.9 (0)	-793.7224 (0.0003)	-358.5969 (0.4453)	7914.6993 (0)	469.2379 (0.5551)	1217.62 (0.6268)
Electricity Price	7.1874 (0.0026)	1.9787 (0.2689)	5.6767 (0.0075)	4.0651 (0.0348)	-3.324 (0.0143)	-3.4246 (0.0046)	-2.0649 (0.2435)	4.4697 (0.0251)	-2.2433 (0.0015)	-1.778 (0.0006)	-4.8781 (0)	0.0789 (0.8855)	2.0202 (0.0063)	1.369 (0.3542)	-1.1392 (0.4942)
Electricity Consumption per Capita	-605.7488 (0.0044)	-1041.8799 (0.0006)	-1043.8415 (0.0001)	-2148.0645 (0)	447.013 (0.0081)	1306.7687 (0)	1055.1589 (0)	-361.9304 (0.0988)	1875.8989 (0)	-536.4998 (0.037)	887.1935 (0.0015)	89.7369 (0.7442)	-1381.5767 (0.0425)	-57.4029 (0.8989)	-235.2865 (0.6579)
Electricity Price Industry	7.0455 (0.0022)	2.04 (0.2809)	6.7899 (0.001)	2.8518 (0.1733)	-3.0331 (0.1512)	-3.057 (0.0082)	-4.625 (0.0191)	4.605 (0.0202)	-3.4723 (0)	-1.4685 (0.004)	-3.9803 (0)	1.6216 (0.0072)	1.4341 (0.0179)	1.0161 (0.5293)	-0.5983 (0.6835)
Electricity Price Residential	8.2492 (0.002)	0.2676 (0.8762)	7.0773 (0.0044)	4.9106 (0.0065)	-5.2484 (0.0002)	-3.0696 (0.0576)	-3.1133 (0.0367)	4.657 (0.0337)	-1.8258 (0.0159)	-2 (0.0314)	-2.9364 (0.0022)	-0.0994 (0.8671)	2.6818 (0.0091)	1.3227 (0.4484)	-0.5885 (0.6674)
GDP in Manufacturing per Capita	-1.8074 (0.0035)	-2.4392 (0)	-1.2392 (0.0421)	0.7318 (0)	-0.263 (0.1979)	-0.5975 (0.2954)	-1.0872 (0)	-1.2451 (0)	-0.2025 (0.5584)	-1.687 (0)	-0.8218 (0.0001)	-0.1339 (0.5816)	0.5587 (0.0247)	-0.9055 (0.0205)	-0.521 (0.3572)
Natural Gas Generation Efficiency	-1.2014 (0.5759)	-4.5424 (0.0119)	-2.7824 (0.0571)	-3.566 (0.1565)	1.8545 (0.6444)	3.4035 (0.3491)	-1.2444 (0.3151)	-3.9459 (0.0041)	-1.4434 (0.7264)	5.3023 (0.0507)	-3.2475 (0.1034)	-4.0755 (0.0245)	-3.0348 (0.6476)	-1.4964 (0.1299)	-1.2639 (0.6059)
Coal Generation Efficiency	-3.27 (0.0055)	-3.0785 (0.0027)	-6.7787 (0.0629)	-2.1229 (0)	17.7862 (0.0056)	-1.5992 (0.0022)	-0.153 (0.5996)	0 (NaN)	0 (NaN)	-0.4228 (0.0043)	-0.9131 (0.0015)	-0.8061 (0.0243)	-0.7529 (0)	0.0871 (0.971)	-0.7237 (0.0064)
Electricity Consumption Industry per Capita	-363.3162 (0.0011)	-1332.5626 (0)	75.7222 (0.7718)	-1808.3448 (0)	-345.6474 (0.1324)	816.4696 (0)	134.8639 (0.4541)	-367.0825 (0.0004)	695.2517 (0.0127)	-703.4844 (0.0053)	987.5622 (0)	26.8283 (0.7691)	-1015.5451 (0.0087)	-277.1829 (0.3618)	-176.1598 (0.7188)
Gasoline Consumption per Capita	-0.0616 (0.1197)	-0.0474 (0.2632)	-0.1952 (0)	0.015 (0.654)	0.0015 (0.9788)	-0.0067 (0.9012)	0.1416 (0)	0.3127 (0.0001)	0.0967 (0.0484)	0.0194 (0.3691)	-0.1928 (0.0001)	-0.0599 (0.1188)	0.1753 (0.0012)	0.0285 (0.5671)	-0.0145 (0.8625)
CDD	-58.8242 (0.4659)	34.3705 (0.6531)	-73.8315 (0.3279)	35.3427 (0.6522)	-147.5463 (0.0141)	-117.2753 (0.0748)	-55.6285 (0.382)	-69.4188 (0.4371)	8.8634 (0.8448)	21.3809 (0.7772)	14.5071 (0.8219)	20.882 (0.7942)	44.6784 (0.4968)	-49.3275 (0.05)	25.3621 (0.0314)

Table B2.10: Individual treatment effects

Variable	Treated Unit													T-Test	
	Connecticut	Delaware	Massa chusetts	Maryland	Maine	New Hampshire	New York	Rhode Island	Vermont	Ohio	Penn sylvania	Virginia	West Virginia	RGGI	Marcellus
CO2 Intensity	-0.0607 (0.198)	-0.1409 (0.0021)	-0.0924 (0.0004)	-0.0023 (0.9359)	-0.0389 (0.1834)	-0.004 (0.8874)	0.0239 (0.3342)	0.1162 (0)	-0.0047 (0.4277)	-0.018 (0.542)	-0.0112 (0.6634)	-0.0076 (0.756)	0.0758 (0)	-0.0226 (0.3816)	0.0097 (0.6892)
Coal Generation Share	-3.4114 (0.1287)	-20.8954 (0.0027)	-5.0826 (0.0941)	-0.1683 (0.9678)	0.5184 (0.4796)	-0.6151 (0.8325)	2.7656 (0.2921)	0.9711 (0.0312)	0.502 (0.0362)	-7.8036 (0.0782)	-7.3402 (0.0488)	-9.6445 (0.0086)	8.1384 (0)	-2.824 (0.2716)	-4.1625 (0.3878)
Natural Gas Generation Share	21.695 (0)	37.7176 (0)	16.148 (0.0002)	-6.8532 (0.0543)	-26.047 (0.0084)	10.5507 (0.0195)	-5.8166 (0.0757)	-5.0555 (0)	-8.7159 (0)	8.5934 (0.0206)	14.4303 (0)	17.4626 (0.0001)	-8.5774 (0)	3.7359 (0.5787)	7.9772 (0.2638)
Nuclear Generation Share	3.663 (0.4698)	0 (NaN)	3.4904 (0.0012)	13.8398 (0)	-0.4104 (0.9195)	0.3287 (0.9092)	4.9921 (0.0001)	0 (NaN)	-30.8169 (0.004)	3.2068 (0)	1.4147 (0.0982)	-0.3691 (0.7832)	0.3472 (0.0442)	-0.5459 (0.8965)	1.1499 (0.2356)
Renewable Generation Share	-5.238 (0)	-4.1055 (0.0001)	0.9225 (0.2538)	-2.5338 (0.0051)	19.5541 (0.0001)	-7.2788 (0.002)	-2.0473 (0.1757)	-7.4484 (0)	32.2739 (0.0003)	-4.4562 (0)	-7.0035 (0)	-8.046 (0)	-0.8363 (0.1767)	2.6776 (0.5766)	-5.0855 (0.0505)
Coal Capacity per Capita	0.0709 (0.0089)	-0.2158 (0.0333)	0.0656 (0.1209)	0.1076 (0.0127)	0.0156 (0.1839)	0.0301 (0.0955)	0.1542 (0.0022)	0.0096 (0.0179)	-0.0736 (0)	-0.0873 (0.3856)	-0.1171 (0.1189)	-0.0409 (0.4287)	-0.4278 (0.0021)	0.0182 (0.6288)	-0.1683 (0.1516)
Natural Gas Capacity per Capita	0.3846 (0.014)	0.8089 (0.0001)	0.1024 (0.5374)	-0.4461 (0.0151)	-0.302 (0.227)	0.1506 (0.3752)	-0.1922 (0.1238)	0.0511 (0.7994)	-0.3641 (0.0006)	0.0158 (0.9032)	0.2003 (0.2024)	0.0703 (0.602)	-0.312 (0.0799)	0.0215 (0.8768)	-0.0064 (0.9568)
Coal Capacity Share	1.6043 (0.2347)	-1.6817 (0.6559)	-1.0689 (0.5591)	10.1658 (0.0002)	1.9327 (0.1169)	0.1621 (0.9049)	4.3344 (0.0136)	0.4114 (0.0378)	0.155 (0.0118)	-1.684 (0.6853)	-1.3988 (0.6287)	0.9869 (0.6916)	2.9275 (0.1985)	1.7795 (0.1772)	0.2079 (0.8605)
Natural Gas Capacity Share	15.6639 (0.0003)	27.8623 (0)	9.5189 (0.0059)	-4.4487 (0.3246)	-4.184 (0.5389)	9.3505 (0.0729)	3.0189 (0.4134)	-1.5655 (0.1953)	-5.5482 (0.0028)	5.9203 (0.1658)	7.3685 (0.0792)	3.3635 (0.3906)	-3.3592 (0.1096)	5.5187 (0.1779)	3.3233 (0.2564)
Natural Gas Price	0.6154 (0.6341)	-1.5521 (0.1868)	0.7644 (0.5364)	-0.4342 (0.7298)	0.2714 (0.8155)	1.6834 (0.1953)	-0.2805 (0.8166)	0.3452 (0.7784)	-0.8948 (0.4492)	-1.4024 (0.2148)	-1.2744 (0.3408)	-0.6207 (0.6263)	-1.6861 (0.1738)	0.0576 (0.8623)	-1.2459 (0.0117)
Pipeline Export Capacity per Capita	-6156.2356 (0)	-2252.6339 (0)	-4487.238 (0)	-237.1448 (0.5836)	-2585.4138 (0)	-533.478 (0.0093)	-1666.7303 (0.0005)	-5209.6337 (0)	-1572.4889 (0)	2419.1371 (0.0732)	6584.8178 (0)	712.8553 (0.1138)	1729.936 (0.2232)	-2744.5552 (0.0042)	2861.6865 (0.1131)
Pipeline Import Capacity per Capita	-4945.1775 (0)	-2278.1594 (0)	-10933.2374 (0)	703.4239 (0.1736)	-4953.5364 (0)	-304.0089 (0.2091)	615.2895 (0.203)	-6565.3038 (0)	-821.3986 (0.0002)	2740.6735 (0.0045)	1246.1681 (0.0013)	437.6142 (0.3182)	437.8061 (0.659)	-3275.7898 (0.0359)	1215.5655 (0.1111)
Natural Gas Price Industry	0.5817 (0.6526)	3.6052 (0.0121)	0.4538 (0.7694)	0.4225 (0.756)	0.1534 (0.9208)	1.0487 (0.4761)	0.2303 (0.8571)	2.8463 (0.0779)	0.3777 (0.767)	-1.0267 (0.4059)	1.5017 (0.2284)	-0.6645 (0.576)	-1.321 (0.2942)	1.08 (0.0328)	-0.3776 (0.597)
Natural Gas Price Residential	-1.2554 (0.2649)	1.4553 (0.3176)	-0.9249 (0.4927)	-1.0154 (0.4388)	1.3188 (0.3777)	1.6848 (0.2007)	-0.9924 (0.4145)	0.4988 (0.7034)	3.2894 (0.0346)	-0.5031 (0.6888)	-0.4507 (0.7186)	-1.1671 (0.3627)	-1.1312 (0.4041)	0.451 (0.4212)	-0.813 (0.0249)
Electricity Net Imports per Capita	-2493.7191 (0.0001)	-808.0509 (0.2532)	-1069.4438 (0.0481)	1930.9892 (0)	5016.8097 (0)	190.4466 (0.8477)	285.2915 (0.2541)	-1749.0781 (0.0012)	3990.583 (0.0009)	-1968.8407 (0)	-1004.7144 (0.0023)	155.2097 (0.7444)	11496.5352 (0)	588.2031 (0.512)	2169.5475 (0.5392)
Electricity Price	9.4498 (0.0002)	2.1279 (0.2163)	6.6308 (0.0018)	4.9572 (0.0113)	-3.743 (0.005)	-1.7057 (0.1504)	-0.1563 (0.9313)	5.0562 (0.0085)	-0.4931 (0.3169)	-1.7271 (0.0007)	-4.2358 (0)	0.6256 (0.2585)	2.3366 (0.0027)	2.4582 (0.1278)	-0.7502 (0.6361)
Electricity Consumption per Capita	-1079.5152 (0)	-1227.5742 (0)	-1464.7347 (0)	-986.6104 (0.0015)	-20.7909 (0.8899)	-1282.8996 (0)	790.1763 (0)	-1318.9564 (0)	873.9367 (0)	-858.0362 (0.0021)	199.2201 (0.471)	-555.3644 (0.0473)	17.2859 (0.9779)	-635.2187 (0.0749)	-299.2237 (0.3109)
Electricity Price Industry	7.8218 (0.0009)	2.9574 (0.1058)	8.4754 (0.0001)	4.5595 (0.0321)	-2.6701 (0.1969)	-2.5793 (0.0223)	-1.4922 (0.4504)	5.2944 (0.006)	-1.9285 (0.0012)	-1.416 (0.0051)	-3.87 (0)	1.6912 (0.005)	1.6143 (0.0125)	2.2709 (0.1707)	-0.4951 (0.7358)
Electricity Price Residential	9.9113 (0.0006)	0.6733 (0.6851)	7.6531 (0.0019)	5.4493 (0.0029)	-6.1273 (0)	-2.2096 (0.179)	-3.314 (0.0314)	5.8174 (0.0058)	0.6205 (0.3278)	-1.9743 (0.0315)	-2.2906 (0.0132)	0.1778 (0.7778)	3.9353 (0.0002)	2.0527 (0.2903)	-0.0379 (0.9805)
GDP in Manufacturing per Capita	-2.1527 (0.0001)	-1.8006 (0.0008)	-1.7764 (0.0513)	0.6157 (0)	-0.3329 (0.1073)	-1.3339 (0.0199)	-1.1394 (0)	-1.8061 (0.0022)	-0.0824 (0.764)	-1.6803 (0)	-0.9734 (0)	-0.7201 (0.0017)	0.236 (0.2563)	-1.0898 (0.0087)	-0.7844 (0.1421)
Natural Gas Generation Efficiency	-1.4507 (0.5161)	-3.2809 (0.0631)	-2.1998 (0.1176)	-3.4159 (0.1428)	0.435 (0.914)	2.5654 (0.4543)	-2.8529 (0.0373)	-3.6605 (0.0054)	-3.0447 (0.4607)	5.8945 (0.0257)	-3.4783 (0.0668)	-3.4014 (0.0181)	-5.45 (0.2383)	-1.8783 (0.0277)	-1.6088 (0.5723)
Coal Generation Efficiency	-3.8311 (0.0013)	-3.5655 (0.0006)	-6.8065 (0.0622)	-2.6712 (0)	18.1422 (0.0048)	-1.8607 (0.0024)	0.1534 (0.6746)	0.0342 (0.1484)	-0.127 (0.0002)	-0.6833 (0)	-0.8936 (0.0054)	-1.3419 (0.0006)	-1.084 (0)	-0.0591 (0.9809)	-1.0007 (0.0057)
Electricity Consumption Industry per Capita	-586.6167 (0)	-1468.2916 (0)	-107.3561 (0.7235)	-917.5706 (0.021)	-483.1717 (0.0376)	-598.5148 (0)	169.2442 (0.1748)	-905.1486 (0)	539.5475 (0.0023)	-880.9935 (0.0006)	565.9689 (0)	-357.9896 (0.001)	270.7347 (0.4087)	-484.2087 (0.0444)	-100.5699 (0.7764)
Gasoline Consumption per Capita	-0.0229 (0.5324)	-0.0824 (0.0601)	-0.2665 (0)	0.0116 (0.7506)	-0.122 (0.0341)	-0.0015 (0.9772)	0.0813 (0.007)	0.1988 (0.0071)	0.1325 (0.0083)	0.0199 (0.3225)	-0.2022 (0)	-0.0618 (0.0995)	0.2066 (0.0003)	-0.0079 (0.8697)	-0.0094 (0.9194)
CDD	22.8839 (0.7541)	82.5387 (0.2458)	-33.4545 (0.6259)	69.6903 (0.3768)	-92.5548 (0.0643)	28.0657 (0.5864)	29.7762 (0.6282)	-54.4252 (0.5203)	-15.7245 (0.7399)	37.3612 (0.6054)	33.0531 (0.6126)	80.8876 (0.2826)	23.4284 (0.7864)	4.0884 (0.8369)	43.6826 (0.0416)

TABLE B2.11: Individual treatment effects equal **V**

Variable	RGGI		Marcellus	
	Estimate	SE	Estimate	SE
CO2 Intensity	-0.009	0.029	0.002	0.039
Coal Generation Share	-0.914	3.186	-4.662	4.884
Natural Gas Generation Share	2.711	2.756	9.149	3.794
Nuclear Generation Share	-1.877	1.002	0.288	1.306
Renewable Generation Share	-0.187	3.010	-4.734	3.846
Coal Capacity per Capita	0.050	0.087	-0.200	0.116
Natural Gas Capacity per Capita	0.113	0.082	0.142	0.102
Coal Capacity Share	0.355	1.770	-2.474	2.325
Natural Gas Capacity Share	4.938	1.855	6.500	2.513
Natural Gas Price	0.146	0.314	-1.355	0.412
Pipeline Export Capacity per Capita	-877.118	840.796	3198.282	1279.456
Pipeline Import Capacity per Capita	-683.049	847.695	1432.709	1380.741
Natural Gas Price Industry	0.445	0.301	-0.577	0.410
Natural Gas Price Residential	0.069	0.318	-1.075	0.448
Electricity Net Imports per Capita	817.401	707.070	1796.675	870.844
Electricity Price	2.272	0.890	-0.182	0.996
Electricity Consumption per Capita	214.155	501.882	-307.488	669.907
Electricity Price Industry	2.591	0.927	0.133	1.236
Electricity Price Residential	1.168	0.929	0.297	1.221
GDP in Manufacturing per Capita	-0.514	0.244	0.004	0.381
Natural Gas Generation Efficiency	-2.199	1.497	0.765	1.955
Coal Generation Efficiency	-1.975	0.295	-0.325	0.429
Electricity Consumption Industry per Capita	105.436	369.173	-399.772	470.822
Gasoline Consumption per Capita	0.000	0.023	-0.081	0.033
CDD	55.989	23.786	32.148	33.557

TABLE B2.12: SDID results.

C1 Additional Tables

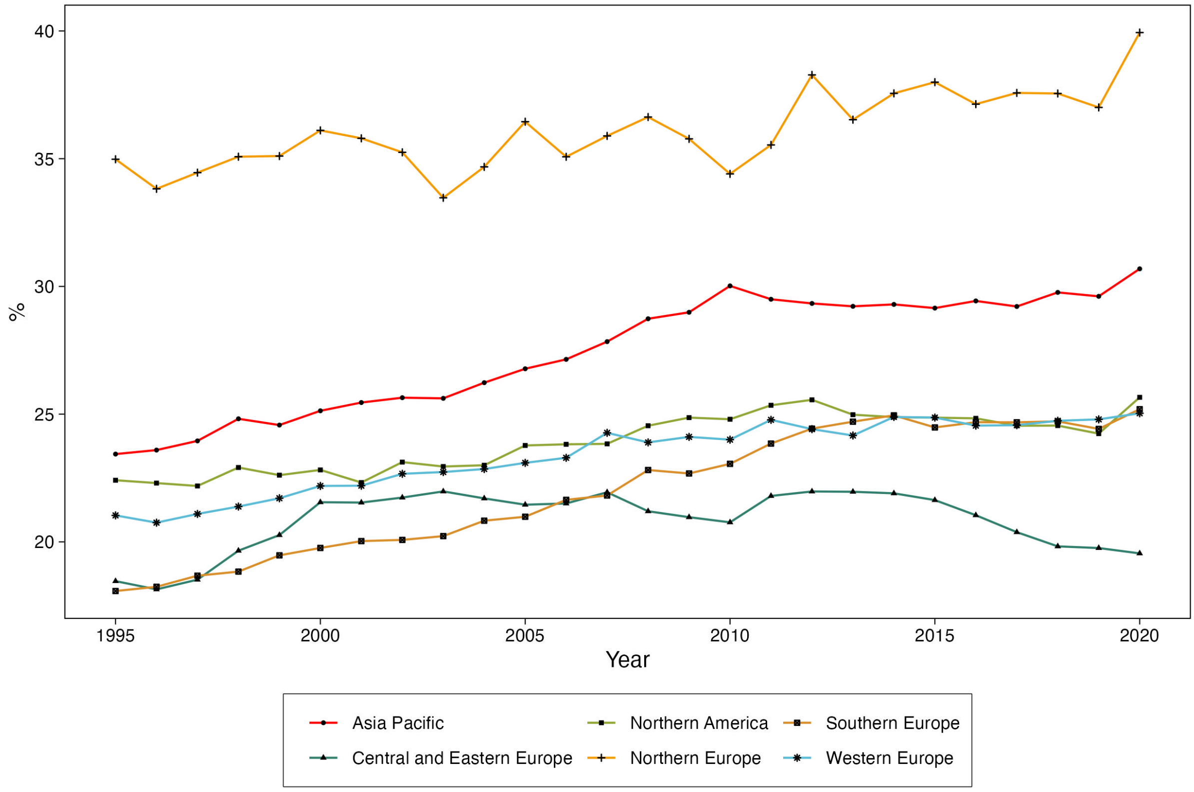


FIGURE C1.1: Energy consumption share of the power sector in selected regions from 1995 to 2020 (International Energy Agency, 2024a).

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