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Essays on Environmental Economics

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I, **Mamdouh Abdelkader**, declare that this thesis titled, *“Essays on Environmental Economics”* and the work presented in it are my own. Chapter three of this thesis is co-authored with Prof. Lilia Karnizova, with equal contribution from both of us. I hereby acknowledge the contribution of Prof. Lilia Karnizova for the research related to chapter three.

I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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Abstract

This dissertation investigates how diverse policy levers can drive the transition to a low-carbon economy. The first chapter uses dynamic system GMM panel estimation on U.S. electricity sector data (2000–2015), grounded in a theoretical framework inspired by the Directed Technical Change literature, to compare carbon pricing, clean energy tax incentives, and R&D subsidies. It finds that price-based instruments, such as carbon pricing and clean energy tax credits, induce a more immediate and pronounced shift toward renewable generation than R&D subsidies, underscoring the effectiveness of price signals in accelerating the energy transition. The second chapter develops a dynamic general equilibrium model to evaluate a broader suite of climate policies. These include carbon pricing, R&D subsidies, dirty investment taxes, and clean investment tax credits. Policies targeting high-emission sectors, notably carbon pricing, effectively cut emissions due to these sectors' significant market share, but may negatively impact economic prosperity. To balance emissions reduction and economic vitality, the essay proposes a clean "double dividend" strategy, using revenues from dirty-sector taxes to fund clean-sector incentives. This provides a balanced pathway toward reducing emissions while sustaining economic performance. Finally, the third chapter turns to monetary policy, using a structural vector autoregression to quantify how interest rate shocks affect CO_2 emissions across U.S. sectors. It finds that contractionary monetary policy produces a persistent yet transitory negative effect on total CO_2 emissions. These monetary policy shocks primarily affect industrial emissions while minimally impacting the residential and commercial sectors. Given central banks' limited capacity to directly influence environmental outcomes, monetary policy should thus be considered complementary to fiscal policy and environmental regulation in addressing climate change.

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General Introduction

This dissertation consists of three essays in environmental economics, each addressing key policy questions at the intersection of economic activity and environmental sustainability. These essays examine crucial topics. This includes the role of carbon pricing and R&D subsidies in accelerating the transition to renewable energy. In addition, it involves exploring the effectiveness of various environmental policy instruments within a dynamic general equilibrium framework. Finally, it involves evaluating the environmental impact of monetary policy. Together, these chapters contribute to the growing literature on the economic forces of the clean technology transition, the design of environmental policies to achieve emission reduction targets, and the relationship between macroeconomic policies and climate change.

The first chapter examines the transition to renewable energy in the U.S. electricity generation sector, focusing on how carbon pricing, clean tax incentives, and R&D subsidies influence the shift from fossil fuels to renewable energy sources. Using a theoretical framework grounded in the literature on directed technical change (DTC), this study analyzes the comparative strength of demand-side measures such as carbon pricing versus supply-side interventions such as R&D subsidies. Employing a System Generalized Method of Moments (GMM) methodology on panel data for electricity generation across U.S. states and various producers between 2000 and 2015, the findings reveal that tax adjustments—fossil fuel taxes and green tax incentives—have a more immediate and pronounced impact on renewable energy transition than R&D subsidies. This chapter highlights the critical role of policy balance, demonstrating that focusing on relative ratios (e.g. tax-inclusive price ratios of clean to dirty energy or R&D subsidy ratios) can drive the green transition effectively. These insights inform policymakers on prioritizing policies that align with climate targets while minimizing economic trade-offs.

The second chapter expands the scope of the analysis by evaluating multiple environmental policy instruments—carbon pricing, R&D subsidies, dirty investment taxes, and clean investment tax credits (ITCs)—within a dynamic general equilibrium (DGE) model inspired by the DTC framework. A key contribution of this chapter is the integration of a savings mechanism into the DTC framework. This allows for an in-depth exploration of how policies influence both relative costs and investment behaviors across clean and dirty sectors. This also allows the analysis to extend the scope of the policies examined to include clean ITCs, which have recently been highlighted in policy discussions. By incorporating endogenous technology and investment dynamics, this model provides a more comprehensive understanding of the impact of policies. The findings reveal that policies targeting the dirty energy sector, such as carbon taxes and dirty investment taxes, are particularly effective in reducing emissions. However, they may slow economic growth because of the sector's large market share. Demand-side policies, such as clean input tax credits, accelerate the transition to cleaner technologies when substituting clean and dirty production is feasible. This chapter also proposes a "clean double dividend" strategy, where revenues from dirty-sector policies fund clean-sector incentives to balance environmental objectives with economic growth.

The third chapter shifts focus to the environmental impact of monetary policy, exploring how monetary policy shocks influence CO_2 emissions in the U.S. Using a structural Vector Autoregressive (VAR) model, the study identifies monetary policy shocks through the recursiveness assumption and assesses their effects on total emissions and emissions from major polluting sectors. The analysis finds that contractionary monetary policy reduces total emissions modestly and temporarily. Industrial emissions show the strongest response, while residential and commercial emissions remain unaffected. By highlighting the heterogeneous impact of monetary policy across sectors, this chapter emphasizes the importance of sectoral disaggregation in both theoretical models and policy design. Although monetary policy has a limited role in directly reducing emissions, it can complement fiscal and environmental policies in addressing climate change.

Methodologically, this dissertation combines theoretical modelling and empirical analysis to address its research questions. The first chapter integrates the DTC-inspired theoretical framework with econometric techniques such as System GMM to deal with endogeneity and unobserved heterogeneity. The second chapter develops a DGE model with endogenous technology and investment dynamics that can be used to simulate policy under different sets of scenarios. The third chapter applies structural VAR models to identify monetary policy shocks and analyze their environmental effects. Across all chapters, methodologies are chosen to ensure robust and policy-relevant insights.

The contributions of this dissertation are diverse. It extends the DTC literature by incorporating savings mechanisms and broadening the range of policies analyzed. It offers new empirical evidence on the drivers of the green transition in the electricity sector. It also provides insights into the environmental consequences of monetary policy. By addressing these issues, this dissertation aims to offer insights that could help policymakers in designing effective and balanced strategies for promoting environmental sustainability and economic prosperity in the face of climate change.

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Chapter 1

Transition to Renewable Energy: The Role of Carbon Pricing and Research Subsidies in Electricity Generation for U.S. Industries

1.1 Abstract

This paper sheds new light on the potential effects of tax reform policy (including fossil fuel taxes and clean energy tax incentives) and R&D subsidies on the transition from fossil fuels to renewable energy. We develop a theoretical framework inspired by the DTC literature, emphasizing the interplay between taxation and R&D subsidies in the green energy transition. This framework allows us to predict the effects and relative strength of these policies. We uniquely apply the DTC framework to U.S. electricity generation, often overlooked in past relevant research. We use data for electricity generation categorized by producer types across states between 2000 and 2015. Our empirical analysis employs System GMM and fixed effects to address potential endogeneity and unobserved heterogeneity. Results align with our theoretical predictions regarding both policy instruments' effects and relative intensities. The results suggest that tax reforms (fossil fuel taxes and green tax incentives) make renewables more price-competitive with fossil fuels. The evident substitutability of renewable and fossil fuels enables this tax adjustment to be superior to R&D subsidies in accelerating the green transition, as it motivates demand-side participants to shift to these green alternatives. We recommend policymakers prioritize tax adjustments over R&D subsidies if the goal is to reduce emissions and accelerate the green transition within a shorter timeframe. We also emphasize that a careful reallocation of R&D subsidies, favouring clean energy, while assessing their genuine impact

on productivity, remains crucial.

1.2 Introduction

Over the recent decades, rising atmospheric temperatures and higher CO_2 emissions, especially since the 1950s, have brought the issue of climate change into the spotlight. Global temperature records from 2013 to 2021 show these years to be the warmest on record, correlating with atmospheric CO_2 peaks (NOAA 2021). This challenges policymakers to devise plans to curtail fossil fuel consumption. The Paris Agreement of 2015, where members committed to reducing emissions, can be seen as a culmination of these ongoing efforts, which started in 1998, toward a climate agreement. To achieve this, dependence on fossil fuels must be reduced, ideally by adopting alternative clean energy sources.

In this study, we examine whether tax adjustments (fossil fuel taxes and green tax incentives) and R&D subsidies can help the U.S. electricity generation sector shift to renewable energy sources such as solar power, wind power, and biofuels. In 2020, renewable energy accounted for only 21% of U.S. electricity production. Research subsidies can encourage innovation in renewable energy, thereby lowering costs and making renewable technologies price-competitive with fossil fuels. The taxation of fossil fuels, combined with tax incentives for using green energy, may also increase the relative cost of fossil fuels, thus making renewable alternatives more competitive. We examine the effects of both policy instruments—tax policy and R&D subsidies—and evaluate their relative strength.

In recent years, a variety of studies have examined policies aimed at reducing carbon emissions, reducing fossil fuel consumption, and promoting clean alternatives; in particular, the literature on DTC that examines the role of different environmental policies in the transition to cleaner technologies. The research in this area includes works such as Acemoglu et al. (2012, 2014, 2016), Mattauch et al. (2015), Hart (2019). Essentially, this literature focuses on three pillars: the substitution of 'dirty' and 'green' production inputs, their innovation potential, and the environmental impact of dirty inputs. Research suggests that carbon taxes and R&D subsidies can promote cleaner alternatives. However, policy effectiveness relies mainly on the assumed substitutability of inputs and how innovation is modeled. Similarly, a number of empirical studies have analyzed environmental policies that support clean technology, such as Aghion et al. (2016), Noailly and Smeets (2015), Lazkano and Pham (2016), Johnstone et al. (2010). For instance, Aghion et al. (2016) constructed firm-level data across 80 countries in the auto industry to evaluate the role of environmental policies, in particular fossil fuel taxes and R&D subsidies, in promoting technical change toward clean technologies. Meanwhile, Noailly and Smeets (2015) follow a relatively similar approach but use firm-level data on a number of European countries in the renewable energy sector.

This research makes the following contributions. To begin with, it focuses on the electricity generation sector in the U.S., which contributes significantly to CO_2 emissions and primary energy consumption. It accounts for 37.25%[1] of the total CO_2 emissions in the U.S. between 2000 and 2022. There has been a noticeable shift toward the use of renewable energy in this sector. The U.S. electricity generation from renewable resources increased from 9 to 21 percent between 2000 and 2020. Studying this sector offers insights into the growing shift towards green energy and valuable lessons for other contexts, especially in the Canadian economy. Further, investigating the drivers of this shift may also stimulate a greater transition to renewable energy.

There have been previous studies that focus on the U.S. electricity generation sector, such as Fischer and Newell (2008) and Borenstein and Kellogg (2023). The current study offers new insights by incorporating the DTC framework theoretically and empirically to evaluate the role of different drivers - including policy variables - of the green transition. With DTC, different policy instruments can be incorporated into a framework for guiding technological change toward cleaner energy alternatives. The empirical studies that have been inspired by the DTC literature, such as those by Aghion et al. (2016) and Noailly and Smeets (2015), have not been extended to the U.S. electricity generation industry. For instance, Noailly and Smeets (2015) empirically examined DTC in the electricity generation sector in several European countries from 1978 to 2006, but a comparable analysis for the electricity generation sector in the U.S. has not been undertaken. In this study, we aim to fill this gap by exploring the transition of the U.S. electricity generation sector to renewable energy sources based on DTC frameworks.

[1] The percentage is calculated based on data on CO_2 emissions from various energy sources within the U.S. economy, obtained from the U.S. Energy Information Administration (EIA).

Second, the current research emphasizes the importance of ratios, not just absolute levels. The research focuses on renewable energy's ratio to fossil fuel energy rather than their absolute levels. Also, we evaluate the effects of tax reforms and research subsidies in terms of their ratios (i.e., how they apply to clean versus dirty energy). A ratio-based approach helps align climate objectives with economic concerns. In other words, the growing ratio of clean energy use to fossil fuel use guarantees a shift toward clean energy while bearing a lower economic burden. By contrast, only focusing on fossil fuel reductions (or associated emissions) may hinder economic growth if clean alternatives do not evolve. Likewise, targeting only clean energy growth is not sufficient to ensure a clean transition if fossil fuel use continues to be dominant. By analyzing the evolving ratios, we can understand the transition from fossil fuels to green energy more clearly. This will help us achieve climate goals while maintaining economic prosperity.

Similarly, our research provides a key insight: it is the comparative ratio within each policy measure that impacts the pace of transition to renewable energy, rather than just the absolute magnitude of these policy measures. For example, while increasing renewable energy research subsidies appears an obvious step toward a green transition, their effects are weakened if fossil fuel research subsidies remain dominant. Accordingly, by considering the evolving ratio of this policy tool (i.e., the ratio of green R&D subsidy to dirty R&D subsidy), we ensure that clean energy promotion exceeds that of fossil fuels. This will accelerate the transition to green energy. Overall, our research delves into studying the impact of these policy balance ratios on green energy shifts, a perspective often overlooked in earlier research (e.g., Aghion et al. 2016, Noailly and Smeets 2015, Lazkano and Pham 2016).

Third, while it may be commonly established in previous empirical research that renewable subsidies increase renewable energy and carbon taxes reduce fossil fuels, our study provides new insights by identifying the measurable parameters on which these effects depend. By developing a robust theoretical framework, we derived definitive relationships that not only identify the key drivers of the green energy transition but also specify the theoretical coefficients associated with these drivers, which are also validated by our empirical analysis. For instance, our framework reveals that the theoretical impact of taxation policy is primarily influenced by the elasticity of substitution between green and dirty energy. Similarly, the effect of R&D subsidies depends on both this substitution elasticity and the elasticity of innovation with respect to research expenditure. Consequently, if we can measure these elasticities in a specific industry, we can predict the impact of these policy instruments, making this framework applicable across different industries and regions.

Based on this analysis, this study also examines the relative strengths of taxation and R&D subsidies. This comparison is crucial for policymakers, especially when aiming to achieve specific goals within a predetermined timeframe, such as reducing fossil fuel reliance in line with the commitments of the Paris Agreement 2015.[2] Identifying which policy is more effective allows for better resource allocation and the formulation of greater impact strategies to meet emission reduction targets— ideally by transitioning from fossil fuels to clean energy— within the agreed timeframes. Fourth, inspired by the DTC literature but tailored to the energy sector, we develop a theoretical framework examining not only the role of taxation but also the direct effects of R&D subsidies on the green energy transition. Following Aghion and Howitt (2008), we incorporate an innovation model from the modern industrial organization theory, emphasizing innovation's role in industrial competition. This model positions growth as a result of vertical innovations, and R&D endeavors play an essential part in driving this innovation.

In this study, we aim to address central questions related to the transition to renewable energy for electricity production within U.S. industry sectors: 1- How do changes in taxation — specifically fossil fuel taxes and tax incentives for green energy — impact the transition to renewable energy? 2- How effectively do research subsidies promote the shift to renewable energy in this sector? 3- Which policy exerts a greater influence on the transition to renewable energy: tax adjustments (through fossil fuel taxes or green tax incentives) or the provision of R&D subsidies? To address these questions, the study conducts an empirical investigation supported by a theoretical framework.

This study utilizes a theoretical framework that will serve as a basis for the empirical analysis. The purpose of this framework is to provide an economic interpretation and predictive

[2]In December 2015, all member nations signed the Paris Agreement, committing to emission reduction responsibilities. In particular, the agreement relies mainly on voluntary reduction pledges from member countries, as well as obligations from developed countries to aid developing countries. Under this framework, members submitted their intended nationally determined contributions. As an example, the U.S. has set a target of reducing greenhouse gas emissions by 26% below 2005 levels by 2025. The European Union has set a more ambitious goal, targeting a 40% reduction from 1990 levels by 2030 (Seo 2017).

assessment of the effect of R&D subsidies and fossil fuel taxes on the transition to renewable energy sources. The framework involves a discrete-time setting with an infinite-horizon economy, where a final good is produced in a competitive market. Two types of energy can be used to produce this good: dirty and clean. Dirty energy refers to fossil fuels like coal, oil, and natural gas. Renewable energy sources include solar, wind, geothermal, and hydropower. In addition to incorporating tax effects, this framework examines the influence of R&D subsidies on energy source innovation and expansion, as well as on the shift to clean energy.

For the empirical analysis, this final good is electricity production - a secondary energy source derived from dirty and clean primary energy. The empirical model examines how taxes and research subsidies affect the shift from fossil fuel to renewable energy in the U.S. electricity generation sector. The data range from 2000 to 2015, and include diverse producer types and state levels of electricity generation. We employ System GMM as described in Arellano and Bover (1995) and Blundell and Bond (1998). System GMM's primary benefit lies in its ability to address fixed effects and endogeneity. In addition, this method offers more consistent and efficient parameter estimations than other panel data methods. We also use a fixed effects approach for additional and robustness estimations, accounting for cluster-robust standard errors.

In our research, theoretical predictions are reinforced by empirical evaluations. Our results reveal that changes in tax reform substantially favour the clean energy sector over the fossil fuel sector. Taxing fossil fuels or increasing green energy tax incentives reduces the relative cost of renewable energy, making it more competitive. This adjustment encourages final goods producers to choose green alternatives over fossil fuels. Our study also highlights the importance of reallocating R&D subsidies towards the green sector. To facilitate a smooth transition to renewables, public R&D subsidies must be increased for green energy and reevaluated and reduced for fossil fuel research.

Furthermore, we find that tax reform has a greater impact on the green energy transition than R&D subsidies. Taxation can directly influence market prices and the behaviour of demand-side participants, leading to rapid changes in energy choices. In contrast, R&D subsidies have a longer-term impact by fostering innovation and reducing green technology costs. The evident substitutability of renewable and fossil fuel energy makes tax reforms superior in motivating demand-side participants to accelerate the transition to renewable energy. However, the effectiveness of R&D subsidies is contingent on their ability to boost productivity, which depends on probabilistic innovation outcomes. Overall, demand-side policies, such as tax reforms, induce a faster shift towards clean energy sources compared to supply-side measures like R&D subsidies. Taxation can significantly change the relative costs between fossil fuel-based energy and renewable energy sources, encouraging shifts to greener alternatives. In contrast, the effects of R&D subsidies are more gradual, as innovation takes time to develop and bring successful new technologies to market.

Policy measures aimed at accelerating the reduction of fossil fuel dependency and curtailing emissions should place a greater emphasis on demand-side measures, such as tax reforms, because of their potential for quick impact. This approach is particularly the relevant when considering emissions reduction targets like those set by the Paris Agreement as benchmarks for environmental progress. Additionally, to ensure that R&D subsidies are driving genuine innovation, their provision should be contingent upon measurable outcomes. Such outcomes might include the achievement of high-value patents or significant productivity enhancements in the green technology sector, thereby supporting the ultimate goal of transitioning to a more sustainable energy sector.

The remainder of this paper unfolds as follows. Section 1.3 reviews relevant literature and confirms the research gap this study aims to fill. Section 1.4 introduces the theoretical framework and outlines the hypotheses to be empirically tested. Section 1.5 presents the data and the empirical methodology. Section 1.6 discuses the study's results and analyzes their robustness. The paper concludes with section 1.7.

1.3 Background and Related work

In this section, we first provide a brief background on the U.S. electricity generation sector to explain why it is suitable to investigate the impact of taxation and research subsidies on its transition to clean energy. We then review related literature, particularly those studies concerning DTC, which are useful in formulating a framework that considers various forces, including policy variables, in facilitating this transition. This section covers both theoretical and empirical literature relevant to the topic.

1.3.1 U.S. Electricity Sector: A Brief Overview

In this study, we primarily focus on the electricity industry, but it is important to examine the broader U.S. energy sector as well for background and justification. There are two types of energy: primary and secondary. Primary energy is the original form of energy found in nature, while secondary energy, mainly electricity, is produced using this primary energy. The primary energy sources in the U.S. are fossil fuels (oil, natural gas, and coal), nuclear energy, and renewables like solar, wind, geothermal, and hydroelectricity. Secondary energy, mainly electricity, is produced from these primary sources. As a secondary energy, electricity consumes a great deal of primary energy. In 2022, electricity generation accounted for 34% of U.S. energy consumption.[3] Electricity plays a significant role in the U.S. energy sector, as shown by this large share. Our study focuses on the role of policies in facilitating the shift of electricity generation from fossil fuels to renewable energy sources.

The electricity generated has different other producers that use it in their production. Specifically, this electricity is distributed to different end-use sectors such as residential, commercial, industrial, and transportation. The residential and commercial sectors, for example, use electricity for lighting, heating, and cooling. The industrial sector also uses electricity extensively, although natural gas and petroleum products remain dominant. Although liquid fuels such as gasoline and diesel continue to dominate the transportation sector, electric vehicles have taken off due to technological advancements and policy incentives. In our empirical analysis, we use panel data on electricity generation categorized by the industries or producers receiving this electricity. This is explained further in the empirical methodology section.

A focus on electricity generation is important. Electricity generation is a significant source of CO_2 emissions. In power plants, fossil fuels, such as coal and natural gas, produce a large amount of greenhouse gases. According to data provided by the U.S. Energy Information Administration (EIA), the sector accounts for 37.25.%[4] Efforts to reduce emissions from this sector can contribute substantially to national and international climate goals, such as those

[3]The percentage is obtained from the EIA website at the following link: https://www.eia.gov/energyexplained/us-energy-facts/data-and-statistics.php.

[4]The percentage is derived from data on CO_2 emissions from various sources within the U.S. economy.

outlined in the Paris Agreement.

The electricity industry is also subject to rapid technological changes in favour of cleaner alternatives. Over time, renewable energy technologies are integrated into power systems as prices fall and policies change. Data on electricity production indicate that renewable energy usage has increased due to policies, technological advancements, and market forces. Since 2000, renewable energy has increased from 9% to 21% of U.S. electricity production. As of 2022, renewable energy contributed 21.5% to U.S. electricity generation.[5] This highlights the sector's great adaptability to green alternatives. Studying this sector offers insights into a major shift towards green energy and can then be applied to other contexts, including the Canadian economy. Furthermore, it demonstrates the potential for a more substantial transition to renewable energy.

1.3.2 Related Works

To establish a framework for investigating the impact of various environmental policies, particularly taxation and research subsidies, we draw extensively from the literature on DTC. Consequently, our review of theoretical literature primarily focuses on this area. Additionally, we present relevant empirical studies, including those that utilize DTC, to provide an overview of empirical findings in this domain and to highlight the gap that our contribution aims to fill.

Theoretical Works:

The DTC literature emphasizes the effects of carbon taxes and government research subsidies in reducing emissions and fostering clean technology. This line of research focuses on the modelling of dirty and clean inputs, clean energy innovation, and the environmental impact of dirty goods. Taxes on carbon and research subsidies play an important role in this transition. A seminal work by Acemoglu et al. (2012) incorporates environmental constraints into the growth model, illustrating the influence of fossil fuel taxes and research subsidies in guiding the transition towards environmentally friendly technologies. R&D subsidies foster innovation and productivity in clean goods by increasing the cost of dirty inputs and expanding the market

[5] Refer to the following report for more details: https://www.eia.gov/energyexplained/electricity/electricity-in-the-us.php

for green alternatives.

Mattauch et al. (2015), building on Acemoglu et al. (2012)'s framework, introduce learning spillover effects in the clean sector. They argue that these spillovers can significantly lower the cost per unit of clean input production. Additionally, they suggest that government intervention is essential to prevent dirty technologies from dominating the market. A constant carbon tax and a learning subsidy[6] for clean technologies are recommended as optimal policy measures. Hart (2019) more directly focuses on the energy sector's role. Because Hart's work relies on a lower assumed value of the substitution elasticity between dirty and clean inputs, as reported by Papageorgiou et al. (2017), his findings suggest a more limited effect of environmental policies compared to earlier studies (e.g., Acemoglu et al. 2012), which assumed a relatively higher elasticity.[7]

Acemoglu et al. (2016) explore the transition towards clean technology by incorporating data from the energy sector into a microeconomic model, demonstrating competition between clean and dirty technologies for production and innovation. They assert that research subsidies and carbon taxes should theoretically encourage clean technology innovation and production. Acemoglu et al. (2014) further expand the scope of their model by including international trade and imitation of innovation, arguing that international policy coordination is necessary for successful transition to cleaner production.

In light of previous research insights, our theoretical framework undertakes a direct analysis of the energy sector. This diverges from traditional studies that concentrate on intermediate goods culminating in a single final good. The reason for this distinction is to directly evaluate the role of environmental policies in the shift to renewable energy. In addition, evaluating the direct effects of R&D subsidies on green energy requires a distinct model of innovation. Specifically, we focus on a model derived from modern organization theory, which views innovation as a crucial component of industrial competition (as described in Aghion and Howitt 2008, Chapter 4). In this model, growth is driven by a series of quality-enhancing (or "verti-

[6]The authors argue that the cumulative output of the clean sector leads to further endogenous technological advancement through learning by doing. Therefore, they describe the subsidy provided for the clean sector production as a "learning subsidy."

[7]In this context, Hourcade et al. (2012) criticize Acemoglu et al. (2012) for their reliance on an implausibly high value for the elasticity of substitution for their less pessimistic case. They argue that the projected high value for this parameter should be considerably lower. This is due to the restrictions of substituting between various fuel types such as natural gas and coal, or even between coal and certain renewable energy sources.

cal") innovations, and R&D effectiveness depends on its productivity adjustment (see the next section for more details). In the theoretical framework section, these features will be discussed in more detail.

Empirical Studies:

The DTC literature has inspired empirical studies such as Aghion et al. (2016) and Noailly and Smeets (2015), among others. Aghion et al. (2016) conducted a notable study using firm-level panel data to examine how environmental policies, such as carbon taxes and R&D subsidies, influence technological changes toward clean technologies within the automotive industry. They differentiated between 'dirty' and 'clean' patents across 80 countries from 1986 to 2005. They then used the Poisson model to estimate firm-level innovation determinants. Their findings highlighted that firms are more likely to innovate in clean technologies and reduce dirty technological innovations when faced with higher tax-inclusive fuel prices. In addition, the study highlighted the path dependency effect, which tends to maintain high carbon emissions, because the dirty sector initially had superior productivity. Moderate carbon taxes and R&D subsidies are then not adequate to lock in this path dependency effect.

Drawing from Aghion et al. (2016), Noailly and Smeets (2015)[8] investigated the impact of governmental policies on firm-level patenting activity in the renewable energy sector. Their study analyzed patent data from 5471 European firms engaged in research on fossil fuel and renewable energy technologies from 1978 to 2006. Their findings indicated a narrowing gap between fossil fuel and renewable energy technologies, largely attributed to the growth of specialized renewable energy firms. They advocated for strengthened policies supporting small firms innovating in renewable energy.

Zhang and Zhang (2023) explored the influence of government R&D subsidies on 578 Chinese firms from 2007 to 2018, discovering that these subsidies significantly enhance corporate innovation performance, especially for firms specializing in renewable energy. This finding aligns with Khezri et al. (2021), who used spatial econometric analysis to show that countries with higher R&D investments are more likely to advance renewable energy. This highlights the critical role of R&D in driving renewable energy development. In a related study, Zhang and

[8] Noailly and Smeets (2015) used an older version of Aghion et al. (2016).

Kong (2022) shifted the focus from patent counts to total factor productivity. This study found a positive correlation between renewable energy policies and energy firms' productivity.

Johnstone et al. (2010) examined how different environmental policies influence renewable energy innovations. Using patent data from 1978 to 2003 across 25 nations, their panel data regression analysis indicated that policies like feed-in tariffs and public R&D spending significantly boost patent filings for renewable energy technologies. Lazkano and Pham (2016) further assessed the impact of policy tools on innovation in the electricity industry across 30 nations and 1,500 companies. Their dynamic count data model revealed that subsidies for renewable energy research and natural gas taxes promote green energy innovation. In contrast, coal taxes inhibit innovation in both fossil fuels and renewable technologies.

In the U.S. context, Fischer and Newell (2008) evaluated various policy scenarios for reducing CO_2 emissions and promoting renewable energy within the electricity generation sector. Their theoretical model (calibrated empirically), which incorporates cost functions and supply curves for electricity consumption and production, found emissions pricing to be an efficient method for reducing emissions and supporting renewable energy. Their results suggest that a combination of policy instruments targeting emissions, learning, and R&D is more cost-effective than any single approach.

Similarly, Borenstein and Kellogg (2023) analyzed different incentive mechanisms for reducing greenhouse gas (GHG) emissions in the electricity sector. Their theoretical model—which was also empirically calibrated—was based on consumer demand, fossil generator costs, and clean generation costs, and found that carbon pricing, clean energy standards, and subsidies are all effective at reducing GHG emissions. Their empirical analysis further confirmed the comparability and effectiveness of these mechanisms in lowering emissions and influencing market behaviour.

Despite these advancements, gaps remain in the literature. For instance, while Fischer and Newell (2008) and Borenstein and Kellogg (2023) have studied the U.S. electricity generation sector, empirical studies inspired by the DTC framework, such as those by Aghion et al. (2016) and Noailly and Smeets (2015), have not focused on this sector in the U.S. Our study aims to bridge this gap by incorporating DTC perspectives in analyzing the influence of environmental policies on the transition to green energy within the U.S. electricity generation industry. Additionally, instead of focusing solely on the absolute levels of renewable and fossil fuel energy, we examine the ratio of renewable to fossil fuel energy, as well as the ratio of R&D subsidies and taxation affecting both. This approach offers a more nuanced perspective on the transition to green energy, balancing climate objectives with economic stability. It also confirms that supporting clean technologies alone does not guarantee a clean transition if the support for fossil fuels continues to dominate.

1.4 Theoretical Framework

Recall that the main questions of this study revolve around the impact of taxes and research subsidies on the transition to renewable energy within the U.S. electricity generation sector. I propose a straightforward framework to underpin my empirical investigation. This framework facilitates both economic interpretation and predictive analysis of the effects of R&D subsidies and taxation on the shift toward renewable energy sources.

1.4.1 Theoretical Model Overview

We examine an economy in a discrete-time setting with an infinite horizon. Our primary focus is on the production sector. For notational simplicity, we exclude the time subscript for variables, employing a prime superscript to denote any lagged values.

In this model, we consider the final good (which is referred to as the electricity production later in the empirical model), generated in a competitive market through the utilization of two energy inputs: dirty and clean. The firm utilizes a Constant Elasticity of Substitution (CES) function[9] as follows:

$$E = \left[\; E_d^{\frac{\epsilon-1}{\epsilon}} + E_g^{\frac{\epsilon-1}{\epsilon}} \; \right]^{\frac{\epsilon}{\epsilon-1}} \tag{1.4.1}$$

where E_d and E_g are the energy inputs from both dirty and green sources respectively. The approach of modeling various energy inputs as imperfect substitutes using a CES function

[9]The CES function is utilized to illustrate the imperfect substitutability between the two types of energy sources, namely dirty and green.

is inspired by the work of Dissou and Karnizova (2016) and Hart (2019). The elasticity of substitution between the two sectors can be expressed as $\epsilon \in (0, \infty)$, with $\epsilon > 1$ indicating that both inputs are substitutes, with the level of substitutability increasing as ϵ rises. The analysis limits the acceptable range of ϵ to values greater than 1, which is a more empirically relevant benchmark (Papageorgiou et al. 2017). The final good firm works in a perfectly competitive market and faces the following profit maximization problem.

$$\max_{E_d, E_g} \quad \Pi^e = P^e E - (1 + \tau_d)\, P_d^e\, E_d - (1 - \tau_g)\, P_g^e\, E_g \tag{1.4.2}$$

where P_d^e and P_g^e are the prices of dirty and clean energy respectively. The final good producer pays tax τ_d and receives production subsidy[10] τ_g for using dirty and green energy respectively. It is pertinent to note that τ_d refers also to a fossil fuel tax (e.g., carbon tax) that is imposed on dirty energy. Here P^e is the price of the final good, which is exogenously determined by the market for this good.

In equilibrium, this tax is varied in order to predict how it affects the share of green energy usage (relative to dirty energy).[11] This will address the first research question of the study, which is how fossil fuel taxes (and green production subsidy) affect green energy transition.

To evaluate the influence of green R&D subsidies on the shift toward green energy, I utilize separate production functions for each type of energy: dirty and green. Within these production functions, both the quantity and quality of machinery serve as crucial factors in the production of each energy source. My approach to modeling these production functions is inspired by Acemoglu et al. (2012).[12] Nevertheless, my approach towards modeling innovation differs from theirs, as I account for innovation by examining the direct impact of R&D expenditure on enhancing capital productivity, as elaborated in Aghion and Howitt (2008, Chapter 4).[13] This

[10]In this study, we treat τ_g as either a production subsidy for the green sector or a tax incentive for green energy. This simplifies our analysis, given that both mechanisms primarily target the promotion of green energy production.

[11]In order to accomplish this, I will first solve for equilibrium and then obtain a formula that illustrates the ratio of E_g to E_d. Subsequently, I will assess the impact of tax rate changes, specifically τ_d (and τ_g), on the aforementioned ratio. This will ultimately allow for an evaluation of the influence of such taxation on the shift toward green energy.

[12]Acemoglu (2012) devised comparable production functions for the manufacture of two intermediate products: dirty and green. I adopt their concept but apply the formulas to energy sources.

[13]It may be beneficial to explore alternative models of innovation. Alternative models may offer fresh insights into the interplay between R&D, innovation, and productivity. One alternative approach that I suggest to explore is a model derived from modern industrial organization theory, which views innovation as a crucial component of industrial competition (as described in Aghion and Howitt (2008, Chapter 4). In this model, growth is driven

enables the assessment of the potential influence of R&D expenditure in promoting innovation and improving machinery quality, thereby facilitating the prediction of the impact of R&D subsidies on the transition towards green energy.

Particularly, in the context of the energy sector, we propose that the production function can be encapsulated by a Cobb-Douglas function unique to each energy type—clean (denoted as g) and dirty (notated as d)—given by the equation[14]:

$$E_i = H_i^{1-\alpha} A_i^{1-\alpha} X_i^{\alpha} \tag{1.4.3}$$

where $i \in (g, d)$, and $\alpha \in (0, 1)$. To simplify the algebra, α is the same across both sectors. Besides labor input (H_i), both types of energy (E_g and E_d) are generated through a continuum of sector-specific capital (X_i), which are indexed within the interval $[0, 1]$.[15] We define $X_i = \int_0^1 X_i^j d_j$, with j signifying the machine type.[16] The average quality of these machines is encapsulated by A_i, and calculated as $A_i = \int_0^1 A_i^j dj$ where A_i^j exemplifies the quality of a machine of type j in the energy sector $i \in (g, d)$. To simplify the analysis, we will henceforth refer to the machines and quality by their respective averages, denoted as X_i and A_i, throughout the remainder of this paper.

It should also be noted that there are two main differences between green energy and dirty energy in this model. Firstly, the initial productivity (i.e., capital quality) in the dirty or fossil fuel sector is assumed to be higher relative to the green sector (i.e., $A_{d0} > A_{g0}$). This is because the fossil fuel sector started much earlier than the green sector, allowing it to accumulate a much

by a series of quality-enhancing (or "vertical") innovations, and the effectiveness of R&D is dependent on its productivity adjustment.

[14]I follow Acemoglu et al. (2012) in having the same exponent for the quality of the machine as for the labor input in the production function. The quality or productivity of a machine represents technological progress, which acts as a force that augments labor. Thus, an improvement in machine quality can be equivalent to an increase in effective labor. Therefore, the return to scale or elasticity of output with respect to machine quality can be the same as that of labor.

[15]Machines generally refer to the physical equipment and infrastructure that are used to produce electricity. This can include wind turbines, hydroelectric turbines, natural gas turbines, photovoltaic solar panels, coal or biomass boilers, nuclear reactors, and related infrastructures such as generators, transformers, and transmission lines, depending on the energy source. To put it another way, the "machinery" variable represents the capital-intensive equipment and technology needed to transform primary energy resources into usable electricity.

[16]It should be mentioned here that machines refer to the intermediate inputs used in the production processes of both the clean (renewable) and fossil fuel-based energy sectors. These machines are not synonymous with capital in the traditional sense but represent the specific tools or equipment used to generate energy. For renewable energy, this includes equipment such as wind turbines and solar panels, while for fossil fuels, it might include coal plants or oil rigs. The model focuses on the improvement and deployment of these machines, as they embody technological advancements and productivity improvements in each sector.

higher knowledge stock. Secondly, the use of more dirty inputs results in CO_2 emissions, which can be represented as $Emit = \varphi E_d$, where φ represents the rate of environmental degradation resulting from the use of dirty energy. For further details regarding the distinction between dirty and green sectors, refer to the DTC literature, such as Acemoglu et al. (2012) and Acemoglu et al. (2014).

The energy producers are presumed to operate within a perfectly competitive market,[17] optimizing their profits in accordance with the following profit function:

$$\pi_i = \max_{X_i, H_i} \{P_i E_i - P_i^x X_i - W H_i\} \tag{1.4.4}$$

Here, P_i^x symbolizes the price of machines in the energy sector $i \in (g, d)$, while W represents the wage rate for labor, which is assumed to be identical across both sectors. Aligning with the literature on endogenous technical change, machines in each energy sector are supplied by monopolistically competitive firms. The cost of machine production remains invariant irrespective of its quality or sector and is envisaged as ψ units of the final good. For simplicity and following Acemoglu et al. (2012), the cost of machines is normalized to $\psi = \alpha^2$ and the price of the machine in both sectors is a fixed markup above marginal cost,[18] i.e $P_i^x = \frac{\psi}{\alpha}$. The profit of producing capital is then:

$$\pi_i^x = P_i^x X_i - \psi X_i = \alpha(1-\alpha) X_i \tag{1.4.5}$$

Regarding innovation, this model postulates that innovative activities enhance the quality of machinery, denoted as A_i. Such quality-boosting innovations catalyze growth within the energy sector in which the innovations were introduced.[19] Within this model, each producer,

[17] In this model, both the final goods producer and the energy producers operate under perfect competition to maintain analytical tractability in evaluating environmental policy impacts. While this may differ from real-world settings—where the electricity sector often exhibits some degree of monopoly power—market power is still present in the model through the behavior of machine producers (as will be discussed in this section). These firms engage in both machine production and R&D activities under imperfect competition, earning monopoly profits from successful innovations. The resulting markup from this market power is ultimately reflected in electricity prices through the cost of capital embodied in machines.

[18] Because machine producers work in monopolistic competition, this allows them to exert control over their machine's pricing, denoted by $P_i^x = \psi/\alpha$.

[19] In developing the innovative component of this model, I adhere to the approach presented by Aghion and Howitt (2008). This approach is rooted in modern industrial organization theory, which posits innovation as a vital element of industrial competitiveness. This concept of innovation is also referred to as the Schumpeterian model, given its origination from Schumpeter's 1942 concept of "creative destruction". Essentially, this proposes that growth-driving innovations, through the introduction of novel technologies, simultaneously displace preceding

or entrepreneur, affiliated with machine type j makes a distinct decision regarding Research and Development (R&D). This could potentially lead to successful innovation, enhancing the quality of the machine A_i^j. It is assumed that there exists an entrepreneur with the opportunity to innovate. When such an entrepreneur accomplishes successful innovation, they gain the capacity to manufacture machinery of superior quality within this period. In the absence of such innovation, the monopoly power to produce the current period's machinery is arbitrarily awarded to an individual capable of producing machinery of the previos period's quality.

In this model, the machine's quality, which is an indicator of productivity, can be then expressed, on average, with the following equation:

$$A_i = \mu_i A_i' \tag{1.4.6}$$

where $i \in (g, d)$. μ_i models innovation in this model. A_i' represents the quality of machinery at the previous period, $t-1$, within this respective sector. For simplicity, we set a lower bound of one for this innovation function, μ_i to normalize the previous period's machine quality. If there is an entrepreneur who is successful in enhancing the machine's quality beyond one, she will be granted the monopoly power to produce this machine in period t. Otherwise, if no such advancement is achieved, the monopoly power will be assigned arbitrarily to any entrepreneur who maintains the machine quality from period $t-1$.

In this model, to determine the innovation function μ_i, conducting research is imperative for such successful innovation. Following Aghion and Howitt (2008, Chapter 4), this innovation can be formulated as follows:

$$\mu_i = \phi \left(\frac{RD_i}{A_i} \right)^{\sigma} = \phi \left(\widetilde{RD}_i \right)^{\sigma} \tag{1.4.7}$$

Here, RD_i represents the R&D expenditure of machine producers within sector $i \in (g, d)$, ϕ denotes the productivity of the research sector, $\widetilde{RD}_i$ is the productivity-adjusted R&D expenditure. The elasticity coefficient σ represents the responsiveness of innovation to changes in productivity-adjusted R&D expenditure. Given its range of $0 < \sigma < 1$, it suggests that the

innovations.

productivity-adjusted R&D expenditure exhibits diminishing returns.[20]

The innovator or entrepreneur who successfully innovates secures monopoly power to produce machines. Subsequently, her return on R&D activity is the profit derived from machine production, denoted as π_i^x (which is determined by Equation 1.4.5), contingent upon the success of the innovation. Consequently, the expected reward for participating in innovative pursuits equals $\mu_i \pi_i^x$. Regardless of the success of the innovation, the entrepreneur incurs a fixed cost equivalent to one unit of the final good. The model posits governmental intervention in the form of subsidies towards the entrepreneur's R&D expenditure. With these R&D subsidies, denoted by R_i^s, the net reward for engaging in research activities is as follows:

$$\pi_i^R = \max_{RD_i} \{\mu_i \pi_i^x - (1 - R_i^s)\, RD_i\} \tag{1.4.8}$$

1.4.2 Impact of Taxes and R&D Subsidies on Green Energy Transition

In this section, we briefly examine the effects of taxes (i.e., fossil fuel taxes, τ_d, and green tax incentive, τ_g), and R&D subsidies, R_g^s and R_d^s[21], on the transition to renewable energy, quantified by the ratio E_g/E_d. To that end, we begin in Appendix G with a solution for the theoretical model at equilibrium. Subsequent to this, in Appendix A.2, we provide additional proofs to complement our discussion. To facilitate our examination, we may structure the analysis based on the perspective of energy sources' demand and supply sides. In this model, the final goods producer is the entity that demands various energy sources. Meanwhile, energy and capital producers, besides R&D activities constitute the actors on the energy supply side.

To start with, based on the optimal conditions for the final good firm that acquires various energy sources on behalf of the final good producer, we can obtain the ratio of their usage or demand for energy sources. By dividing Equation A.1.7 by Equation A.1.6, we get the ratio of

[20]Equation 1.4.7 illustrates that as technology progresses (i.e., the quality of machinery, denoted by A_i, improves), it becomes increasingly challenging to further enhance. Therefore, it isn't merely R&D expenditure that is significant but also productivity-adjusted R&D expenditure, i.e., the ratio RD_i/A_i. A detailed explanation of this notion can be found in Aghion and Howitt (2008).

[21]In our analytical framework, we distinguish between two forms of subsidies: production subsidies (or tax incentives), denoted by τ_g, and research and development (R&D) subsidies, represented by R_g^s.

clean energy used to dirty energy:

$$\frac{E_g}{E_d} = \left(\frac{(1-\tau_g)\ P_g^e}{(1+\tau_d)\ P_d^e} \right)^{-\epsilon} \tag{1.4.9}$$

From Equation 1.4.9, it's evident that higher tax-inclusive prices on dirty energy inputs - represented by $(1+\tau_d)P_d^e$ - decrease the demand for such energy types, thus fostering a transition to renewable sources. The key factor in assessing the response of the energy composition to changes in taxation is the elasticity of substitution, ϵ. A larger ϵ suggests greater substitutability between dirty and green energy, meaning an increase in the tax rate on dirty energy (or providing green tax incentives) could result in a more substantial shift to renewable energy. On the contrary, a smaller ϵ implies less substitutability between these energy types, indicating that an identical tax increase would result in a less pronounced shift to renewable energy. Therefore, the degree of substitutability among different energy types is an essential consideration when evaluating the potential effects of environmental tax policies.

To assess the impact of R&D subsidies on the shift towards green energy, denoted by $\frac{E_g}{E_d}$, it is imperative to first understand how R&D expenditure influences the production ratio of green energy to dirty energy.[22] We can identify the direct effect of R&D expenditure on the transition to green energy through the following equation (see Appendix A.2, for more details).

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \times \left(\frac{\widetilde{RD}_g}{\widetilde{RD}_d}\right)^{\sigma} \times \left(\frac{A'_g}{A'_d}\right) \times \left(\frac{H_g}{H_d}\right) \tag{1.4.10}$$

In fact, the formula shows that when productivity-adjusted R&D investment is directed toward green energy, there ensues a transition toward this energy source (given that $0 < \sigma < 1$). Furthermore, we can rearrange the equation to separate the impact of R&D expenditure from its productivity adjustment, as outlined below:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \times \left(\frac{RD_g}{RD_d}\right)^{\sigma} \left(\frac{A_g}{A_d}\right)^{-\sigma} \times \left(\frac{A'_g}{A'_d}\right) \times \left(\frac{H_g}{H_d}\right) \tag{1.4.11}$$

Additionally, the relative productivity between green and dirty energy adheres to the fol-

[22] Using the optimal conditions for energy producers illustrated in Equation A.1.12, and given that $P_g^x = P_d^x = \alpha$ (by assumption), we are able to substitute the quantity of machine production in the equilibrium into the production function of each type of energy, as demonstrated in Equation 1.4.3.

lowing relationship (for detailed proof, refer to Appendix A.2):

$$\frac{A_g}{A_d} = \left(\frac{P_g}{P_d}\right)^{-(\frac{1}{1-\alpha})} \tag{1.4.12}$$

Equation 1.4.12 shows the intuitive concept that energy generated using more productive machines will be comparatively less expensive. By substituting this relation into Equation 1.4.11, we obtain the resulting formula.

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha+\sigma}{1-\alpha}} \times \left(\frac{RD_g}{RD_d}\right)^{\sigma} \times \left(\frac{A'_g}{A'_d}\right) \times \left(\frac{H_g}{H_d}\right) \tag{1.4.13}$$

Thus, it is inferred from Equation 1.4.13 that a higher allocation of R&D expenditures in the green sector (RD_g) stimulates energy producers to augment their green energy production (E_g) relative to fossil fuel energy (E_d). In equilibrium, the determination of relative R&D expenditure is driven by the objective of entrepreneurs or machine manufacturers to maximize their net reward from engaging in research activity, as outlined in Equation 1.4.8. By obtaining the ratio between these optimized amounts, we arrive at the following relation[23] (For more details, refer to Appendices G and A.2).

$$\frac{RD_g}{RD_d} = \left(\frac{A_g}{A_d}\right)^{-\frac{\sigma}{1-\sigma}} \left(\frac{1-R^s_g}{1-R^s_d}\right)^{-\frac{1}{1-\sigma}} \left(\frac{\pi^x_g}{\pi^x_d}\right)^{\frac{1}{1-\sigma}} \tag{1.4.14}$$

Equation 1.4.14 implies that an increase in the level of green R&D subsidies (R^s_g) compared to those allocated to fossil fuel energy (R^s_d) motivates entrepreneurs to expand their R&D expenditure to the green sector relative to the dirty one, as represented by the ratio $\frac{RD_g}{RD_d}$.[24]

In order to establish the explicit impact of R&D subsidies on the transition towards green energy, denoted by the fraction $\frac{E_g}{E_d}$, [25] we can incorporate Equation 1.4.14 into Equation 1.4.13,

[23] The optimal quantities of R&D expenditure determined by Equations A.1.27 and A.1.28.

[24] In circumstances where non-renewable energy is predominant, as seen in our current global context, it can be expected that productivity and machine profit ratios in this sector are superior. If we were to consider a counterpart to Equation 1.4.14 that illustrates the impact of R&D subsidies to the dirty energy sector, it can be anticipated that the positive effect of a given subsidy, such as R_d, would have a significantly greater influence on R&D spending in the dirty sector (RD_d) compared to the effect of an equivalent subsidy, R_g, on R&D spending in the green sector (i.e., RD_g). Thus, to accelerate the shift towards green energy, it is suggested that policymakers either decrease the R&D subsidies allocated to the fossil fuel energy sector or incrementally expand the R&D subsidies dedicated to green energy, ensuring they outpace those devoted to their non-renewable counterparts.

[25] The ratio $\frac{E_g}{E_d}$ is always well-defined. Since the elasticity of substitution, ε, is finite (i.e., $\varepsilon < \infty$), neither type of energy can fully substitute for the other in production. Consequently, the ratio $\frac{E_g}{E_d}$ remains defined within the theoretical framework.

which yields the subsequent expression:

$$\frac{E_g}{E_d}=\left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}}\times\left(\frac{A_g}{A_d}\right)^{\frac{-\sigma}{1-\sigma}}\times\left(\frac{1-R_g^s}{1-R_d^s}\right)^{-\frac{\sigma}{1-\sigma}}\times\left(\frac{\pi_g^x}{\pi_d^x}\right)^{\frac{\sigma}{1-\sigma}}\times\left(\frac{A'_g}{A'_d}\right)\times\left(\frac{H_g}{H_d}\right) \quad (1.4.15)$$

It can be inferred from Equation 1.4.15 that redirecting R&D subsidies from fossil fuel energy to green energy (i.e., increasing R_g^s and/or decreasing R_d^s) will stimulate the transition to green energy, as captured by the ratio $\frac{E_g}{E_d}$. Equation 1.4.15 can be characterized as the equation illustrating the ratio of green and dirty energy determined on the supply side. It signifies the interaction between energy producers, and machinery producers, as well as R&D activity in equilibrium. To derive the ratio $\frac{E_g}{E_d}$, which is determined by the interaction of both the demand and supply sides, it is imperative to integrate equation 1.4.9 with equation 1.4.15. This integration requires two identities. Firstly, the identity that connects relative prices with relative productivity as shown in Equation 1.4.12, and secondly, the following identity concerning machines' profitability (The proofs for these identities can be found in Appendix A.2):[26]

$$\frac{\pi_g^x}{\pi_d^x}=\frac{X_g}{X_d}=\frac{P_g}{P_d}\frac{E_g}{E_d} \quad (1.4.16)$$

Accordingly, we establish the subsequent definitive relationship:[27]

[26]To grasp the intuition of the relationship in Equation 1.4.16, let's recall that the machine manufacturers operate within a framework of monopolistic competition, allowing them to exert control over their machine's pricing, denoted by $P_i^x=\frac{\psi}{\alpha}$. Conversely, energy producers, who are on the demand side for these machines, determine the quantity of machines they desire at this given price. The quantity of machines, X_i, is then determined by the first-order conditions of both green and dirty energy producers. Specifically, by incorporating the machine price set by the machine producer into the first order condition of the green energy producer as shown in Equation F.2.11, the quantity for green machines can be derived as $X_g=\frac{\alpha^2 P_g E_g}{\psi}$. Similarly, the quantity for dirty machines is given by $X_d=\frac{\alpha^2 P_d E_d}{\psi}$. According to Equation 1.4.5, the machine profit is $\pi_i^x=\alpha(1-\alpha)X_i$, where $i\in(g,d)$. Thus, when we compute the ratio of machine profit between the green and dirty sectors, we obtain Equation 1.4.16, given that ψ, and α are identical in both sectors (by assumption).

[27]From Equation 1.4.15, we observe that the price effect works in such a way that an increase in the relative price of green energy compared to dirty energy promotes a shift towards green energy. However, a different perspective of the price effect is illuminated in Equation 1.4.9, which suggests that an increased relative price of green energy can actually inhibit the shift towards it. This apparent contradiction can be reconciled by considering the different perspectives from which these Equations are derived. Specifically, Equation 1.4.15 approaches the ratio E_g/E_d from a supply-side standpoint. In this view, a higher relative price of green energy enhances its profitability, incentivizing machine manufacturers to expand their production in this sector.On the other hand, Equation 1.4.9 interprets the ratio E_g/E_d from a demand-side viewpoint. When green energy becomes comparatively more costly, it dissuades final goods producers from using it, leading to a decrease in their relative demand for green over dirty energy. Inserting Equation 1.4.9 into Equation 1.4.15 helps to reconcile these contrasting effects and extract a net outcome.

$$\underbrace{\frac{E_g}{E_d}}_{\text{Renew/Fossil Ratio}} = \underbrace{\left(\frac{P_g}{P_d}\right)^{\frac{-\epsilon\sigma(1-\alpha)+\alpha}{(1-\sigma)(1-\alpha)}}}_{\text{Price effect}} \times \underbrace{\left(\frac{1-\tau_g}{1+\tau_d}\right)^{\frac{-\epsilon\sigma}{1-\sigma}}}_{\text{Taxation effect}} \times \underbrace{\left(\frac{1-R_g^s}{1-R_d^s}\right)^{-\frac{\sigma}{1-\sigma}}}_{\text{R\&D subsidy effect}} \times \underbrace{\left(\frac{A_g'}{A_d'}\right)}_{\text{Direct productivity effect}} \times \underbrace{\left(\frac{H_g}{H_d}\right)}_{\text{Market size effect}} \tag{1.4.17}$$

Equation 1.4.17 is designated as the final equation which identifies the determinants influencing the transition towards green energy. Recall that the model operates over an infinite horizon, and for simplicity, we have omitted the time subscript, using a prime notation to indicate lagged variables. Accordingly, Equation 1.4.17 captures variables within a dynamic framework, reflecting their evolution over time. The equation assesses the interaction of final good producers—representing the demand side of energy—and energy and machinery producers—serving as the supply side. Furthermore, the equation incorporates the effects of R&D subsidies and taxation within the same analytical framework. Equation 1.4.17 illustrates that the transition to green energy is influenced by five distinct forces: price, taxation, R&D subsidy, market size, and direct productivity effects.

The Price Effect is embodied by the term $(P_g/P_d)^{\frac{-\epsilon\sigma(1-\alpha)+\alpha}{(1-\sigma)(1-\alpha)}}$, where $\frac{-\epsilon\sigma(1-\alpha)+\alpha}{(1-\sigma)(1-\alpha)} < 0$.[28] This effect stimulates production in the sector that offers a lower price. As such, we anticipate a transition from fossil fuels to green energy when there is either an increase in the price of fossil fuel energy (P_d) and/or a decrease in the price of green energy (P_g).

There are two key points to underscore in this context. First, in this model, the dominant determinant of energy prices is their relative productivity. As indicated by Equation 1.4.12, the sector that offers lower prices tends to be the one with greater productivity. Therefore, it can be asserted that it is crucial to improve productivity or machinery quality in the green energy sector. This could potentially be realized through innovation and investments in research and development. Such advancements would ultimately lower the cost of green energy and expedite

[28]The price effect coefficient, inferred from the numerator, reveals two contrasting forces, as indicated by terms with opposing signs. The negative first term implies that lower green energy prices relative to fossil fuels promote the transition to renewable sources. Conversely, the second term suggests that a decrease in green energy prices relative to fossil fuels discourages this transition. This contradiction stems from the price impact on both the demand and supply sides of the energy market. The demand side is naturally drawn to the more inexpensive energy source, whereas the supply side tends to favor the production of more profitable, higher-priced energy. The prevailing effect is contingent upon the dominance of one of these opposing forces, which is largely determined by the values of the parameters ϵ, σ, and α. Notably, a higher substitution elasticity, ϵ, magnifies the demand-side force. Later in this section, we will demonstrate that the calibrated values of ϵ are relatively high, ranging between 4 and 6.5, with σ reaching up to 0.16, and α set at 1/3. Consequently, the negative component of the price effect coefficient dominates, resulting in an overall negative price ratio effect.

the shift towards more sustainable energy sources. Second, the intensity of the price effect is substantially affected by the substitutability between green and dirty energy, denoted by ϵ. In simpler terms, if there is a higher elasticity of substitution between the two energy forms, the price effect will be more pronounced.

The Taxation Effect is represented by the term $((1-\tau_g)/(1+\tau_d))^{\frac{-\epsilon\sigma}{1-\sigma}}$. This effect implies that a raise in taxes on fossil fuels (i.e., carbon tax), denoted by τ_d, or an increase in tax credits for green energy, indicated by τ_g, is expected to accelerate the transition to greener energy sources. This shift is due to changes in the relative tax-inclusive price, as detailed in Equation 1.4.9, which makes green energy less costly compared to dirty energy sources. These changes incentivize the final good producer to increase demand for green energy. The magnitude of this tax effect is also significantly determined by the elasticity of substitution, represented by ϵ. A larger value of ϵ reinforces this effect, further favoring the move towards greener energy sources.

The R&D Subsidy Effect is denoted by the term $\left((1-R_g^s)/(1-R_d^s)\right)^{-\frac{\sigma}{1-\sigma}}$, where $0<\sigma<1$. If these subsidies are directed toward machinery for green energy production (R_g^s), a shift to green energy sources is expected. However, if these subsidies are allocated to machinery for dirty energy production (R_d^s), this could deter the transition to cleaner energy alternatives. R&D subsidies encourage machine manufacturers to enhance investment in these areas, as indicated by Equation 1.4.8. The resulting improvement in productivity in the green sector could reduce its relative price, promoting a stronger preference for the adoption of green energy.

In other words, an increase in the R&D subsidies for renewable energy relative to fossil fuel, represented by $\frac{R_g^s}{R_d^s}$, leads to a decrease in the term $\frac{1-R_g^s}{1-R_d^s}$, in turn amplifying the renewable-to-fossil energy output ratio $\frac{E_g}{E_d}$. In contrast, a reduction in $\frac{R_g^s}{R_d^s}$ augments $\frac{1-R_g^s}{1-R_d^s}$, resulting in a decrease in $\frac{E_g}{E_d}$. This direct positive link between $\frac{R_g^s}{R_d^s}$ and $\frac{E_g}{E_d}$ is profoundly influenced by the exponent $\frac{\sigma}{1-\sigma}$, highlighting the essential role of R&D subsidies in driving the transition to renewable energy. Specifically, the impact of R&D ratio is contingent on the value of σ, which represents the elasticity of innovation with respect to productivity-adjusted R&D expenditures. A higher σ indicates a more pronounced influence of the $\frac{R_g^s}{R_s^s}$ ratio on the transition to renewable energy. It is pertinent to mention that, for our empirical analysis, data pertaining to the ratio $\frac{R_g^s}{R_s^s}$

will be used to evaluate its impact on the green transition.

The Direct Productivity Effect[29] is denoted by the term $\frac{A'_g}{A'_d}$, which promotes the sector with initially greater productivity.[30] The direct productivity effect facilitates innovation directed at technologies with higher productivity or existing knowledge stocks. This effect is akin to the term "building on the shoulders of giants," meaning that future innovations rely on existing technology or knowledge stocks, thus generating dependencies in the process of knowledge creation (Aghion et al. 2016, Acemoglu et al. 2012, Noailly and Smeets 2015). Consequently, if the accumulation of knowledge is more extensive in the realm of dirty energy, it may foster a bias against the shift toward green energy.

The Market Size Effect[31] - represented by the term $\frac{H_g}{H_d}$, is also pivotal as it motivates the production of the energy source in the sector with higher employment. The market size effect stimulates innovation in the sector with higher employment, which corresponds to a larger market for machinery. A larger market size implies increased potential demand for new machinery, thereby providing firms with a greater incentive to innovate within that sector. This rationale aligns with the arguments put forth by Acemoglu et al. (2012, 2014) regarding the role of market size. Consequently, a larger market size in the dirty energy sector, for example, may impede the transition towards green energy.

From the analysis presented, it is apparent that implementing fossil fuel taxes, coupled with providing tax incentives for green energy initiatives and favoring green energy in the allocation of research and development subsidies, is expected to play a pivotal and beneficial role in accelerating the shift from fossil fuel dependency to sustainable green energy sources. If we only consider the effects of market size and technology, without any government intervention, economies tend to stick to high carbon emissions by only relying on dirty energy. This is because the dirty sector is currently larger and more productive than the green one. To change this, we might need to take strong action now by adjusting taxation (i.e., fossil fuel tax, or green tax incentives) and providing subsidies for R&D efforts, which will help shift towards green

[29]Given that we are working within a discrete-time framework for an economy with an indefinite horizon, the ratios A'/A'_d and H_g/H_d are dynamic, varying over time and influencing the *Renew/Fossil* ratio. In other words, a general equilibrium effect is going on here.

[30]From equation 1.4.6, it can be deduced that the energy source with superior machine quality should display increased production, as indicated in equation 1.4.3.

[31]As per Acemoglu et al. (2012), I'm using the employment ratio in both sectors to represent the market size in their analysis.

energy. Over time, as the market and knowledge lean more towards green alternatives, we can ease off these measures. This argument highlights the crucial role of fossil fuel taxes, green tax incentive, and subsidies of R&D activities.

Moreover, the relative proportions of taxes and research subsidies focused on clean energy as opposed to dirty energy sources are more critical than the actual levels. For example, while raising the research subsidies for renewable energy might boost its growth, it may not necessarily accelerate the transition to this form of energy if subsidies for fossil fuel research remain superior. Put differently, in order for these policy measures to effectively stimulate the shift to clean energy, their scale must surpass those aimed at fossil fuel energy. Consequently, in our empirical analysis, we will primarily focus on how the relative ratios of taxes and research subsidies, rather than just the quantities, influence the transition from fossil fuel energy to renewable energy. This is one of the key contributions of our research - shedding light on the impact of these policy ratios on the transition to renewable energy, rather than focusing solely on their absolute values. This shifts the narrative from a simplistic perspective of just increasing policy measures to a deeper understanding of the balanced allocation between green and traditional energy sources, emphasizing the role of effective resource distribution in promoting a sustainable future.

Different Scenarios of both Taxation and R&D Subsidy Effects:

In this theoretical framework, we can also draw insights into how the effects of taxation and R&D subsidies compare when transitioning to renewable energy. Notably, the influences of taxation and R&D subsidies primarily depend on the values of two parameters: ϵ, and σ. With regard to the elasticity of substitution ϵ, Papageorgiou et al. (2017) were the pioneers in empirically estimating this substitution value between the green and dirty energy sectors, focusing primarily on the CES production function. Their findings suggest that the elasticity of substitution between clean and dirty energy (ϵ) within the electricity generation sector is approximately 1.8. However, Papageorgiou et al. (2017) give a concise overview of the estimates associated with this substitution. Stöckl and Zerrahn (2023) provide a detailed bottom-up perspective to complement the broader, top-down approach to estimating such elasticity. As part of their study, the researchers distinguished between estimations of such substitutions in various scenarios. For example, when there is a high or low share of renewable energy and whether energy storage capacity is available. In sum, the elasticity of substitution is proven to be higher than unity in line with Papageorgiou et al. (2017). Different specifications yield different values for substitution elasticity. According to average estimates, it shows values of 3.94 and 6.46.

The value of elasticity coefficient of innovation, σ, has not been measured in previous research. From our empirical assessment of the coefficient pertaining to the R&D subsidy ratio in the next section, it is possible to deduce the value of σ. Through various specifications, empirical evidence—within the U.S. electricity generation— suggests that this coefficient lies within an approximate range of 0.108 to 0.186. Consequently, this range indicates that $\frac{\sigma}{1-\sigma}$ falls within these bounds. As a result, σ can be anticipated to range between approximately 0.098 and 0.157.

According to the identification of these parameters, we may deduce different scenarios of the elasticity coefficients of taxation and R&D effects. Denote the elasticity coefficients for the taxation and R&D effects, respectively, as:

$$\theta_1 = \frac{-\epsilon\sigma}{1-\sigma}, \quad \text{and} \quad \theta_2 = \frac{\sigma}{1-\sigma}$$

To systematically analyze their behavior, we set up different scenarios based on varying values of ϵ and σ. The scenarios are structured around the ϵ ranging between 1.8 and 6.5, consistent with the values estimated by Papageorgiou et al. (2017) and Stöckl and Zerrahn (2023). Additionally, these scenarios keep the value of σ in the interval 0 to 1 as specified by the model above. In this interval, we allow σ to take different values from 0.02 to 0.20. This range includes the values of 0.098 and 0.16 as deduced from our empirical investigation. Table B.1 presents the calculated values of θ_1 and θ_2 for each of these scenarios, providing a general view of how these coefficients might behave under different economic conditions. As an example, we can get the coefficient of taxation effect is -0.75 and the R&D effect is 0.19 when $\epsilon = 3.94$, and $\sigma = 0.16$. Additionally, when $\epsilon = 6.46$, and $\sigma = 0.098$, the taxation effect is -0.702, and the R&D effect is 0.11. Overall, the taxation coefficient (θ_1) ranges from -0.11 to -1.615, while the R&D coefficient (θ_2) ranges from 0.020 to 0.250.

The analysis of different scenarios reveals insightful trends[32] in the behavior of these effects. The elasticity coefficients θ_1 and θ_2 consistently maintain their negative and positive signs, respectively, across all scenarios. Notably, the absolute values of θ_1 are consistently higher than those of θ_2, highlighting a stronger elasticity response to taxation effects compared to R&D effects. This consistent pattern underscores the significant impact of taxation policies on green energy transition, as opposed to the relatively moderate influence of R&D activities.

This notion becomes apparent when examining the primary distinction between θ_1 and θ_2 in absolute terms: the existence of the parameter ϵ in the taxation effect (θ_1). The fact that ϵ exceeds one implies a more substantial impact of taxation compared to R&D on the green transition. The rationale behind this is that tax adjustments directly influence the demand side in the energy market (in this model, the final good producer is the demand side), driving them to favor energy sources subject to lower taxation. This influence intensifies as substitution elasticity increases. Additionally, another factor potentially weakening the R&D subsidy effect relative to the taxation effect is its reliance primarily on σ. This parameter largely depends on the success rate of R&D efforts in generating innovations, which inherently entails a certain level of uncertainty. These findings can guide environmental policy decisions, especially in areas where taxation and R&D subsidies play pivotal roles.

In summary, based on the preceding analysis, we can articulate the main theoretical predictions of this study. Our first prediction asserts that tax policy adjustments, particularly the introduction of fossil fuel taxes or enhanced tax incentives for renewable energy, are expected to enhance the transition to renewable energy. This tax reform is anticipated to enhance the competitive pricing of green energy, encouraging industry producers to gravitate towards these green alternatives. By increasing the fossil fuel tax, represented by τ_d, or enhancing green tax incentives τ_g, the relative expense of using fossil fuels compared to renewable energy rises. This facilitates a shift towards green energy, as denoted by E_g/E_d. This effectively limits fossil fuel utilization in production processes, expediting the shift toward renewable energy sources.

The second prediction suggests that allocating a greater proportion of R&D subsidies to green energy, as opposed to fossil fuels, facilitates the shift to renewable energy sources.

[32] These trends or facts hold even if we open the scenarios to include values of σ to be between 0 and 1 and all values of ϵ to be greater than one.

Specifically, redirecting R&D subsidies to green energy relative to fossil fuel energy, or increasing the ratio R_g^s/R_d^s, is expected to accelerate the transition to green energy, denoted by E_g/E_d. This is because it encourages innovation and productivity in the renewable energy sector compared to fossil fuel energy sources, thereby reducing the Rrenewable energy over time. Furthermore, tax adjustments, such as increasing fossil fuel taxes or enhancing green tax incentives, are anticipated to have a more immediate and stronger impact on the transition to green energy compared to redirecting R&D subsidies to green energy. This is because tax reforms directly affect both supply and demand in the energy market, thereby promoting the substitution of fossil fuels with renewable energy sources. On the other hand, the success of R&D subsidies depends on achieving innovation outcomes, which inherently involves a degree of uncertainty and requires more time to impact productivity and then the green transition. In the empirical section, we evaluate these theoretical predictions regarding the impact of taxation and R&D subsidies on the green transition, utilizing data from the U.S. electricity generation sector.

Furthermore, we will employ Equation 1.4.17 to select control variables for the empirical assessment in the subsequent section. This includes the market size, knowledge stock, and comparative prices of both renewable and fossil fuel energy. It's expected that as the market size of renewable energy expands relative to dirty energy, denoted by H_g/H_d, the possibilities of transitioning to green energy (E_g/E_d) would be expanded. Additionally, increasing the knowledge stock, or past productivity in green energy compared to dirty energy, indicated by A'_g/A'_d, is predicted to augment the shift towards green energy (E_g/E_d). This illustrates the impact of the "standing on the shoulders of giants" effect as previously discussed. Additionally, a decrease in the price of green energy relative to dirty energy, represented by P_g/P_d, is anticipated to stimulate the transition to green energy, E_g/E_d.

1.5 Data and Empirical Methodology

In seeking to address the primary research questions of this study, namely the impact of taxation and R&D subsidies on the shift from fossil fuels to renewable energy sources, we determine that such a transition is predominantly influenced by five categories of effects. These include:

price, taxation, R&D subsidies, past productivity, and market size. The determination of these factors is consistent with the theoretical framework provided earlier. Most of these effects are compatible with some of the theoretical studies previously mentioned such as Acemoglu et al. (2012) and Acemoglu et al. (2014). They are also consistent with earlier empirical studies such as Noailly and Smeets (2015) and Aghion et al. (2016). We estimate the role of these effects on our dependent variable within the context of the electricity generation for different industries in the U.S. between 2000 and 2015.

We are concentrating on the electricity generation sector. The EIA provides data on electricity generation, categorized by the type of producer receiving electricity. Therefore, we have aggregated data on electricity generation by industry type for each state and year. Specifically, we analyze electricity generation for the following types of industries: (1) Electric Generators within Electric Utilities; (2) Electric Generators operating as Independent Power Producers; (3) Combined Heat and Power producers in the Industrial sector; (4) Combined Heat and Power producers in the Commercial sector; and (5) Combined Heat and Power producers within the Electric Power sector. Therefore, our analysis centers on the aggregate amount of electricity generated and provided to these various industry categories. Data was obtained for these producer categories from all 50 states. Our study period is limited to 2015 because data on R&D subsidies is only available up to that year. To begin, we define the variables, including their measurements and data sources. We then introduce the proposed empirical methodology aimed at adequately addressing the research questions of this study.

1.5.1 Data

In this section, we outline the definitions, measurements, and sources of the data employed for our empirical analysis. We begin with the dependent variable and then proceed to discuss the explanatory variables under study.

Renew/Fossil Ratio

In our research, the dependent variable is the "Renewable/Fossil Fuel" ratio, which denotes the proportion of energy obtained from renewable sources compared to that from fossil fuels.[33]

$$\text{Renew/Fossil Ratio, } \widetilde{E_{it}} = \left(\frac{\text{Renewable Energy, } E_{g,it}}{\text{Fossil Fuels Energy, } E_{d,it}} \right) \times 100$$

Specifically, the dependent variable is denoted by $\widetilde{E_{it}} = \frac{E_{g,it}}{E_{d,it}}$, which represents the ratio of renewable energy to fossil fuel energy. In this study, "energy" refers to the inputs used in electricity generation, including both renewable and fossil fuel sources. "Electricity" is the final output produced by these energy inputs. Due to data limitations, we use the ratio of electricity generated from green energy to electricity generated from fossil fuels as a proxy[34] for the ratio of renewable to fossil fuel energy inputs. Here $E_{g,it}$ is the electricity generated from renewable sources and $E_{d,it}$ is the electricity generation from fossil fuels. The measures are quantified as the aggregate number of megawatt-hours (MWh) generated, categorized by producer type in each state across the study period. The EIA provides data on power production from various energy sources across the five specified producer types. We obtain the 'dirty' energy use, denoted as $E_{d,it}$, by aggregating the power generated from all fossil fuels. Similarly, we combine the power generated from all renewable energy sources to determine the 'green' energy variable $E_{g,it}$.[35]

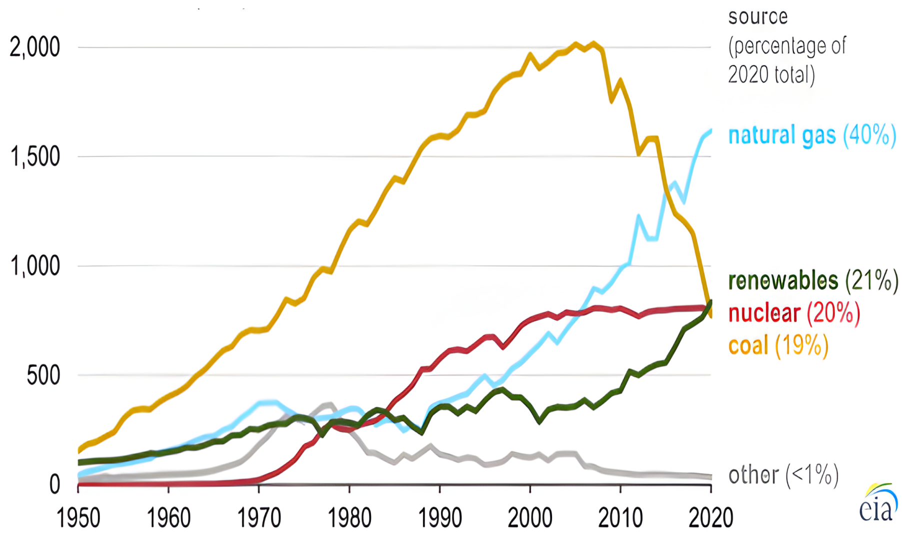
In Figure 1.1, we can see how the energy sector in the U.S. has undergone a significant transformation. In 2020, coal's contribution to electricity generation has declined by 20% from its peak in 2007, and is exceeded by renewable energy for the first time. Meanwhile, natural

[33] The current paper abstracts from nuclear energy as a low-carbon energy source primarily due to its lack of variation. During the study period from 2000 to 2020, nuclear power electricity's share in the U.S. remained relatively constant. In this period of time, the percentage of electricity generated by nuclear power has risen to 19-20%, according to the EIA. Due to this lack of variation, we exclude nuclear energy and focus on the shift to renewable energy, which experienced significant variation and growth during the study period. This shift makes it beneficial to investigate the roles of policy variables, such as R&D subsidies and taxation, in promoting renewable energy adoption.

[34] This is a reliable proxy because the electricity generated from each energy source is directly proportional to the amount of that energy source used. Essentially, the process of converting energy inputs into electricity has a consistent and measurable efficiency for both renewable and fossil fuel sources. This means that the ratio of electricity output accurately reflects the underlying energy inputs.

[35] It is pertinent to highlight that the electricity output from fossil fuel sources constitutes the cumulative total of MWh produced from coal, natural gas, and petroleum. Meanwhile, the electricity output from renewable energy consists of the sum of MWh generated from the renewable energy sources, which include wind, solar, conventional hydroelectric, wood and wood-derived fuels, other biomass, geothermal and solar thermal and photovoltaic sources. You can access the data through the following link: `https://www.eia.gov/electricity/data/state/`.

Figure 1.1: Annual U.S. Electricity Generation from All Sectors (1950–2020)



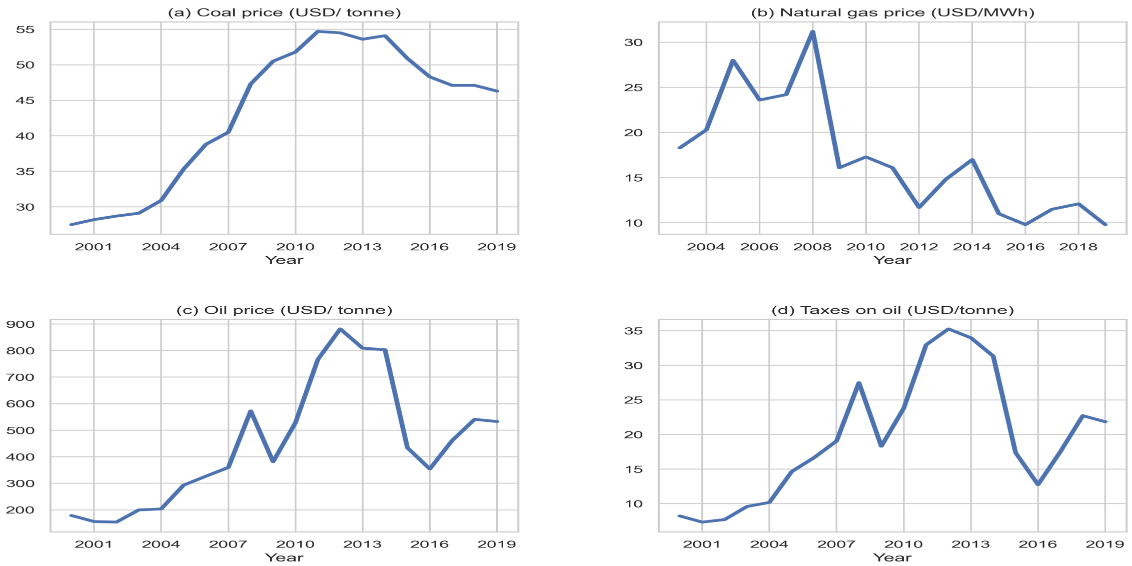
Source: U.S. Energy Information Administration.
Note: In 2020, renewable energy sources, led by wind and solar, surpassed coal and nuclear power for the first time, contributing to 21% of all electricity generated in the U.S. This record, set against a backdrop of a 20% decline in coal use, signals an accelerating shift towards a sustainable energy mix despite natural gas's current dominance.

gas production has risen significantly, which has cemented its role as a major player. These transitions emphasize the energy sector's shift from fossil fuels such as coal towards more renewable sources, though this has been accompanied by an increased reliance on natural gas, another fossil fuel source. Notable, the use of coal and natural gas by electricity plants in the U.S. has indeed gone in opposite directions over the study period, with a significant decrease in coal usage and an increase in natural gas usage. In this analysis, it is appropriate to take into account total fossil fuels since emissions, which are the ultimate concern, are produced by both coal and natural gas, in addition to oil. By focusing on total fossil fuel usage, the analysis captures the comprehensive (implicit) impact on emissions, providing insight into the process of the transition from fossil fuels to renewables.

Tax-inclusive Energy Price

The first explanatory variable in our study is the ratio of tax-inclusive energy prices. Specifically, this ratio is determined by dividing the tax-inclusive price of fossil fuels by the price of renewable energy. Energy taxes in the U.S. are a combination of federal and state taxes. It is mainly the fuel excise tax. Federal excise taxes apply to gasoline and diesel. Those taxes contribute largely to the Highway Trust Fund, which helps improve and maintain transportation infrastructure. The state-level fuel taxes vary significantly, with every state imposing its fuel tax on gasoline and diesel to fund various projects. State taxes have a significant impact on the overall fuel tax burden. Furthermore, the federal government does not impose any broad-based carbon taxes. Figure 1.2 shows the changes in fuel taxes, both on gasoline and diesel, throughout the study period.

Figure 1.2: Yearly Tax-Inclusive Prices of Fossil Fuels Utilized for Electricity Generation in the U.S. (2000–2019)



Source: Graph created by author, data from the International Energy Agency (IEA).
Note: The graph depicts a consistent and significant upward rise in coal prices over time, though this increase tempered slightly from 2014 onwards. Oil prices exhibited a parallel trend, albeit marked with some fluctuations. Since oil taxes are proportional to the price, their trend aligns with that of the oil price. Conversely, the price of natural gas showed a marked decline, accompanied by occasional fluctuations.

In addition to direct taxation, the U.S. provides some tax incentives to enhance energy efficiency and promote renewable energy. Federal incentives include the Production Tax Credit (PTC) and the Investment Tax Credit (ITC), which offer financial support for renewable energy projects, which include wind and solar power. There are tax credits available to improve energy efficiency in residential and commercial properties. This is mainly to reduce the cost of energy-saving upgrades. Access to specific data on energy taxation, whether it pertains to fossil fuel taxes or clean energy incentives, is limited. Therefore, we use tax-inclusive energy prices as a proxy for taxation. We will discuss this in more detail below.

Tax-inclusive fossil fuel Prices

Electricity production involves the utilization of fossil fuels, including coal, natural gas, and petroleum. While price data for these fuels is accessible, only petroleum has available taxation data. To address the data limitation on taxation, we propose the use of tax-inclusive fossil fuel prices as a proxy for taxation, a strategy aligned with Aghion et al. (2016). We further substantiate this view by positing that taxation changes the final price paid to achieve a specified objective. This proposition is supported by the data in Figure 1.2, which illustrates that variations in petroleum taxation closely mirror changes in their tax-inclusive prices. This correlation further bolsters our argument that changes in tax-inclusive prices are related to shifts in taxation. For tax-inclusive prices, we use the tax-inclusive costs of fossil-fuel receipts at electric generating plants (coal, oil, and natural gas). These data are derived from EIA and measured uniformaly by USD per million Btu, which facilitates a uniform measurement.[36]

The production of electricity involves the use of fossil fuels, such as coal, natural gas, and petroleum, so calculating their average prices is essential. Since producers may use different energy sources in different amounts, we use a production-weighted average for oil, natural gas, and coal prices. In this calculation, the weight assigned to each fuel's price corresponds to its percentage contribution to fossil fuel-based power generation. In particular, the weighted average of the prices is calculated as follows:

$$p_{d,it} = \sum_{f \in oil,coal,gas} w_{f,it} \cdot p_{f,it} \tag{1.5.1}$$

where $w_{f,it}$ is defined as:

$$w_{f,it} = \frac{E_f}{\sum_f E_f} \tag{1.5.2}$$

In these Equations, $p_{d,it}$ denotes the production-weighted average price of a given fuel type at time t for producer i. The term $w_{f,it}$ represents the weight for each fuel type at time t for producer type i, determined by the proportion of electricity (E_f) generated by that fuel type to the total electricity produced by all fossil fuel types ($\sum_f E_f$). The variable $p_{f,t}$ signifies the

[36]The data is accessible at: `https://www.eia.gov/totalenergy/data/monthly/`.

price of each fuel type f at time t, for producer type i.

Figure 1.2 shows the annual prices, including taxes, of fossil fuels used for electricity generation in the U.S. between 2000 and 2019. This graph illustrates a steady, substantial increase in coal prices, with this rise showing signs of moderation from 2014. Oil prices tend to follow a similar trend, despite some fluctuations. Oil taxes, being linked to oil prices, reflect a similar trend. On the contrary, prices of natural gas show a distinct reduction, marked by some fluctuations.

Renewable energy price

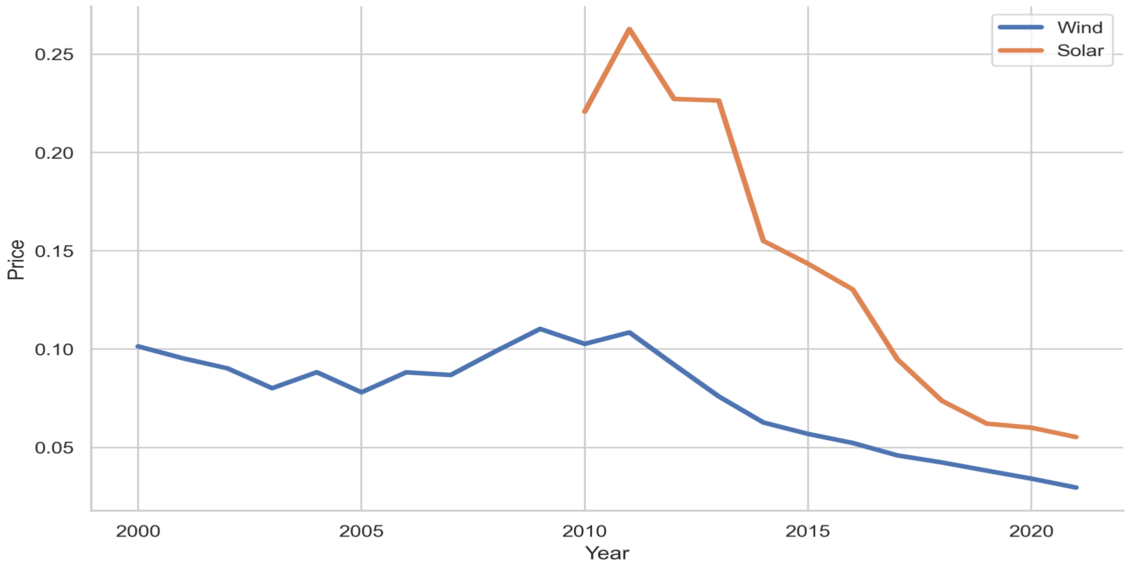
Establishing the cost of renewable energy ($p_{g,it}$) can prove challenging due to the high initial investments, low operational costs, and long lifespan of related projects. However, a measure called the Levelised Cost of Energy (LCOE), provided by the International Renewable Energy Agency, simplifies this task. The LCOE for Renewable Energy signifies the average net cost to establish and manage a renewable energy generation system (such as a wind turbine or a solar power plant) per unit of total electricity produced by the system over its lifetime[37]. It has therefore gained widespread acceptance for cost comparison across various energy projects, as cited in Bruck et al. (2018) and Branker et al. (2011). LCOE has limitations as a proxy for energy prices, as it doesn't account for intermittency, integration costs, temporal and spatial variations, externalities, or regulatory risks. Despite these drawbacks, LCOE remains a useful proxy for our analysis due to data limitations. It provides a consistent cost measure across different energy technologies over time, allowing for meaningful comparisons. Therefore, LCOE can still effectively capture pricing variations for renewable energy within the scope of our study.

LCOE data for wind energy, utilized in electricity generation throughout the study period, is readily available, while data for solar energy is available starting from 2010. Since wind represents the largest source of renewable energy (accounting for approximately 50%)[38] used in electricity generation, we consider using the LCOE for wind as a proxy for the price or cost of renewable energy sources in electricity generation (for more details regarding the LCOE,

[37]The data can be accessed through this link: https://www.irena.org/publications/2022/Jul/Renewable-Power-Generation-Costs-in-2021. You can also access the data from the Our World in Data database using the following link: https://ourworldindata.org/grapher/levelized-cost-of-energy.

[38]The data for this ratio is sourced from the IEA and can be accessed via the following link: https://www.eia.gov/energyexplained/electricity/electricity-in-the-us.php.

Figure 1.3: Levelised Cost of Energy (LCOE) (USD/MWh)



Source: Graph created by author, data from the International Renewable Energy Agency.
Note: The figure shows a consistent decline in the average unit cost of wind and solar energy generation beginning in 2000. Notably, data for solar pricing is unavailable prior to 2010.

see Borenstein (2012)).[39] Figure 1.3 illustrates a steady reduction in the average unit cost of wind and solar energy production since 2000.[40] Similar to our approach to fossil fuel prices, the cost of renewable energy can also serve as a proxy for green tax incentives, given that these incentives directly impact the prices associated with green energy. Green tax incentives reduce the effective costs captured by the LCOE. These incentives lower the initial cost and operational costs, thereby enhancing the financial viability of renewable energy projects (U.S. Energy Information Administration 2023).

[39]The formula used to compute the LCOE for renewable energy technologies is as follows:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t+M_t+F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{El_t}{(1+r)^t}}$$

In this formula, $LCOE$ stands for the average levelized cost of electricity generation throughout the system's lifespan. The variable I_t denotes the investment costs incurred in the year t, whereas M_t symbolizes the expenses related to operations and maintenance within the same year. F_t represents the fuel costs for the year t. The term El_t refers to the amount of electricity generated in the year t. r is the discount rate used in the calculation, and n signifies the total operational lifespan of the system. For more details on the formula of LCOE, refer to IRENA (2022) and Krey et al. (2014)

[40]Importantly, the LCOE also accounts for the learning curve effect, meaning that as the cumulative installed capacity of renewable energy technologies increases, the LCOE decreases. This decline is due to technological improvements, increased efficiencies, and economies of scale associated with higher deployment levels. Studies have shown that the cost-based learning rates for wind and solar are approximately 15% and 24%, respectively, reflecting considerable cost reductions with each doubling of installed capacity (Laboratory 2022). It is also noteworthy that our theoretical framework highlights the negative relationship between the price of energy and advancements in technology or productivity, as discussed in Equation 33.

For our empirical analysis, we require a price ratio between green and fossil fuel energy. Yet, the challenge lies in their differing units of measurement: fossil fuel energy is measured in Dollars per million Btu, inclusive of taxes, whereas the green energy price is denoted in USD/MWh. To compare them directly, it is crucial to align these units. As a solution, we developed price indices for both types of energy[41]: fossil and renewable as:

$$\text{Price Index} = \left(\frac{\text{Price in Year } t}{\text{Price in Base Year}} \right) \times 100$$

where price in year t is the price of energy (either green or fossil) in each year of the study period. The price in the base year is the price of that energy type in the chosen base year, specifically 1990 for our study. By doing so, we were able to derive the price ratio, measured as $\widetilde{p}_{it}$, by dividing the green energy index in time t by the fossil energy index in time t.

$$\text{Tax-inc. Price Ratio} = \left(\frac{\text{Green price index}}{\text{Fossil fuel price index}} \right)$$

R&D Subsidies Ratio

The second variable we examine is $\widetilde{R}_{it}$ which is the ratio of subsidies for renewable energy, $R^s_{g,it}$, relative to those for fossil fuel energy, $R^s_{d,it}$, expressed as:

$$\text{R\&D subsidy Ratio} = \left(\frac{\text{Green R\&D subsidy, } R^s_{g,it}}{\text{Fossil fuel R\&D subsidy, } R^s_{d,it}} \right) \times 100$$

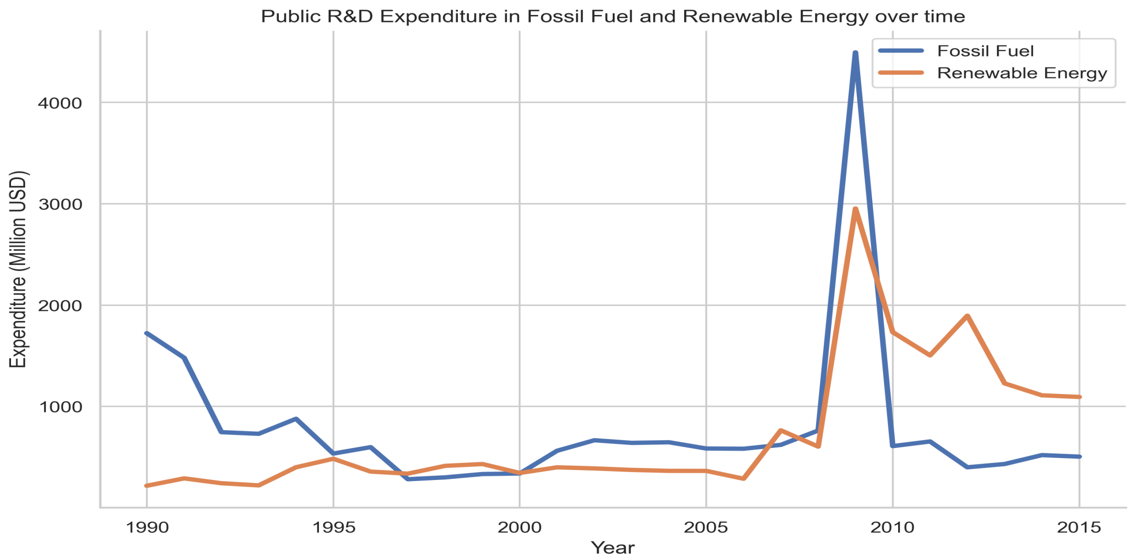
Variables $R^s_{g,it}$ and $R^s_{d,it}$ represent R&D subsidies for renewable energy and fossil fuel energy, respectively. In accordance with Aghion et al. (2016), the public-sector expenditures on renewable energy R&D are used to proxy R&D subsidies. Specifically, the RD&D Budgets database provided by the International Energy Agency (IEA) is employed, which has offered information on energy technology spending to researchers and policymakers since 1974[42]. The R&D

[41] The use of price indices addresses the different units of measurement for green and fossil fuel energy prices by normalizing them to a common base year. This normalization makes the prices comparable on the same scale. When calculating ratios, the ratio of price indices remains consistent with the ratio obtained if prices were converted to the same unit, yielding the same percentage change in both ratios whether calculated with indices or actual prices.

[42] Data can be accessed at: https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2.

subsidy measure is based on USD at constant prices in 2021 utilizing the GDP deflator.

Figure 1.4: Annual U.S. Public R&D Spendings on Renewable and Fossil Fuel Energy: 1990–2015



Source: Graph created by author, data from the International Energy Agency (Million USD at constant 2021 prices using the GDP deflator). ***Note***: The graph shows an initial lag in renewable energy R&D funding compared to fossil fuels. Post-1990, however, there's a reversal with declining fossil fuel funding and increasing renewable energy spending. Despite a shared decline post-2009, renewable energy R&D not only outpaced fossil fuels but also exceeded its 1990s' spending, signaling a substantial shift towards green energy.

Figure 1.4 illustrates the comparative evolution of public R&D funding for renewable and fossil fuel energy sources. Initially, R&D spending in renewable energy lagged behind fossil fuel expenditures. However, a transformative trend emerged post-1990, characterized by a diminishing commitment towards fossil fuel R&D, coinciding with a gradual expansion in renewable energy R&D spending. A significant surge in funding for both sectors was witnessed as the 2000s approached closure, followed by a mutual downturn from 2009 onwards. Notwithstanding this drop in expenditures, R&D spending on renewable energy not only exceeded that of fossil fuels but also surpassed its own earlier levels from the 1990s, indicating a shift towards green energy.

Knowledge stock Ratio

Our empirical analysis includes the knowledge stock ratio (or past productivity ratio), denoted by $\widetilde{A}_{it}$, as a control variable, consistent with the theoretical framework and with other relevant empirical studies, such as Aghion et al. (2016) and Noailly and Smeets (2015). This is quantified by evaluating the past productivity ratio between the green and dirty energy sectors.[43]

$$\text{Knowledge stock Ratio} = \left(\frac{\text{Green knowledge stock, } A'_{g,it}}{\text{Fossil fuel knowledge stock, } A'_{d,it}} \right) \times 100$$

We use the approach from prior research such as Popp (2002), Aghion et al. (2016), and Noailly and Smeets (2015) to determine past productivity levels, A'_g and A'_d, in green and fossil fuel energy sectors, respectively. We construct the knowledge stock for each sector using cumulative patent counts. The knowledge stock in each sector is likely to evolve along with the history of innovation in that sector. However, knowledge stocks may depreciate due to technological advancements over time. Thus, we incorporate an annual depreciation rate of 20% for these knowledge stocks, consistent with suggestions from previous literature such as Aghion et al. (2016).

In the calculation of knowledge stocks, we apply the perpetual inventory method: $K_t = K_{t-1}(1 - \delta) + Pat_t$, where δ signifies the depreciation rate and Pat_t refers to the annual patent count. We establish the initial knowledge stock in renewable and sossil fuel energy technologies as the cumulative total from 1978 until the year 2000, which marks the first year of our sample period. It is worth noting that patent data for both renewable and fossil fuels energy is accessible from the IEA's database from the year 1978 onward. This timeframe provides a sufficient historical perspective for constructing the knowledge stock.

Figure E.3 displays the U.S. renewable and fossil fuel energy patents and knowledge stocks from 1978 to 2020. Despite an increase in both fossil fuel and clean energy patents between 1978 and 2021, clean energy patents exceeded fossil fuel patents, indicating a shift in focus towards green energy technologies. Patent numbers for clean energy peaked at 3,959 in 2011, while those for dirty energy peaked at 2,384 in 2013. Despite these peaks, both categories have

[43] To reaffirm the difference between the R&D subsidy ratio and the knowledge stock ratio and what they capture: Recalling from our theoretical framework, the R&D subsidy ratio indicates the flow of current support for R&D activities in renewable versus fossil fuel energy. It captures how government expenditures on R&D influence the direction of productivity improvements, particularly towards green energy. In contrast, the knowledge stock ratio reflects the accumulated stock of technological progress or past productivity in each energy sector. This ratio captures the extent to which historical innovations and accumulated knowledge influence the transition to green energy, emphasizing the path dependency where sectors with greater past productivity attract more innovation. The flow of R&D subsidies can be a key policy used to shift this dependency, allowing the clean energy knowledge stock to surpass that of fossil energy over time.

experienced significant declines since 2015.

Market Size Ratio

We also incorporate a control variable for market size ratio, denoted by $\widetilde{h}_{it}$, in accordance with the theoretical model and relevant empirical studies. This is determined by the ratio of the market sizes of the green to the fossil fuel energy sectors.

$$\text{Market Size Ratio} = \left(\frac{\text{Green market size, } H_{g,it}}{\text{Fossil fuel market size, } H_{d,it}} \right) \times 100$$

Adopting a similar approach to Noailly and Smeets (2015), we proxy the market size of both renewable and fossil fuel energy sectors using data on their respective installed capacities. This information is derived from EIA database[44]. For the renewable energy sector, the installed capacity is the aggregate of the Nameplate Capacity (in Megawatts) of conventional hydroelectric, wind, wood and wood-derived fuels, biomass, geothermal, and solar energy - encompassing both thermal and photovoltaic sources. In contrast, the installed capacity for the fossil fuel energy sector is quantified as the total Nameplate Capacity (in Megawatts) for coal, natural gas, and petroleum.[45] This methodology provides us with an effective representation of market size for both types of energy.[46] Figure E.4 shows the U.S. electricty generation capacity by major energy source in 1990, 2005, and 2022. The chart illustrates a significant increase in the capacity of renewable energy to generate electricity in 2022, compared to 1990 and 2005. In contrast, a noticeable reduction is seen in electricity generation capacity by coal in recent years. Furthermore, electricity generation capacity by natural gas has shown a steady rise over time.

[44] You can access the data via the following link: https://www.eia.gov/electricity/data/state/.

[45] One can inquire about the difference between a market size ratio and a renewable/fossil fuel ratio. The "renewable/fossil fuel ratio" measures the actual energy produced by renewable and fossil fuels, expressed in megawatt-hours (MWh). In contrast, the "market size ratio" reflects the installed capacity for energy production, measured in nameplate capacity (Megawatts). This distinction is relevant because the market size ratio captures the potential capacity available for energy production, while the Renew/Fossil Ratio captures the actual production. Including the market size ratio as a control variable is crucial because it helps account for the underlying facilities and capacity that can influence actual energy production.

[46] The installed capacity serves as a reliable indicator of market size and prospective production volume of electricity stemming from each type of energy source. It signifies the maximal output achievable by power plants under optimal circumstances. Essentially, this indicator provides a good estimation of the market size associated with electricity output from each distinct energy source. For example, a greater market share in one energy sector requires increasing capacity in that sector and expanding employment. Therefore, we can use either employment or capacity as a proxy for market size. Because we have capacity data, we can use it to measure the size of the market.

Table 1.1: An Overview of Study Variables: Definitions, Measurements, and Data Sources

Variable Name	Definition	Measurement	Data Source
Renewable output, $E_{g,it}$	Renewable energy-based electricity output	Megawatt-hours (MWh)	U.S. Energy Information Administration (EIA)
Fossil-fuel output, $E_{d,it}$	Fossil fuel energy-based electricity output	Megawatt-hours (MWh)	U.S. Energy Information Administration (EIA)
Green R&D subsidies, $R^s_{g,it}$	Public R&D expenditure for renewable energy	Million USD	RD&D Budgets Database, the International Energy Agency (IEA)
Fossil-fuel R&D subsidies, $R^s_{g,it}$	Public R&D expenditure for fossil fuel energy	Million USD	RD&D Budgets Database, the International Energy Agency (IEA)
Average fossil fuel price, $p^s_{d,it}$	Cost of fossil fuel -coal, oil, gas- receipts at electric generating plants (including tax)	USD per million Btu	U.S. Energy Information Administration (EIA)
Tax-inclusive coal price	Steam coal prices for electricity generation in USD/tonne	USD	International Energy Agency (IEA)
Tax-inclusive oil price	Heavy fuel oil prices for electricity generation in USD/tonne	USD	International Energy Agency (IEA)
Tax-inclusive natural gas price	Natural gas prices for electricity generation in USD/MWh (GCV basis)	USD	International Energy Agency (IEA)
Green energy price, $p_{g,it}$	Levelised Cost of Energy (LCOE): the average cost per unit of renewable energy generation.	USD/MWh	International Renewable Energy Agency
Green knowledge stock, $A'_{g,it}$	Cumulative patent counts in renewable energy	Count	Patents-Technology Diffusion, OECD database
Green market size, $H_{g,it}$	Nameplate capacity of renewable energy sources	Megawatts	U.S. Energy Information Administration (EIA)
Fossil-fuel market size, $H_{d,it}$	Nameplate capacity of fossil fuel energy sources	Megawatts	U.S. Energy Information Administration (EIA)

Overall, Figure 1.1 illustrates a noticeable transition in the U.S. energy sector towards renewable energy. The renewable energy's share in U.S. electricity generation rose from 9% in 2000 to 21% in 2020. Associated with this shift are several pivotal trends: an increase in tax-inclusive fossil fuel prices, a decrease in renewable energy costs, and a heightened public R&D

expenditures in renewables compared to fossil fuels, as shown in Figures 1.2, E.1, 1.3, and 1.4. Further, Figures E.3 and E.4 depict the growth in the renewable energy market size and the growing knowledge base within this domain. Taken together, these trends lend support to our theoretical predictions concerning the roles of energy taxation, relative energy prices, and R&D subsidies in the transition toward green energy.

Table 1.1 provides an overview of the study variables, their definitions, measurement units, and sources. Table B.2 illustrates the summary statistics of the log-transformed ratio variables from the sample data. For the output ratio of renewable to fossil fuel energy, $ln\left(\frac{E_{g,it}}{E_{d,it}}\right)$, it has a mean value of -1.93 with a high standard deviation of 2.05, demonstrating a wide variation. The price ratio, $ln\left(\frac{p_{g,it}}{p_{d,it}}\right)$, averages -1.549 and varies with a standard deviation of 0.571, suggesting that prices for fossil fuels tend to be higher than renewable sources. The ratio of R&D subsidies, $ln\left(\frac{R^s_{g,it}}{R^s_{d,it}}\right)$, has an average of 0.18 with a standard deviation of 0.72. It spans from a low of -0.71 to a high of 1.56, signifying some instances where renewable energy receives more subsidies than fossil fuels. The market size ratio, $ln\left(\frac{h_{g,it}}{h_{d,it}}\right)$, has a mean value of -1.91, indicating a generally smaller market size for renewable energy. However, the substantial standard deviation of 1.91 reflects large fluctuations in the market size ratio across different industries and years. Lastly, the knowledge stock ratio, $ln\left(\frac{A'_{g,it}}{A'_{d,it}}\right)$, averages 0.89 with a smaller standard deviation of 0.145. This ratio varies from 0.70 to 1.11, implying a generally higher knowledge stock for renewable energy from 1978 onward.

1.5.2 Empirical Methodology

In this section, the suggested empirical approach to tackle the research questions of the study is presented. As a baseline specification, I use the panel regression shown below.

$$\widetilde{E}_{it} = \beta_0 + \beta_1 \widetilde{R}_{it} + \beta_2 \widetilde{p}_{it} + \beta_3 \widetilde{A}_{it} + \beta_4 \widetilde{h}_{it} + \eta_i + u_{it}, \tag{1.5.3}$$

In this equation, i denotes industries, ranging from 1 to N, and t represents time, spanning from 1 to T. The coefficient η_i accounts for cross-industry effects, and u_{it} is the error term.

All variables are expressed in natural logarithms.[47] The dependent variable, $\widetilde{E}it = E_{g,it}/E_{d,it}$, indicates the ratio of electricity generated from renewable energy to that produced from fossil fuel sources.

The variables $\widetilde{R}_{it} = R^s_{g,it}/R^s_{g,it}$ correspond to the R&D subsidies ratio. The variable $\widetilde{p}_{it} = p_{g,it}/p_{d,it}$ represents the tax-inclusive price ratio of renewable energy to fossil fuel energy. This serves as a proxy of taxation effects on the dependent variable (more details in the data section). The variable $\widetilde{A}_{it} = A_{g,it}/A_{d,it}$ denotes the knowledge stock ratio, or previous productivity, within the renewable energy sector to that within the fossil fuel sector. Similarly, $\widetilde{h}_{it} = h_{g,it}/h_{d,it}$ represents the market size ratio of renewable electricity generation to fossil fuel-based generation.

In estimating the empirical model in Equation 1.5.3, it is also crucial to recognize that it is grounded in a general equilibrium effects as highlighted in Equation 1.4.17.[48] Inherently, such models emphasize the simultaneous determination of multiple economic variables across different markets or sectors. Consequently, the assumption of strict exogeneity, which implies that explanatory variables are uncorrelated with future, current, and past values of the error terms, may be a strong assumption in this context. Violation of this assumption may introduce biases and inconsistency in the estimates derived from conventional panel data techniques.

Given the potential for endogeneity arising from lagged dependent variables and unobserved heterogeneity, it is also imperative to adopt an estimation strategy that accounts for these issues. To this end, we utilize a dynamic Panel Data model. Specifically, we employ the System GMM estimator, introduced by Arellano and Bover (1995) and further developed by Blundell and Bond (1998), to address the concerns about dynamic panel bias and the potential endogeneity of the regressors. In addition, System GMM addresses dynamic panel bias and potential endogeneity by using lagged levels of the dependent and explanatory variables as internal instruments. This method is particularly well-suited to our theoretical framework, where

[47] The variables in this equation are expressed as ratios (e.g., the ratio of green to dirty energy), which are strictly positive. This can be problematic for SGMM estimation, which assumes unbounded variables. To address this, all variables are transformed using the natural logarithm. This transformation (1) removes the lower bound, making the variables more suitable for SGMM; (2) reduces skewness and stabilizes variance; and (3) improves interpretability, as coefficients in a log-log model can be interpreted as elasticities.

[48] In spite of focusing solely on the production sector, ignoring household sector, government sector, and environment constraint, our theoretical framework can still capture certain general equilibrium effects. These simultaneous effects emerge in the equilibrium, whether contemporaneously or with lags. As an example, energy usage influences its price, and this price impacts energy usage as well. Furthermore, past productivity levels affect energy consumption, which in turn impacts current productivity, etc.

the dynamic interactions among variables over time are a fundamental feature of the model structure.

The System GMM offers consistent and efficient estimations in scenarios where explanatory variables might not adhere strictly to exogeneity, or when there is potential for heteroscedasticity and autocorrelations within cross-section units (Roodman 2009b). This approach mitigates endogeneity concerns by utilizing lagged values of the dependent variable, and other endogenous variables as instruments—given that these instruments are uncorrelated with fixed effects (Roodman 2009b).

Based on the analysis presented above, we propose the following dynamic panel equation to estimate the ratio of renewable energy to fossil fuel:

$$\widetilde{E}_{it} = \gamma_1 \widetilde{E}_{i,t-1} + \gamma_2 \widetilde{R}_{it} + \gamma_3 \widetilde{p}_{it} + \gamma_4 \widetilde{A}_{it} + \gamma_5 \widetilde{h}_{it} + \eta_i + \phi_t + \nu_{it}, \tag{1.5.4}$$

where $\widetilde{E}_{i,t-1}$ refers to the dependent variable (the share of renewable to fossil fuel energy) in period $t-1$, and ν_{it} denotes the idiosyncratic error term, and varies across industries i and time periods t. Additionally, we include time dummies, ϕ_t, to the regression since this will make the assumption of no correlation across individuals in the idiosyncratic disturbances more likely to hold (Roodman 2009b). The estimation procedure starts with taking the first difference transformation to remove industry-specific effects:

$$\Delta\widetilde{E}_{i,t} = \gamma_1 \cdot \Delta\widetilde{E}_{i,t-1} + \gamma_2 \cdot \Delta\widetilde{R}_{i,t} + \gamma_3 \cdot \Delta\widetilde{p}_{i,t} + \gamma_4 \cdot \Delta\widetilde{A}_{i,t} + \gamma_5 \cdot \Delta\widetilde{h}_{i,t} + \Delta\phi_t + \Delta\nu_{i,t},$$
$$\text{for} \quad i = 1, ..., N, \quad t = 3, ..., T.$$

There are two assumptions. First, the transitory errors are serially uncorrelated:

$$E(\nu_{it}\nu_{is}) = 0, \quad \text{for} \quad t \neq s$$

Additionally, the initial conditions $\widetilde{E}_{i1}$ are predetermined. i.e.:

$$E(\widetilde{E}_{i1}\nu_{it}) = 0, \quad \text{for} \quad t \geq 2$$

These last two assumptions lead to the following moment restrictions, from Arellano and Bond (1991):

$$E(\widetilde{E}_{i,t-s} \cdot \Delta\nu_{it}) = 0, \quad \text{for} \quad t = 3, .., T, \quad s \geq 2$$
$$E(X_{i,t-s} \cdot \Delta\nu_{it}) = 0, \qquad \text{for} \quad t = 3, .., T, \quad s \geq 2,$$

where X is the vector of other explanatory variables including $\widetilde{R}$, $\widetilde{p}$, $\widetilde{A}$, and $\widetilde{h}$. However, Blundell and Bond (1998) indicate that lagged explanatory variables are weak instruments for first-differenced equations with persistent series and short-time dimensions. They propose differentiating instruments rather than regressors for exogeneity to fixed effects. This method switches the approach from Difference GMM to System GMM estimator, integrating level and first-difference estimations. In sum, to counter finite sample biases from weak instruments, Blundell and Bond (1998) introduce the following moment restrictions:

$$E(\Delta\widetilde{E}_{i,t-1}(\eta_i + \nu_{i,t})) = 0, \quad \text{for} \quad t = 3, .., T.$$
$$E(\Delta X_{i,t-1}(\eta_i + \nu_{i,t})) = 0, \quad \text{for} \quad t = 3, ..., T.$$

The lagged values of the dependent variable and other endogenous variables are often used as instruments in System GMM. Typically, these lagged values correlate with current endogenous variables, but not with error terms. The choice helps deal with endogeneity and unobserved heterogeneity Roodman (2009b). We evaluate the system GMM estimator's consistency through three diagnostic examinations. Initially, we use the Hansen (1982) test for overidentifying restrictions to ensure the overall validity of the instruments, given that they should not be correlated with the error term. Secondly, it is imperative to ensure the absence of autocorrelation in the error term. Therefore, we employ the Arellano and Bond (1991) test to detect both first and second-order serial correlations in the first-differenced residuals. Our primary focus is on the second-order correlation in differences as this sheds light on the first-order serial correlation in levels. This is essential because it establishes the correlation between ν_{it-1} in $\Delta\nu_{it-1}$ and ν_{it-2} in $\Delta\nu_{it-2}$, as detailed by Roodman (2009b). Moreover, to prevent finite sample biases from overfitting, we confirm that the instrument number is less than or equivalent to the group number in the regression (Roodman 2009a).

1.6 Results and Discussion

Recalling our research questions, we aimed to examine the role of tax policies—both fossil fuel taxes and green tax incentives—and R&D subsidies in promoting a shift towards renewable energy. In this section, we present the estimation results of the main sample, followed by robustness checks and supplementary estimations to confirm the reliability of the results. Subsequently, we discuss these results and provide policy recommendations.

1.6.1 Main Estimation

The estimation results from the System GMM, focusing on the renewable to fossil fuel energy ratio across various industries in different states from 2000 to 2015, are presented in Table 1.2. In our System GMM model, we use the second through fifth lagged values of the dependent variable, along with the first lagged values of the explanatory variables, as instruments. We chose these specific lagged values because they are likely to be related to the current values of the endogenous variables but not to the current error term, which helps deal with endogeneity.

From an economic perspective, we claim that there is persistence in the dependent variable. This suggests that clean energy technologies are persistent over time. This means that the current values of the dependent variable (the ratio of clean to dirty energy) are influenced by their past values. Similarly, the explanatory variables—knowledge stock, market size, and policy variables (such as the ratio of tax-inclusive prices and R&D subsidies)—are also likely to rely on their past values due to the path-dependent nature of technological progress and market adjustments. Our theoretical framework also reinforces this reasoning.

We validated these instruments using Hansen's test for overidentifying restrictions, which confirmed that they are suitable for our model. The Hansen test's p-value for all specifications does not reject the null hypothesis, suggesting the instruments used are valid. Furthermore, with the AR(2) p-value exceeding 5%, the null hypothesis implying an absence of serial correlation is not rejected. Also, the instrument number remains less than the group number, reinforcing the model's consistency. It is also worth highlighting that the variable $\widetilde{A}_{it}$ was automatically

Table 1.2: System GMM Estimates from a Panel of Industry Level During (2000-2015)

VARIABLES	(1) Ren/Fossil Ratio	(2) Ren/Fossil Ratio	(3) Ren/Fossil Ratio
Ren/Fossil Ratio (-1)‡	0.732***	0.738***	0.422***
	(0.009)	(0.010)	(0.006)
Tax-inc. Price Ratio		−0.261***	−0.561***
		(0.022)	(0.056)
R&D Subsidy Ratio (d)°			0.062***
			(0.015)
Market Size Ratio			0.198***
			(0.016)
Constant	0.802***	0.334***	0.132
	(0.043)	(0.064)	(0.096)
Observations	2,119	2,119	1,464
Instruments/ Groups	92/134	93/134	78/130
Year Dummies	YES	YES	YES
Hansen test	72.72	74.74	71.58
p-value	0.388	0.327	0.145
AR(2)	1.17	1.20	0.37
p-value	0.241	0.229	0.715

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.
‡ The notation "(-1)" indicates lagged values.
°The symbol "(d)" denotes the first difference.

Table 1.3: Long-Run Coefficients for the System GMM Estimation (2000-2015)

	Coefficient			95% Conf. Interval	
Variable	Estimate	Std. Err.	Z-stat	Lower	Upper
Tax-inc. Price Ratio	−0.971***	0.1007	-9.64	-1.168	-0.773
R&D Subsidy Ratio	0.108***	0.0254	4.23	0.058	0.158
Market Size Ratio	0.342***	0.027	12.51	0.288	0.397

*** p<0.01, ** p<0.05, * p<0.1.

excluded due to collinearity issues. Furthermore, to prevent being automatically excluded for the same reason, $\widetilde{R}_{it}$ was transformed into its first difference. All the included variables show significance at one percent level.

The results across all specifications in Table 1.2, while not identical, consistently align in terms of the direction and relative magnitude of the coefficients. We use the specification in column 3 of this table to briefly address the research questions. The results demonstrate that this $Tax\ Inc.\ Price\ Ratio$ *negatively* and *significantly* affects the the Renew/Fossil Ratio (i.e., the transition from fossil fuel to renewable energy). Therefore, a decrease in this price ratio, achievable by increasing fossil fuel taxation or raising the green tax incentive, would promote a renewable energy shift. Specifically, a 10 percent reduction in this price ratio corresponds to a 5.61 percent increase in the renewable energy transition.

On the other hand, the findings suggest that the ratio of R&D subsidies has a positive and significant influence on the transition to renewable energy. In particular, a 10 percent growth in public R&D subsidies designated for green energy relative to those for fossil fuel energy is associated with a 0.62 percent rise in the Renew/Fossil Ratio. Market size positively influences the ratio of renewable to fossil energy, in line with theoretical expectations. This is indicated by an elasticity coefficient of 0.198, showing the significant effect of market size on the shift towards renewable energy. For example, a 10 percent increase in market size is associated with a 1.98 percent increase in the transition to renewable energy.

We also followed the approach outlined by Papke and Wooldridge (2005) regarding the calculation of both coefficients and standard errors in the long run within a dynamic panel data model, as presented in Table 1.3. In dynamic panel models, the long-run effect (or multiplier) for a dynamic model can be calculated as follows:

$$\text{Long-run effect} = \frac{\text{Coefficient of the independent variable}}{1 - \text{Coefficient of the lagged dependent variable}}$$

. The results in Table 1.3 show that these coefficients not only remain significant in the long run, but the impacts of both policy strategies also intensify. Specifically, a permanent 10 percent reduction in the price ratio, achieved either by escalating the fossil fuel tax or enhancing green tax incentives, results in a 9.71 percent upsurge in the Renew/Fossil ratio over the long run. In parallel, a sustained 10 percent augmentation in the R&D subsidy ratio, whether by boosting the green or curtailing the dirty R&D subsidy, results in a 1.08 percent enhancement in the shift towards renewable energy. These empirical results resonate well with the anticipations and hypotheses set out in our theoretical framework, especially regarding the pivotal role of tax policies and R&D subsidies in driving the renewable energy transition. Moreover, adjusting taxation through changing price ratios appears to have a more substantial influence on the transition to green energy compared to the effects of R&D subsidies, an outcome that also aligns with the theoretical predictions.

1.6.2 Robustness Checks and Supplementary Estimations

To bolster the robustness of our analysis, we conducted our estimation using the System GMM on the specifications detailed in Equation 1.5.4, but examined them across two distinct periods: 2005-2015 and 2009-2015. The findings from this examination are presented in Table B.3. When compared with the results from the primary timeframe (2000-2015) in Table 1.2, there is discernible consistency in the effects of taxation and R&D subsidies, albeit with subtle differences in their magnitudes.

To further enhance the robustness of our analysis, it would be advantageous to perform empirical estimations across various data levels. The estimation in Table B.5 is similar to Table B.4 but for a sample at the state level during the same study period 2001-2015.[49] The state-level regression results reinforce the industry-level findings, affirming the robustness of the study. Specifically, the Tax-inc. Price Ratio negatively impacts the Renew/Fossil Ratio, while the R&D Subsidy Ratio and Market Size Ratio boost it. The improved R-squared values indicate a stronger model fit at the state level. These findings underscore the consistent influence of taxation and R&D subsidy on the U.S. energy transition across different empirical levels.

Table B.5 also presents one more model where the focus shifts to the actual level of renewable energy. In this models, a decrease in the Tax-inc. Price Ratio (achieved through higher fossil fuel taxes or increased green tax incentives) is shown to promote renewable energy. Furthermore, augmenting R&D subsidies, either by boosting green R&D or reducing the ratio of

[49]The System GMM is not suitable at the state level since the instrument number exceeds the number of groups, namely states. Therefore, we used the Fixed Effects method.

subsidies in favor of fossil fuels, is seen to favor renewable energy. The market size ratio aligns with predictions, indicating that an increase in the market size ratio (achieved by expanding the green market or contracting the fossil fuel market) favoring renewable energy encourages renewable energy adoption while discouraging fossil fuel use. Additionally, we include total electricity output as a control variable, recognizing its significance in models where the dependent variables are measured in levels rather than ratios. This control variable demonstrates a positive influence in both model specifications.

There could be important implications for using public R&D subsidies instead of private R&D subsidies due to data limitations on the latter. Public R&D typically targets early-stage research, which often takes longer to commercialize compared to private R&D, which tends to be more directly linked to immediate market applications and innovations. Consequently, this may challenge the assumption of a contemporaneous relationship between the R&D subsidies ratio and the electricity generation ratio. To address this, we have added another specification in the fixed effect model, we included the R&D subsidies ratio with lags to address these delayed effects.[50] Using a two-period lag for the R&D subsidy yields consistent estimates compared to the contemporaneous specification. Notably, the effect slightly improves, as the elasticity increases from 0.115 to 0.179. Additionally, the knowledge stock ratio becomes significant at the 1% level, indicating that this specification reduces collinearity concerns between knowledge stock and R&D subsidy, thereby enhancing the overall model results.

To dig deeper into the underlying dynamics of energy utilization in the U.S. electricity generation sector, a deeper analysis in Table B.6 was introduced by decomposing the previously used ratios, both for the dependent and explanatory variables, into their individual levels. This approach provides a more detailed insight into the direct effects of R&D subsidies, tax-inclusive prices, and market sizes on renewable and fossil fuel energy generation. At both the industry and state levels (columns 1 and 2, respectively), higher tax-inclusive fossil fuel prices and R&D subsidies for renewable energy sources significantly increase renewable energy generation. Conversely, a decline in renewable prices marginally encourages renewable energy production. Similarly, R&D subsidies for fossil fuels negatively impact renewable energy. As

[50]The system GMM inherently accounts for the dynamic relationships and the potential delayed effects of variables like R&D subsidies.

anticipated, a larger market size for renewable energy strongly bolsters renewable energy generation, while a larger market size for fossil fuels significantly suppresses this generation of the renewable energy. In columns 3 and 4, tax-inclusive fossil fuel prices exert a negative, albeit insignificant, influence on fossil fuel energy production, whereas renewable prices have a positive impact. Fossil fuel R&D subsidies positively impact fossil fuel production, contrasting with the negative effect of renewable R&D subsidies. A rise in the market size of fossil fuels promotes fossil fuel production, while an expanded renewable market size corresponds with a decrease in fossil fuel production. The consistency of these results in Table B.6 with the findings presented in Tables B.4 and B.5 further reinforces the robustness of the results of this study.

Table 1.4 shows different theoretical scenarios for taxation and R&D effects when $\epsilon > 1$ and $0 < \sigma < 1$. To give some insight into their comparison with empirical investigations, the table also presents these coefficients in various empirical models. Results of the empirical analysis align with theoretical predictions, particularly for the sign and relative strength of taxation and R&D coefficients. Taxation consistently has a negative impact, while R&D subsidies have a positive impact, and the taxation effect is greater than the R&D effect in absolute value, in line with theoretical expectations.

Substitution and Innovation Elasticities:

Lastly, our estimation results allow us to approximate the values of two important parameters: the elasticity of substitution ϵ between green and dirty energy in the U.S. electricity generation sector and the elasticity of innovation with respect to research expenditure in the same sector. Papageorgiou et al. (2017) were pioneers in estimating the substitution value between clean and dirty energy, followed by Stöckl and Zerrahn (2023), who provided a bottom-up perspective in their estimation. However, neither study applied their estimation specifically to the U.S. electricity generation sector. The former used panel data from various OECD countries, while the latter focused on German data.

To the best of our knowledge, no prior research has comprehensively estimated both the substitution elasticity in the context of U.S. electricity generation and the elasticity coefficient

Table 1.4: **Taxation and R&D Effects: Theoretical Predictions and Empirical Findings**

Theoretical Predictions		
Range of Scenarios	**Taxation Coef.** ($\frac{-\epsilon\sigma}{1-\sigma}$)	**R&D Coef.** ($\frac{\sigma}{1-\sigma}$)
$\epsilon = 1.8, \sigma = 0.020$	-0.037	0.020
$\epsilon = 3.9, \sigma = 0.098$	-0.428	0.109
$\epsilon = 6.5, \sigma = 0.058$	-0.398	0.062
$\epsilon = 6.5, \sigma = 0.200$	-1.615	0.250
Empirical Analysis		
Model	**Taxation Coef.**	**R&D Coef.**
System GMM	-0.561	0.062
System GMM (Spec.2)	-0.608	0.085
Fixed Effects	-0.385	0.126
Fixed Effects (States)	-0.380	0.186

Note: Taxation effect is always negative. R&D subsidy effect is always positive. Taxation effect is stronger than R&D effect. Empirical estimates align within the range of theoretical predictions.

of innovation with respect to research expenditures (i.e., the parameter σ). Our study offers an opportunity to approximate the range of these elasticities within the U.S. electricity generation sector. However, a more in-depth analysis is required to obtain precise estimations of these parameters, which is beyond the scope of this current research.

In this regard, our empirical analysis allows us to infer the estimated values of the elasticity of substitution and innovation elasticity in the U.S. electricity generation sector. Specifically, Table 1.4 presents the results indicating that the coefficient of R&D subsidy (i.e., $\frac{\sigma}{1-\sigma}$ at the industry level, using the Fixed Effects method) is 0.126, suggesting that the value of σ is 0.112. In the same model specification, the coefficient for Taxation (i.e., $\frac{-\epsilon\sigma}{1-\sigma}$) is -0.385, indicating that the value of ϵ is approximately 3. Similarly, our analysis reveals that the estimated values of σ and ϵ are approximately 0.157 and 2, respectively, at the state level, as inferred from the R&D subsidy and taxation coefficients, as shown in Table 1.4. Summing up, σ ranges from 0.112 to 0.157 and ϵ ranges from 2 to 3.[51]

[51]The estimated elasticity of substitution in our results aligns with the findings of Papageorgiou et al. (2017)

1.6.3 Comparison with Earlier Work

It is also pertinent to highlight the link between our results and those of other empirical works within the domain of DTC literature, such as Aghion et al. (2016) and Noailly and Smeets (2015). Our study differs from previous studies, as our research highlights ratios rather than absolute levels, focusing on the ratio of clean to fossil fuels, as well as the effects of tax reforms and research subsidies in terms of their ratio of clean versus dirty energy. This approach aligns climate goals with economic concerns, ensuring a shift to clean energy with minimal economic burden. Solely reducing fossil fuels can hinder growth if clean alternatives don't evolve, and only boosting clean energy is not adequate if fossil fuel use continues to remain high.

Analyzing these ratios helps achieve climate goals while maintaining economic prosperity. Additionally, comparative ratios within policy measures impact the transition pace more than absolute values. For instance, increasing renewable energy research subsidies is essential, but their effects are weakened if fossil fuel research subsidies remain high. Considering the increasing ratio of green to dirty R&D subsidies ensures clean energy promotion outpaces fossil fuels, and then accelerates the transition. This perspective on policy balance ratios is often overlooked in earlier studies (e.g., Aghion et al. 2016, Noailly and Smeets 2015, Lazkano and Pham 2016).

Aghion et al. (2016) explored the impact of tax-inclusive fuel pricing, path dependency, and R&D subsidies on the adoption of clean, gray, and dirty technologies (as proxied by patent counts) in the automotive sector across a diverse sample of 80 countries. Our analysis offers some compelling comparisons. Firstly, our results support the widely recognized finding that tax-inclusive fuel pricing significantly encourages the shift towards cleaner technologies, as indicated by strong and positive coefficients.

Secondly, Aghion et al. (2016) analysis reveals that the coefficient associated with R&D subsidies is positive and statistically significant at the 10 percent level in the equation for gray innovation, yet it is not significant for clean innovation (despite being positive) and is negative but not significant for purely dirty innovation. In our analysis, R&D subsidies have a highly

and Stöckl and Zerrahn (2023). Our estimated range for this elasticity is close to the values obtained by these authors in different scenarios.

significant impact.[52] Thirdly, an interesting observation in the work of Aghion et al. (2016) is that the coefficients for R&D subsidies are consistently lower in absolute value compared to those for tax-inclusive fuel pricing. It is important to note that they applied the natural logarithm to all variables, making the comparison between the effects of tax and R&D subsidies valid. This observation aligns closely with our findings. However, Aghion et al. (2016) did not highlight or investigate the underlying reasons for this distinction.

Broadly, across studies that have investigated the effects of energy taxes or prices, and R&D subsidies on cleaner innovation, a consistent observation emerges where such a comparison is relevant: the coefficient associated with R&D subsidies tends to be significantly lower than that of energy taxes (or prices). This pattern suggests that energy taxes have a more substantial impact on promoting cleaner innovation than R&D subsidies do. For instance, in a related study, Costantini et al. (2017) examined the impact of demand-side policies, including energy taxation and energy prices, alongside technology-driven policies, such as R&D subsidies, on the innovation performance of energy efficiency technologies within the residential sector across 23 OECD countries during the 1990-2010 period. Their findings align with ours, showing that the impact of technology-push policies is less pronounced than that of demand-pull policies. However, Costantini et al. (2017) did not address this observation in their study. Additionally, a similar observation that resonates with our findings is presented in the study by Popp (2002). This research explored the impact of energy prices and R&D subsidies on the innovation of energy-efficient technologies by analyzing U.S. patent data from 1970 to 1994. Notably, it was discovered that the coefficients for R&D subsidies were considerably lower than those for energy price.

Considering the relative impacts of taxation and R&D subsidies as observed in various studies, it is notable that none of these studies investigated, analyzed, or explicitly mentioned the relative strengths of both policy instruments. Our research makes a significant contribution to the field. In particular, we offer a theoretical framework explaining why the impacts of

[52]It is important to consider the apparent lack of significance associated with R&D subsidies in Aghion et al. (2016)'s results. In their equations, R&D subsidies were included alongside the knowledge stock (i.e., a measure of path dependency) for each type of technology. This might raise concerns about multicollinearity, which could diminish the significance of the variables involved. Specifically, the knowledge stock was calculated based on the cumulative number of patents, suggesting a likely positive correlation between patent counts and R&D subsidies. This potentially introduces the concern of multicollinearity. In our analysis, the System GMM automatically excluded knowledge stock from the estimation to address multicollinearity, as such automatic exclusion aligns with the methodological procedures of this estimation technique.

taxation and R&D subsidies vary in their intensity, as detailed in the theoretical framework section, particularly in the discussion pertaining to equation 1.4.17. Through this analysis, we emphasize our important contribution to the existing body of literature in this domain.

Moreover, in a study focusing on European firms within the electricity generation sector, Noailly and Smeets (2015) examined the impact of fossil fuel prices, market sizes and knowledge stocks on both renewable and non-renewable energy technologies. Their analysis concluded that among these variables, only knowledge stocks exerted a substantial influence on narrowing the technological gap between fossil fuel and clean energy. Our approach goes beyond the mere number of patents to consider the ratio of clean to dirty energy usage, offering a direct measure of the industry's shift towards greener energy sources. Our findings reveal the substantial effects of tax-inclusive pricing and R&D subsidies on this transition, reinforcing their importance in the shift to sustainable energy production.

1.6.4 Discussion and Policy Implications

In Summary, the empirical evidence of this study aligns closely with the predictions and hypotheses advanced by our theoretical framework. Specifically, the tax-inclusive price ratio negatively influences renewable energy transition. This suggests that an increase in tax-inclusive fossil fuel prices, serving as a proxy for fossil fuel taxes, and/or a reduction in renewable energy prices, serving as a proxy for an increase in green tax incentives, expedite the shift from fossil to renewable energy sources. Such tax modifications render renewable energy more economically competitive, thereby incentivizing its adoption over fossil fuels. Moreover, the R&D subsidy ratio demonstrates a significant positive effect. This implies that prioritizing R&D subsidies in renewable energy over those in fossil fuels could stimulate innovation and productivity in the green sector, thereby accelerating the transition to sustainable energy options.

Moreover, our findings reveal that taxation's role in facilitating the shift towards renewable energy is significantly stronger than that of R&D subsidies, aligning with the predictions of our theoretical model. This prominent effect of taxation or price adjustments could be attributed to the evident substitutability between renewable and fossil fuel energy sources. Such substitutability likely acts as an additional driver for demand-side entities to accelerate their transition towards renewable energy sources. On the other hand, the impact of R&D subsidies is more conditional, depending on whether these investments genuinely enhance productivity, which is in turn predicated on the uncertain outcomes of innovation efforts, as discussed in our theoretical framework. In essence, demand-side policy measures like tax reforms are shown to catalyze a quicker transition to greener energy alternatives in comparison to supply-side initiatives like R&D subsidies. Specifically, taxation can exert an immediate influence by altering the relative price of fossil fuel energy versus green energy, thereby motivating demand-side actors to replace their fossil fuel consumption with cleaner alternatives. Conversely, the influence of R&D subsidies occurs over a longer period of time, as the innovation process inherently requires time to develop and actualize successful innovations.

Our research reveals key policy recommendations for accelerating renewable energy transition. Firstly, we suggest prioritizing tax adjustments, specifically through the implementation of fossil fuel taxes and the introduction of green tax incentives, over sole reliance on R&D subsidies. Essentially, if policymakers aim to diminish fossil fuel dependency and curtail emissions within a timeframe aligned with specific targets like those set out in the Paris Agreement, then a greater emphasis should be placed on demand-side measures such as tax reforms, given their capacity for a more immediate impact.

Secondly, considering that the effectiveness of R&D subsidies is contingent upon the realization of commercially viable innovations, we recommend that the provision of these subsidies be contingent on tangible innovation achievements. This could be determined by the generation of high-value patents or an enhancement in green sector productivity. Thirdly, our findings indicate that the impact of R&D subsidies becomes significantly more evident when subsidies for green R&D outweigh those allocated to fossil fuels. Therefore, any augmentation in clean R&D subsidies should also involve a reduction in R&D subsidies for fossil fuel research. It is crucial to recognize that simply elevating subsidies for green technologies is insufficient; a thorough reevaluation and decrease in the support for fossil fuel research are essential steps.

1.7 Conclusion

This study explores the impact of tax adjustments—particularly fossil fuel taxes and green tax incentives, as a demand-side measure— and R&D subsidies, as a supply-side measure, on the transition to renewable energy. We develop a theoretical framework tailored to the energy sector and inspired by the DTC literature, which places a unique emphasis on the interplay between taxation and R&D subsidies in the green energy transition. This framework allows us to predict the effects and relative strength of these policies. With our empirical analysis, we validate our theoretical predictions by analyzing U.S. electricity production data across states and producer types between 2000 and 2015. We employ the System GMM methodology as outlined by Arellano and Bover (1995) and Blundell and Bond (1998) to account for fixed effects and potential endogeneity in the explanatory variables. This approach provides more reliable and efficient estimates than traditional panel data estimates. Moreover, we use the fixed effects model, using cluster-robust standard errors where producer types are the clusters, allowing a better understanding of variations within groups.

The empirical findings of our study are in strong concordance with the theoretical predictions, supporting the validity and robustness of our approach. These findings reveal several key insights. Primarily, we observe that the ratio of tax-inclusive prices between green energy and fossil fuels significantly influences the shift from fossil fuels to renewable energy sources. More specifically, a reduction in this price ratio—achieved either by increasing the fossil fuel tax or by introducing green tax incentives—appears to expedite the transition towards renewable energy. Such fiscal adjustments effectively lower green energy's relative cost compared to fossil fuels, thereby improving its economic competitiveness.

In addition, our study shows that reallocating R&D subsidies from fossil fuels to green energy has a significant positive impact. By skewing the R&D subsidies in favour of green energy, we stimulate innovation and enhance productivity within the renewable energy sector. Essentially, a critical insight from our findings is the relative importance of the R&D subsidy ratio over the absolute levels of these subsidies. For instance, solely expanding green R&D subsidies may not be adequate to stimulate a significant shift towards green energy if R&D subsidies for fossil fuel continue to dominate.

Tax reform (particularly fossil fuel taxes and green tax incentives) has a superior effect on the green transition than reallocating R&D subsidies. The evident substitutability of renewable and fossil fuel energy enables such tax reform— as a demand-side policy— to be preferable to R&D subsidy. Taxation can lead to more rapid change by making fossil fuels more expensive relative to green energy. This will encourage demand-side stakeholders to switch to cleaner alternatives. On the other hand, the effects of R&D subsidies are more gradual as innovation takes time to evolve and bring successful new technologies. In other words, tax reform is a short- and medium-term policy, while R&D subsidies are long-term.

Regarding policy recommendations, we advocate prioritizing tax reforms, particularly elevating fossil fuel taxes and expanding green tax incentives, over R&D subsidies. This policy suggestion is especially relevant for governments that aim to reduce emissions (ideally by reducing fossil fuel consumption) within a specific timeframe, such as those outlined in the Paris Agreement. Focusing on more superior policy options can help governments transition to clean energy more rapidly. For the R&D subsidy, we emphasize the necessity of a dual approach: merely increasing R&D subsidies for renewable energy is insufficient. There is a fundamental need to reassess and actively reduce fossil fuel R&D subsidies. Furthermore, providing R&D subsidies should be closely linked to innovation and productivity outcomes. In this way, subsidies promote innovation rather than being just financial expenses. Lastly, policymakers may consider a 'double dividend' strategy in instances where green policy incentives burden the fiscal budget. In this approach, fossil fuel taxes fund green initiatives, contributing to environmental objectives while maintaining fiscal balance.

Appendix A

Theoretical Framework

A.1 Solving for Equilibrium

A.1.1 The final good producer

We assume that the final good producer (the electricity producer in the empirical model) can use either dirty or clean inputs for their production, E. This production process is modeled using a Constant Elasticity of Substitution (CES) function.

$$E = \left[E_d^{\frac{\epsilon-1}{\epsilon}} + E_g^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \tag{A.1.1}$$

where E_d and E_g are the energy inputs from both dirty and green sources respectively. The elasticity of substitution between the two sectors can be expressed as $\epsilon \in (0, \infty)$. The profit maximization problem of the final good firm is as follows:

$$\max_{E_d, E_g} \quad \Pi^e = P^e E - (1 + \tau_d)\, P_d^e\, E_d - (1 - \tau_g)\, P_g^e\, E_g \tag{A.1.2}$$

where P^e is the price of final good, the price of the final good, which is exogenously determined by the market for this good. P_d^e and P_g^e are the prices of dirty and clean energy respectively. The final good firm pays tax τ_d and receives a subsidy to the green input τ_g.

This firm wants to maximize its profit, Π^e, which is equal to the total revenue generated from selling this composite energy minus the cost of the dirty energy and the cost of the green energy. The first order conditions are as follows:

$$\frac{\partial E}{\partial E_d} = P^e \left[E_d^{\frac{\epsilon-1}{\epsilon}} + E_g^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{1}{\epsilon-1}} E_d^{-\frac{1}{\epsilon}} - (1+\tau_d)\, P_d^e = 0 \tag{A.1.3}$$

$$\frac{\partial E}{\partial E_g} = P^e \left[E_d^{\frac{\epsilon-1}{\epsilon}} + E_g^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{1}{\epsilon-1}} E_g^{-\frac{1}{\epsilon}} - (1-\tau_g)\, P_g^e = 0 \tag{A.1.4}$$

With a few rearrangements for eqaution A.1.3, we can obtain the value for E_d as follows

$$E_d^{-\frac{1}{\epsilon}} = \frac{(1+\tau_d)\, P_d^e}{P^e} \left[E_d^{\frac{\epsilon-1}{\epsilon}} + E_g^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{-1}{\epsilon-1}} \tag{A.1.5}$$

$$E_d = \left(\frac{P^e}{(1+\tau_d)\, P_d^e} \right)^{\epsilon} E \tag{A.1.6}$$

By similarity:

$$E_g = \left(\frac{P^e}{(1-\tau_g)\, P_g^e} \right)^{\epsilon} E \tag{A.1.7}$$

A.1.2 The green and dirty energy firms

In terms of energy, we suggest that each type—clean (g) and dirty (d)—can be described by a specific Cobb-Douglas function. Let's first focus on clean energy production. Here's the production function:

$$E_g = H_g^{1-\alpha} A_g^{1-\alpha} X_g^{\alpha} \tag{A.1.8}$$

Clean energy E_g is generated using labor (H_g) and machines (X_g), indexed $[0,1]$. $X_g = \int_0^1 X_g^j d_j$, where j represents the machine type. Machine quality, noted as A_g, is $A_g = \int_0^1 A_g^j dj$, where A_g^j is machine type j quality in clean energy.

The green energy producers aim to maximize profits based on this profit function:

$$\pi_g = \max_{X_g, H_g} \{ P_g E_g - P_g^x X_g - W\ H_g \} \tag{A.1.9}$$

Here, P_g^x refers to the price of machines in the green energy sector, while W represents the wage rate for labor, which is assumed to be identical across all sectors. The first order conditions are as follows:

$$\frac{\partial \pi_g}{\partial X_g} = \alpha P_g H_g^{1-\alpha} A_g^{1-\alpha} X_g^{\alpha-1} - P_g^x = 0 \tag{A.1.10}$$

Rearranging gives us:

$$\alpha P_g H_g^{1-\alpha} A_g^{1-\alpha} X_g^{\alpha-1} = P_g^x \tag{A.1.11}$$

This implies:

$$X_g = \left(\frac{\alpha P_g}{P_g^x}\right)^{\frac{1}{1-\alpha}} H_g \; A_g \tag{A.1.12}$$

Similarly, for H_g:

$$\frac{\partial \pi_i}{\partial H_g} = (1-\alpha) P_g H_g^{-\alpha} A_g^{1-\alpha} X_g^{\alpha} - W = 0 \tag{A.1.13}$$

Rearranging gives us:

$$(1-\alpha) P_g H_g^{-\alpha} A_g^{1-\alpha} X_g^{\alpha} = W \tag{A.1.14}$$

This implies:

$$H_g = \left(\frac{(1-\alpha) P_g A_g^{1-\alpha} X_g^{\alpha}}{W}\right)^{\frac{1}{\alpha}} \tag{A.1.15}$$

These two conditions represent the quantities of X_g and H_g that maximize π_g, given the constraints. The firm, in a perfectly competitive market, should adjust its input choices until these conditions are met.

By similarity, we can obtain the quantities of X_d and H_d in the dirty energy sectors by the following two equations:

$$X_d = \left(\frac{\alpha \; P_d}{P_d^x}\right)^{\frac{1}{1-\alpha}} H_d \; A_d \tag{A.1.16}$$

$$H_d = \left(\frac{(1-\alpha) P_d A_d^{1-\alpha} X_d^{\alpha}}{W}\right)^{\frac{1}{\alpha}} \tag{A.1.17}$$

A.1.3 Capital producers

In line with the literature on endogenous technical change, firms supplying machines in each energy sector compete in a monopolistic manner. The production cost for machines stays the same regardless of quality or sector, and is assumed to be ψ units of the final product. For simplicity, the cost is normalized to $\psi = \alpha^2$, and the price, P_g^x, at which machinery producers maximize profit is a constant markup over the marginal cost, that is, $P_x = \frac{\psi}{\alpha}$ as suggested by Acemoglu et al. (2012). The quantity of machines depends on the profit function, $\pi_i^x = \max_{X_i} P_i^x X_i - \psi X_i$, where $i \in (d, g)$. Accordingly, the machine producer's profit in equilibrium is:

$$\pi_g^x = \alpha(1-\alpha)X_g \tag{A.1.18}$$

$$\pi_d^x = \alpha(1-\alpha)X_d \tag{A.1.19}$$

The price of machines in both sectors is:

$$P_g^x = P_d^x = \alpha \tag{A.1.20}$$

In this model, the machine producers are spending on R&D to innovate and improve the quality of their machines. It is assumed that there exists an entrepreneur with the opportunity to innovate. When such an entrepreneur accomplishes successful innovation, they gain the capacity to manufacture machinery of superior quality within that given period. In this model, the machine's quality, which is an indicator of productivity, can be then expressed, in average, with the following equation:

$$A_i = \mu_i A_i' \tag{A.1.21}$$

where $i \in (g, d)$. μ_i models innovation in this model. A_i' represents the quality of machinery at the previous period, $t-1$, within this respective sector. For simplicity, we set a lower bound of one for this innovation function, μ_i to normalize the previous period's machine quality. If there is an entrepreneur who is successful in enhancing the machine's quality beyond one, she will be granted the monopoly power to produce this machine in period t. Otherwise, if no such advancement is achieved, the monopoly power will be assigned arbitrarily to any entrepreneur who maintains the machine quality from period $t-1$.

In this model, conducting research is required for successful innovation, μ_i. In accordance with Aghion and Howitt (2008), this innovation can be formulated as follows:

$$\mu_i = \phi \left(\frac{RD_i}{A_i} \right)^{\sigma} = \phi \left(\widetilde{RD}_i \right)^{\sigma} \tag{A.1.22}$$

Here, RD_i represents the R&D expenditure of machine producers within sector $i \in (g, d)$, ϕ denotes the productivity of the research field, $\widetilde{RD}_i$ is the productivity-adjusted R&D expenditure, and $0 < \sigma < 1$ implies diminishing returns of the productivity-adjusted R&D expenditure[1].

The model posits governmental intervention in the form of subsidies towards the entrepreneur's R&D expenditure. With these R&D subsidies, represented as R_s, the net reward for engaging in research activities is as follows:

$$\pi_i^R = \max_{RD_i} \{ \mu_i \pi_i^x - (1 - R_s) \; RD_i \} \tag{A.1.23}$$

The entrepreneur chooses the amount of RD_i that maximizes the above net reward. Let's focus first on the machine producers of the green energy sectors.

$$\pi_g^R = \max_{RD_i} \left\{ \phi \left(\frac{RD_g}{A_g} \right)^{\sigma} \pi_g^x - (1 - R_g^s) \; RD_g \right\} \tag{A.1.24}$$

To find the optimal quantity of RD_g that maximizes π_g^R, we take the derivative of the profit function with respect to RD_g and set it to zero.

The derivative of π_g^R with respect to RD_g is:

$$\frac{\partial \pi_g^R}{\partial RD_g} = \phi \sigma \pi_g^x \left(\frac{RD_g}{A_g} \right)^{\sigma - 1} \frac{1}{A_g} - (1 - R_g^s) = 0 \tag{A.1.25}$$

Setting the derivative equal to zero, we get the first order condition:

$$\phi \sigma \pi_g^x \left(\frac{RD_g}{A_g} \right)^{\sigma - 1} \frac{1}{A_g} = (1 - R_g^s) \tag{A.1.26}$$

[1]Equation 1.4.7 illustrates that as technology progresses (i.e., the quality of machinery, represented by A_i, improves), it becomes increasingly challenging to further enhance. Therefore, it isn't merely R&D expenditure that is significant but also productivity-adjusted R&D expenditure, i.e., the ratio RD_i/A_i. A detailed explanation of this notion can be found in Aghion and Howitt (2008).

Rearranging for RD_g, we find:

$$RD_g = A_g \left(\frac{(1 - R_g^s) A_g}{\phi \sigma \pi_g^x} \right)^{\frac{1}{\sigma - 1}} \tag{A.1.27}$$

This quantity of RD_g maximizes π_g^R, given the constraints. The firm should adjust RD_g until this condition is met. By similarity

$$RD_d = A_d \left(\frac{(1 - R_d^s) A_d}{\phi \sigma \pi_d^x} \right)^{\frac{1}{\sigma - 1}} \tag{A.1.28}$$

A.2 Theoretical Model: Supporting Proofs

This appendix provides further proofs that are essential in examining the influence of taxes and subsidies on the transition toward green energy.

A.2.1 Proof of Identity One

In order to establish proof for the identity in Equation 1.4.12, we substitute the value of the machine at equilibrium from Equation A.1.12 into the first-order condition with respect to labor in Equation A.1.14 (considering the assumption that $P_g^x = P_d^x = \alpha$). This yields the following equation:

$$w = (1 - \alpha) P_g^{\frac{1}{1-\alpha}} A_g$$

With minor rearrangement, we ascertain the price of green energy as follows:

$$P_g^{\frac{1}{1-\alpha}} = W \left((1 - \alpha) A_g \right)^{-1} \tag{A.2.1}$$

Likewise, a similar equation can be obtained for the fossil fuel sector as follows:

$$P_d^{\frac{1}{1-\alpha}} = W \left((1 - \alpha) A_d \right)^{-1} \tag{A.2.2}$$

By dividing Equation A.2.1 by A.2.2, we derive the final relationship between prices and the productivity of both sectors:

$$\frac{A_g}{A_d} = \left(\frac{P_g}{P_d}\right)^{-\left(\frac{1}{1-\alpha}\right)} \tag{A.2.3}$$

This equation affirms the principle that the sector with higher productivity experiences a lower price.

A.2.2 Proof of Identity Two

To establish proof for the identity in Equation 1.4.16, we divide the profit of machines in both sectors (i.e., divide Equation A.1.18 by Equation A.1.19). This yields the following equation:

$$\frac{\pi_g^x}{\pi_d^x} = \frac{X_g}{X_d} \tag{A.2.4}$$

By incorporating the value of green energy production from Equation A.1.8 into the first-order condition with respect to the machine in Equation A.1.11, we can rearrange the first-order condition into the following expression:

$$P_g^x = \alpha \ P_g \ \frac{E_g}{X_g}$$

With minor rearrangement (considering the assumption that $P_g^x = P_d^x = \psi/\alpha$):

$$X_g = \frac{\alpha^2 P_g \ E_g}{\psi}$$

Similarly, we can derive a similar equation for the fossil fuel sector:

$$X_d = \frac{\alpha^2 P_d \ E_d}{\psi}$$

By dividing Equation A.2.2 by A.2.2 and using Equation A.2.4, we get

$$\frac{X_g}{X_d} = \frac{\pi_g^x}{\pi_d^x} = \frac{P_g}{P_d} \frac{E_g}{E_d} \tag{A.2.5}$$

A.2.3 Detailed Steps for Equation 1.4.17

In this subsection, we present the detailed steps to verify the relation obtained in Equation 1.4.17. We commence by dividing Equation A.1.7 by Equation A.1.6, which allows us to obtain the ratio of clean energy use to that of fossil fuel energy:

$$\frac{E_g}{E_d} = \left(\frac{(1-\tau_g)}{(1+\tau_d)}\right)^{-\epsilon} \left(\frac{P_g^e}{P_d^e}\right)^{-\epsilon} \tag{A.2.6}$$

Utilizing the optimality conditions for energy producers as outlined in Equation A.1.12, and considering that $P_g^x = P_d^x = \alpha$ (by assumption), we substitute the equilibrium quantity of machine production into each energy source's production function, as demonstrated in Equation A.1.8.

$$E_g = P_g^{\frac{\alpha}{1-\alpha}} A_g H_g \tag{A.2.7}$$

Given that the quality of machines is given by Equation A.1.21 and the innovation probability by Equation A.1.22, we can obtain the value of machine quality in the green sector as follows:

$$A_g = \phi \left(\frac{RD_g}{A_g}\right)^{\sigma} A'_g \tag{A.2.8}$$

By substituting Equation A.2.8 into A.2.7, we can obtain the following equation:

$$E_g = P_g^{\frac{\alpha}{1-\alpha}} \phi \left(\frac{RD_g}{A_g}\right)^{\sigma} A'_g H_g \tag{A.2.9}$$

Similarly, we can obtain a corresponding equation for the non-renewable sector:

$$E_d = P_d^{\frac{\alpha}{1-\alpha}} \phi \left(\frac{RD_d}{A_d}\right)^{\sigma} A'_d H_d \tag{A.2.10}$$

As a result, we can identify the direct effect of R&D expenditure on the transition to green energy by dividing Equation A.2.9 by Equation A.2.10 and obtaining the following relation:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \times \left(\frac{\widetilde{RD}_g}{\widetilde{RD}_d}\right)^{\sigma} \times \left(\frac{A'_g}{A'_g}\right) \times \left(\frac{H_g}{H_d}\right) \tag{A.2.11}$$

We can also rearrange the equation to separate the impact of R&D expenditure from its productivity adjustment, as outlined below:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \times \left(\frac{RD_g}{RD_d}\right)^{\sigma} \left(\frac{A_g}{A_d}\right)^{-\sigma} \times \left(\frac{A'_g}{A'_d}\right) \times \left(\frac{H_g}{H_d}\right) \tag{A.2.12}$$

By dividing Equations A.1.27 and A.1.28, we can determine the impact of R&D subsidies on R&D expenditures:

$$\frac{RD_g}{RD_d} = \left(\frac{A_g}{A_d}\right)^{-\frac{\sigma}{1-\sigma}} \left(\frac{1-R^s_g}{1-R^s_d}\right)^{-\frac{1}{1-\sigma}} \left(\frac{\pi^x_g}{\pi^x_d}\right)^{\frac{1}{1-\sigma}} \tag{A.2.13}$$

In order to establish the explicit impact of R&D subsidies on the transition towards green energy, denoted by the fraction $\frac{E_g}{E_d}$, we can incorporate Equation A.2.13 into Equation A.2.12, which yields the subsequent expression:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \times \left(\frac{A_g}{A_d}\right)^{\frac{-\sigma}{1-\sigma}} \times \left(\frac{(1-R^s_g)}{1-R^s_d}\right)^{-\frac{\sigma}{1-\sigma}} \times \left(\frac{\pi^x_g}{\pi^x_d}\right)^{\frac{\sigma}{1-\sigma}} \times \left(\frac{A'_g}{A'_d}\right) \times \left(\frac{H_g}{H_d}\right) \tag{A.2.14}$$

By substituting the value of $\frac{A_g}{A_d}$ and $\frac{\pi^x_g}{\pi^x_d}$ with their corresponding values from Equations A.2.3 and A.2.5, respectively, we can deduce the following:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \left(\frac{P_g}{P_d}\right)^{\frac{\sigma}{(1-\sigma)(1-\alpha)}} \left(\frac{1-R^s_g}{1-R^s_d}\right)^{-\frac{\sigma}{1-\sigma}} \left(\frac{P_g}{P_d}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{E_g}{E_d}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{A'_g}{A'_d}\right) \left(\frac{H_g}{H_d}\right) \tag{A.2.15}$$

To evaluate the influence of taxation within the same context, and to incorporate the adjustment in demand for both energy sources by the final goods producer, we substitute the value of $\frac{E_g}{E_d}$ on the right-hand side with its corresponding value from Equation A.2.6. This results in the following derived expression:

$$\frac{E_g}{E_d} = \left(\frac{P_g}{P_d}\right)^{\frac{\alpha}{1-\alpha}} \left(\frac{P_g}{P_d}\right)^{\frac{\sigma}{(1-\sigma)(1-\alpha)}} \left(\frac{1-R^s_g}{1-R^s_d}\right)^{-\frac{\sigma}{1-\sigma}} \left(\frac{P_g}{P_d}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{P_g}{P_d}\right)^{\frac{-\epsilon\sigma}{1-\sigma}} \left(\frac{1-\tau_g}{1+\tau_d}\right)^{\frac{-\epsilon\sigma}{1-\sigma}} \left(\frac{A'_g}{A'_d}\right) \left(\frac{H_g}{H_d}\right) \tag{A.2.16}$$

After some rearrangement, we can condense the equation to the following final form:

$$\frac{E_g}{E_d} = \underbrace{\left(\frac{P_g}{P_d}\right)^{\frac{-\epsilon\sigma(1-\alpha)+\alpha}{(1-\sigma)(1-\alpha)}}}_{\text{Price effect}} \times \underbrace{\left(\frac{1-\tau_g}{1+\tau_d}\right)^{\frac{-\epsilon\sigma}{1-\sigma}}}_{\text{Taxation effect}} \times \underbrace{\left(\frac{1-R_g^s}{1-R_d^s}\right)^{-\frac{\sigma}{1-\sigma}}}_{\text{R\&D subsidy effect}} \times \underbrace{\left(\frac{A_g'}{A_d'}\right)}_{\text{Direct productivity effect}} \times \underbrace{\left(\frac{H_g}{H_d}\right)}_{\text{Market size effect}} \tag{A.2.17}$$

Appendix B

Tables

Table B.1: Different Scenarios for Taxation and R&D Elasticity Coefficients

Scenario	Taxation Coefficient (θ_1)	R&D Coefficient (θ_2)
$\epsilon = 1.8, \quad \sigma = 0.020$	-0.037	0.020
$\epsilon = 1.8, \quad \sigma = 0.058$	-0.111	0.062
$\epsilon = 1.8, \quad \sigma = 0.098$	-0.196	0.109
$\epsilon = 1.8, \quad \sigma = 0.160$	-0.343	0.190
$\epsilon = 1.8, \quad \sigma = 0.200$	-0.450	0.250
$\epsilon = 3.9, \quad \sigma = 0.020$	-0.080	0.020
$\epsilon = 3.9, \quad \sigma = 0.058$	-0.243	0.062
$\epsilon = 3.9, \quad \sigma = 0.098$	-0.428	0.109
$\epsilon = 3.9, \quad \sigma = 0.160$	-0.750	0.190
$\epsilon = 3.9, \quad \sigma = 0.200$	-0.985	0.250
$\epsilon = 6.5, \quad \sigma = 0.020$	-0.132	0.020
$\epsilon = 6.5, \quad \sigma = 0.058$	-0.398	0.062
$\epsilon = 6.5, \quad \sigma = 0.098$	-0.702	0.109
$\epsilon = 6.5, \quad \sigma = 0.160$	-1.230	0.190
$\epsilon = 6.5, \quad \sigma = 0.200$	-1.615	0.250

Note: This table presents different potential scenarios of the predictions relevant to the theoretical coefficients of both taxation and R&D subsidy effects. For more details, refer to subsection 1.4.2.

Table B.2: Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum
Renewable output, $ln(E_{g,it})$	14.06	2.251	1.099	20.52
Fossil-fuel output, $ln(E_{d,it})$	16.03	2.406	4.635	21.81
Renewable R&D subsidies , $ln(R^s_{g,it})$	6.621	0.723	5.658	7.991
Fossil-fuel R&D subsidies , $ln(R^s_{d,it})$	6.446	0.546	5.824	8.411
Renewable energy price, $ln(p_{g,it})$	-2.663	0.398	-3.520	-2.205
Fossil-fuel weighted average price , $ln(p_{d,it})$	1.077	0.407	0.185	2.393
Renewable market size, $ln(h_{g,it})$	5.985	2.178	0	12.59
Fossil-fuel market size, $ln(h_{d,it})$	7.929	2.320	1.253	13.69
Renewable knowledge stock, $ln(A'_{g,it})$	9.396	0.727	7.332	10.056
Fossil-fuel knowledge stock, $ln(A'_{d,it})$	8.486	0.689	6.496	9.216
Total electricity output, $ln(E_{it})$	16.57	2.210	5.004	22.15
Renew/Fossil output ratio, $ln\left(\frac{E_{g,it}}{E_{d,it}}\right)$	-1.93	2.05	-11.52	5.79
Tax-inclusive Price Ratio, $ln\left(\frac{p_{g,it}}{p_{d,it}}\right)$	-1.549	0.571	-3.686	-0.284
R&D subsidies ratio, $ln\left(\frac{R^s_{g,it}}{R^s_{d,it}}\right)$	0.18	0.72	-0.71	1.56
Market Size Ratio, $ln\left(\frac{h_{g,it}}{h_{d,it}}\right)$	-1.91	1.91	-9.57	4.66
Knowledge Stock Ratio, $ln\left(\frac{A'_{g,it}}{A'_{d,it}}\right)$	0.89	0.145	0.70	1.11

Note.—These are the values from our main regression sample of 1670 observations across 144 industry types in different states between 2001 and 2015. For more details, refer to section I.

Table B.3: System GMM Estimates from a Panel of Industry Level in Different Periods

VARIABLES	(1) Ren/Fossil Ratio	(2) Ren/Fossil Ratio	(3) Ren/Fossil Ratio	(4) Ren/Fossil Ratio
Ren/Fossil Ratio (-1)‡	0.751***	0.461***	0.739***	0.208***
	(0.005)	(0.006)	(0.006)	(0.007)
Tax-inc. Price Ratio	−0.167***	−0.487***	−0.105**	−0.608***
	(0.021)	(0.050)	(0.041)	(0.055)
R&D Subsidy Ratio (d)°		0.032**		0.085***
		(0.015)		(0.015)
Market Size Ratio		0.220***		0.669***
		(0.016)		(0.023)
Constant	0.311***	0.099	0.634***	−0.566***
	(0.066)	(0.077)	(0.065)	(0.084)
Observations	1.731	1.076	1.379	724
Instruments/ Groups	89 /133	74 /127	85/126	70 /120
Time Period	2005-2015	2005-2015	2009-2015	2009-2015
Year Dummies	YES	YES	YES	YES
Hansen test	73.86	71.32	67.99	60.51
p-value	0.353	0.150	0.546	0.457
AR(2)	1.17	0.41	1.12	0.29
p-value	0.240	0.684	0.261	0.774

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.
‡ The notation "(-1)" indicates lagged values.
°The symbol "(d)" denotes the first difference.

Table B.4: Regression Results across Industry Type Level in the U.S. (Using Fixed Effects)

VARIABLES	(1) Renew/Fossil Ratio	(2) Renew/Fossil Ratio	(3) Renewable Energy	(4) Fossil-Fuels Energy
Tax-inc. Price Ratio	−0.385***	−0.385***	−0.245***	0.116***
	(0.107)	(0.106)	(0.055)	(0.043)
R&D Subsidy Ratio	0.115**	0.126***	0.131***	−0.007
	(0.051)	(0.041)	(0.024)	(0.023)
Market Size Ratio	0.438***	0.437***	0.282***	−0.130***
	(0.075)	(0.074)	(0.050)	(0.040)
Knowledge St. Ratio	0.133			
	(0.207)			
Total Electricity Output			0.492***	1.097***
			(0.057)	(0.118)
Constant	−0.396	0.284	3.887***	−1.568
	(1.153)	(0.267)	(0.978)	(1.911)
Observations	1,670	1,670	1,666	1,666
R-squared	0.311	0.311	0.328	0.706
Number of Groups	144	144	143	143

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table B.5: Regression Results across State Level in the U.S. (Using Fixed Effects)

VARIABLES	(1) Renew/Fossil Ratio	(2) Renew/Fossil Ratio	(3) Renewable Energy
Tax-inc. Price Ratio	−0.385***	−0.311***	−0.209***
	(0.107)	(0.099)	(0.063)
R&D Subsidy Ratio	0.115**		
	(0.051)		
Market Size Ratio	0.438***	0.361***	0.240***
	(0.075)	(0.069)	(0.049)
Knowledge Stock Ratio	0.133	0.625***	0.463***
	(0.207)	(0.173)	(0.115)
R&D Subsidy Ratio (two lags)		0.179***	0.157***
		(0.044)	(0.033)
Total Electricity Output			0.637***
			(0.080)
Constant	−0.396	−3.083***	−0.896
	(1.153)	(1.082)	(1.656)
Observations	1,670	1,550	1,548
R-squared	0.311	0.316	0.396
Number of Groups	144	130	130

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table B.6: Regression Results for Renewable and Fossil Fuel Energy across State and Industry Levels (Using Fixed Effects)

VARIABLES	(1) Renewable Energy	(2) Renewable Energy	(3) Fossil-Fuels Energy	(4) Fossil-Fuels Energy
Tax-inclusive FF Price	0.241***	0.316***	-0.128	-0.001
	(0.068)	(0.075)	(0.090)	(0.025)
Renewable Price	-0.207**	-0.432***	0.083	0.020
	(0.092)	(0.085)	(0.095)	(0.055)
Renew R&D subsidies	0.117***	0.186***	-0.023	-0.037***
	(0.026)	(0.044)	(0.028)	(0.012)
FF R&D subsidies	-0.046**	-0.057*	-0.020	0.028**
	(0.019)	(0.029)	(0.015)	(0.012)
Renew Market Size	0.409***	0.360***	-0.122***	-0.015**
	(0.068)	(0.107)	(0.036)	(0.007)
FF Market Size	-0.187***	-0.265***	0.136***	0.025
	(0.035)	(0.073)	(0.046)	(0.025)
Total Electricity Output	0.420***	0.681***	1.091***	1.126***
	(0.065)	(0.123)	(0.114)	(0.109)
Constant	4.665***	0.699	-1.715	-2.740
	(1.101)	(2.078)	(2.124)	(1.712)
Observations	1,666	652	1,666	652
R-squared	0.382	0.517	0.708	0.822
Number of Groups	143	50	143	50
Industry Level	YES	NO	YES	NO
State Level	NO	YES	NO	YES

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix C

Diagnostics Analysis

To estimate Equation 1.5.3, we compared a number of econometric techniques to control for industry-level fixed effects. We first used the Breusch and Pagan Lagrange Multiplier (LM) test for random effects in panel data models, rejecting the null hypothesis, thus indicating a panel data model (either Fixed E or Random Effects (RE)) would better fit our data than a Pooled OLS model. We then conducted the Hausman test, leading us to reject its null hypothesis, thus indicating a correlation between the unobserved effects and the model's regressors and directing us towards an FE model over an RE model. We also carried out the Modified Wald Test and the Wooldridge test, revealing groupwise heteroskedasticity and autocorrelation in our model. Consequently, we adopted a fixed effects model using cluster-robust standard errors to account for the heteroskedasticity and autocorrelation in the model.

Table C.1: Breusch and Pagan Lagrangian Multiplier Test for Random Effects

	Equation	Variance (Var)	Standard Deviation ($\sqrt{\text{Var}}$)
Model	$Y[id,t] = Xb + u[id] + e[id,t]$		
Y		4.221	2.055
Residual (e)		0.493	0.702
Individual effect (u)		0.498	0.706
Test Statistic $\chi^2(01)$		1362.64	Prob > χ^2 = 0.000

Notes: The table shows the Breusch and Pagan LM test results. The null hypothesis that Var(u) = 0 is strongly rejected with a test statistic chibar2(01) = 1362.64 and Prob > χ^2 = 0.000. This indicates the suitability of a panel data method. Either a fixed effect or random effects approach would be appropriate based on further diagnostics.

Table C.2: Hausman Fixed Random Test Results

	Fixed (b)	Random (B)	Difference (b-B)
Tax-inc. Price Ratio	-0.385	-0.395	0.009
R&D Subsidies Ratio	0.115	0.074	0.041
Market Size Ratio	0.438	0.578	-0.140
Knowledge Stock Ratio	0.133	0.140	-0.006
Test Statistic $\chi^2(4)$	150.38		Prob > χ^2 = 0.000

Notes: The Hausman test evaluates the systematic differences between the fixed and random effects estimators. A significant chi-squared statistic suggests the random effects model may be inappropriate, and the fixed effects model is preferred.

Table C.3: Cluster-Robust Hausman Test

	Value
Test Statistic $\chi^2(4)$	25.73
Prob $> \chi^2$	0.0000

Notes: The Cluster-Robust Hausman Test assesses the consistency between fixed effects and random effects. The test hypothesis is that the difference in coefficients is not systematic. The test is based on 500 bootstrap repetitions, and the chi-squared test statistic indicates a significant systematic difference in the coefficients, and thus the fixed effects model is preferred.

Table C.4: Diagnostic Tests for Panel Data

Test	Statistic	Prob > Statistic
Modified Wald Test (Groupwise Heteroskedasticity)	$\chi^2(144) = 1.2 \times 10^{32}$	0.0000
Wooldridge Test (First-order Autocorrelation)	$F(1, 124) = 27.496$	0.0000

Notes: The Modified Wald test examines groupwise heteroskedasticity under the null hypothesis of homoskedasticity, while the Wooldridge test checks for first-order autocorrelation with a null hypothesis of no autocorrelation. The low p-values strongly reject both null hypotheses, indicating the presence of heteroskedasticity and autocorrelation in the panel data.

Appendix D

Additional Robustness Checks

The empirical model illustrated in the main text may exclude a number of variables that could have a relevant effect on the outcome of taxation and R&D subsidies. To do so, including these variables in our analysis would be quite important in making our findings robust. One crucial variable is called the Renewable Portfolio Standards, or for short, the RPS, which will be explained as a policy instrument requiring utilities to derive a certain percentage of their electricity from renewable sources of energy. The RPS thus aims at developing and increasing the use of renewable energy sources all given reducing dependence on fossil fuels. However, it is not applied uniformly to all states; its implementation varies due to factors such as political dynamics, public support, and renewable energy resources availability. In addition, the timing of RPS differs between states in which it has been adopted (Joshi 2021).

This state-level indicator will help us strengthen our empirical model. It is expected that RPS will contribute positively to the renewable energy transition in the states where it is implemented. Table D.1 provides an overview of those states that have adopted RPS mandatory and the year of its implementation. Note that this table excludes states with non-binding or voluntary renewable portfolio goals. The content of this table is mainly sourced from the Database of State Incentives for Renewables & Efficiency (DSIRE).[1] We can introduce RPS into our empirical model to better understand the various forces involved in the transition to renewable energy. This additional analysis will enhance the robustness of our findings. The RPS is included using a dummy variable, which takes the value of one for states that implemented this policy during the years it was effective, and zero otherwise.

[1] https://www.dsireusa.org.

Additionally, there is indeed a lot of innovation going on in renewable energy technologies outside the U.S. For example, according to a report from the International Energy Agency (IEA), significant advancements in clean energy technologies, including solar photovoltaics, wind power, and battery technologies, have primarily been driven by efforts in Europe and Asia, particularly China and Japan. This trend underscores the global nature of technological innovation in the renewable energy sector, highlighting the substantial contributions of non-US countries to advancements in these technologies (International Energy Agency 2020).

To address this aspect in our empirical model, we incorporated the ratio of patents in clean energy to those in fossil fuels, using data obtained from the International Energy Agency (IEA). These patent numbers are aggregated at the global level and at another time they are based on the number of patents granted in China, which is a significant contributor to the global patent market. This inclusion helps account for the international dimension of renewable energy innovation. Specifically, by including the ratio of world patents in clean energy to those in fossil fuels, we consider the broader scope of innovation beyond the US, reflecting the global trend in renewable energy technological advancements.

Table D.2 presents the results of the estimation with different specifications, adding the following variables to the main model: Renewable Portfolio Standard (RPS), the World Clean Patent Ratio (measured by dividing the number of patents in clean energy by those for fossil fuels across the study periods), and the China Clean Patent Ratio (calculated similarly for China). From the table, we can observe that our primary findings on the effects of the tax-inclusive price ratio and the R&D subsidy ratio (along with market size and knowledge stock ratios) remain robust and consistent with our main estimation. Although the significance of the R&D subsidy effect is reduced in two of the five specifications, the overall outcomes are still consistent.

Additionally, the RPS variable shows a positive effect in all specifications, though it lacks statistical significance. The impact of international innovation in clean energy, particularly the global clean patent ratio, appears to have a significant positive effect on the transition to renewable energy in the U.S.

Table D.1: Features of Renewable Portfolio Standard in the US

State	Enactment Year	Effective Year	Requirement
Arizona	2006	2006	15% by 2025
California	2002	2002	33% by 2020, 40% by 2024, 45% by 2027, 50% by 2030
Colorado	2004	2004	30% by 2020
Connecticut	1998	2004	27% by 2020
Delaware	2005	2007	25% by 2025-2026
Hawaii	2001	2001	30% by 2020, 40% by 2030, 70% by 2040, 100% by 2045
Illinois	2007	2008	25% by 2025-2026
Iowa	1983	1983	105 MW
Maine	1999	2000	40% by 2017
Maryland	2004	2006	20% by 2022
Massachusetts	1997	2003	15% by 2020 and an additional 1% each year after
Michigan	2008	2012	10% by 2015
Minnesota	2007	2007	26.5% by 2025
Missouri	2007	2011	15% by 2021
Montana	2005	2008	15% by 2015
Nevada	1997	2003	25% by 2025
New Hampshire	2007	2009	24.8% by 2025
New Jersey	1999	2001	24.5% by 2020
New Mexico	2002	2005	20% by 2020
New York	2004	2006	50% by 2030
North Carolina	2007	2008	12.5% by 2021
Ohio	2008	2009	25% by 2026
Oklahoma	2010	2010	15% by 2015
Oregon	2007	2011	25% by 2025
Pennsylvania	2004	2006	18% by 2020-2021
Rhode Island	2004	2007	14.5% by 2019
Texas	1999	2000	10,000 MW by 2025
Washington	2006	2012	15% by 2020
Wisconsin	1998	2000	10% by 2015

Table D.2: Regression Results for Renewable/Fossil Fuel Energy Ratio (Using Fixed Effects)

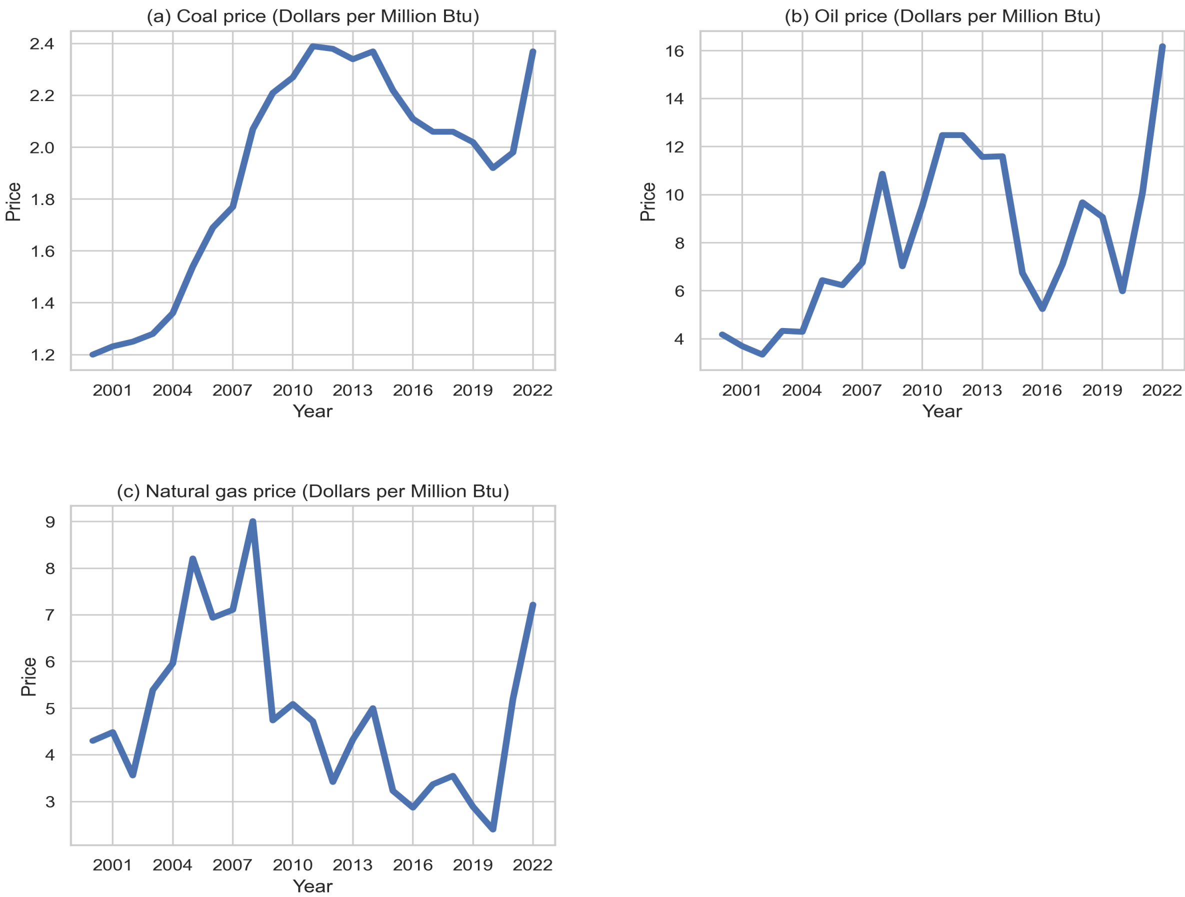
VARIABLES	(1) Renew/Fossil Ratio	(2) Renew/Fossil Ratio	(3) Renew/Fossil Ratio	(4) Renew/Fossil Ratio	(5) Renew/Fossil Ratio
Tax-inc. Price Ratio	-0.385***	-0.385***	-0.352***	-0.297***	-0.348**
	(0.106)	(0.107)	(0.105)	(0.108)	(0.158)
R&D Subsidy Ratio	0.126***	0.115**	0.099*	0.091*	0.098**
	(0.041)	(0.051)	(0.051)	(0.050)	(0.046)
Market Size Ratio	0.437***	0.438***	0.438***	0.433***	0.437***
	(0.074)	(0.075)	(0.075)	(0.075)	(0.077)
Knowledge Stock Ratio		0.133	0.081	-1.034**	0.069
		(0.207)	(0.207)	(0.450)	(0.375)
RPS			0.130	0.113	0.129
			(0.098)	(0.100)	(0.102)
World Clean Patent Ratio				0.691***	
				(0.207)	
China Clean Patent Ratio					0.006
					(0.109)
Constant	0.284	-0.396	-0.032	5.010**	0.033
	(0.267)	(1.153)	(1.144)	(2.168)	(2.044)
Observations	1,670	1,670	1,670	1,670	1,670
R-squared	0.311	0.311	0.313	0.317	0.313
Number of id	144	144	144	144	144

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix E

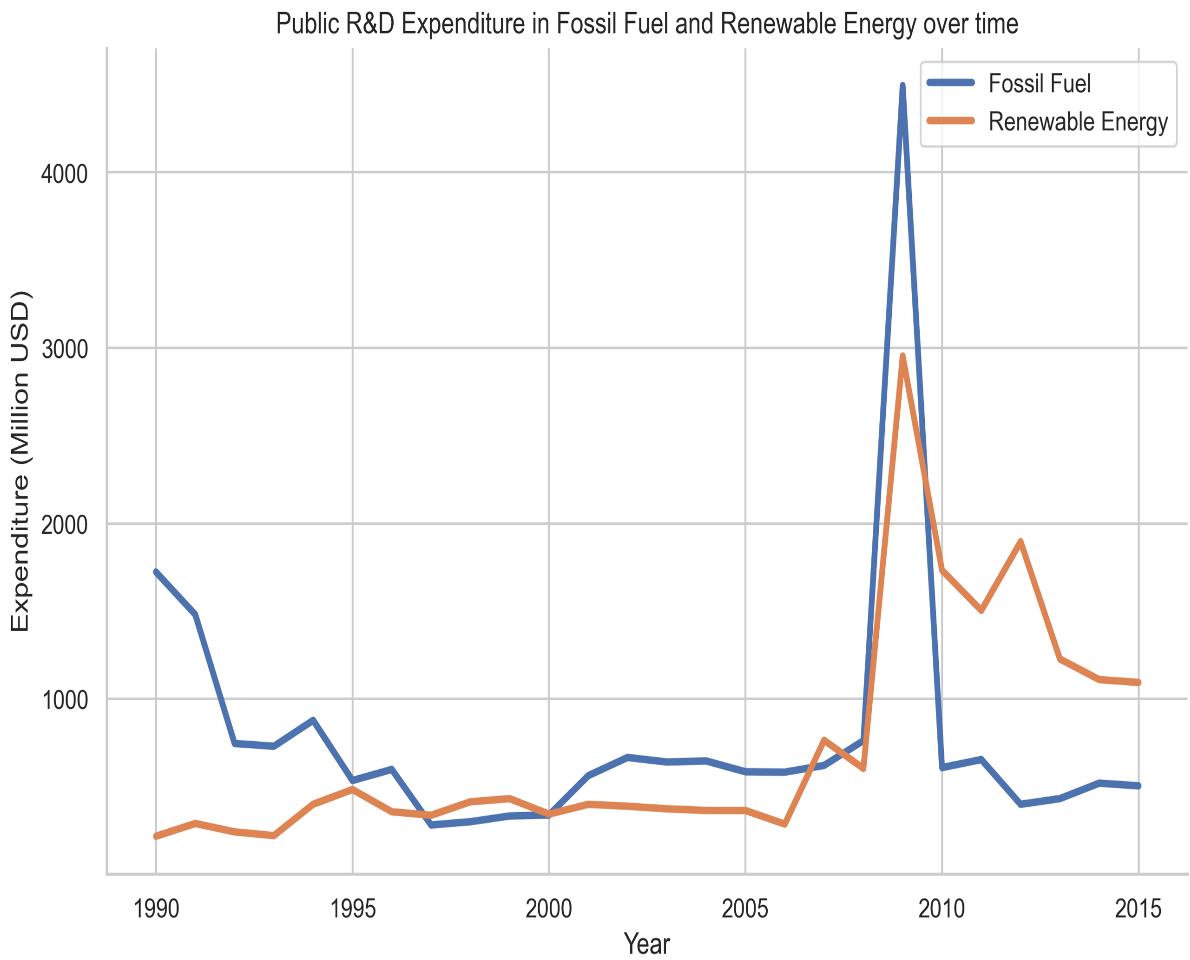
Figures

Figure E.1: Cost of Fossil Fuel Receipts at Electric Generating Plants (Dollars per Million Btu, Including Taxes)



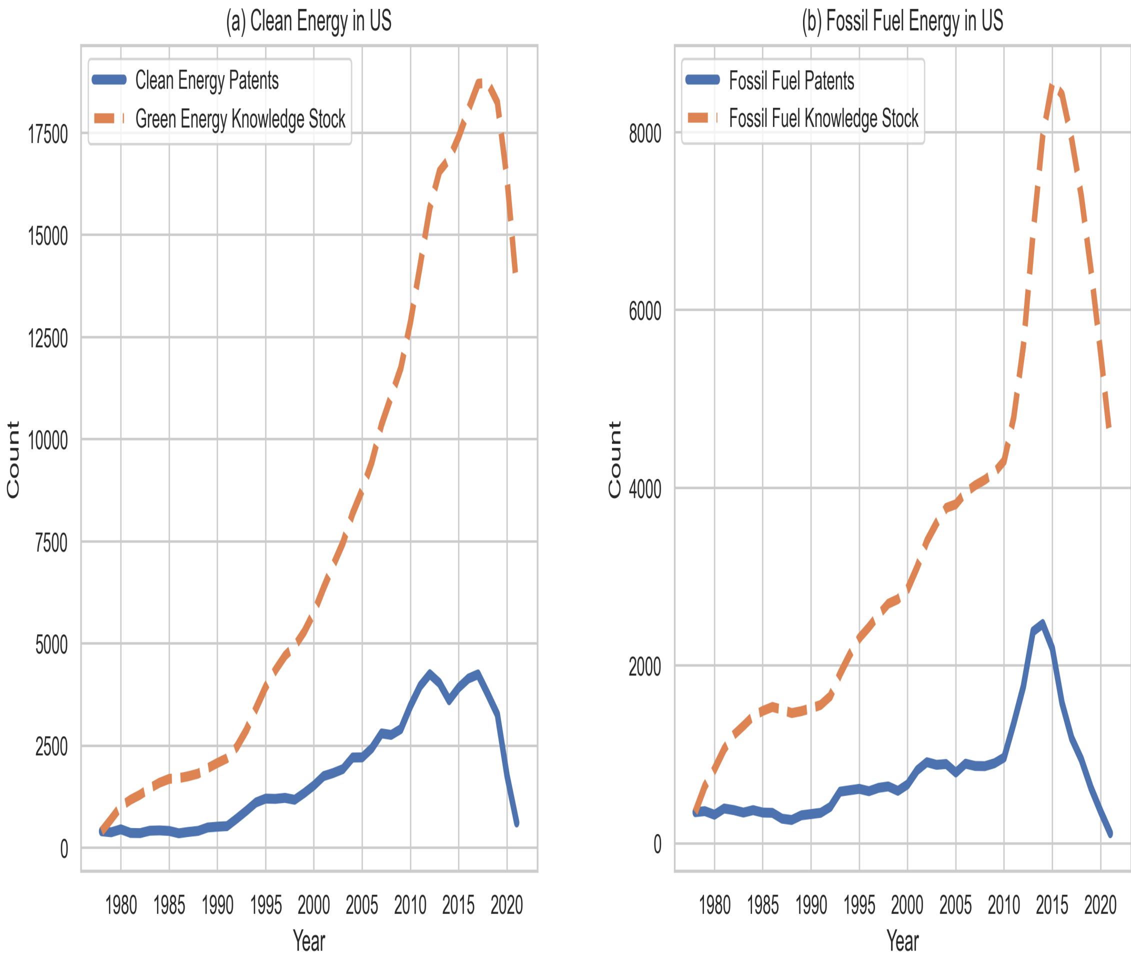
Source: Graph created by author, data from the EIA. Note: The chart ranks oil as the most expensive fossil fuel, followed by natural gas and coal. Coal prices consistently rose over the years, stabilizing post-2014. Oil prices, although fluctuating, showed a similar trend. In contrast, natural gas prices largely decreased but saw an increase in 2020.

Figure E.2: Annual U.S. Public R&D Spendings on Renewable and Fossil Fuel Energy: 1990-2015



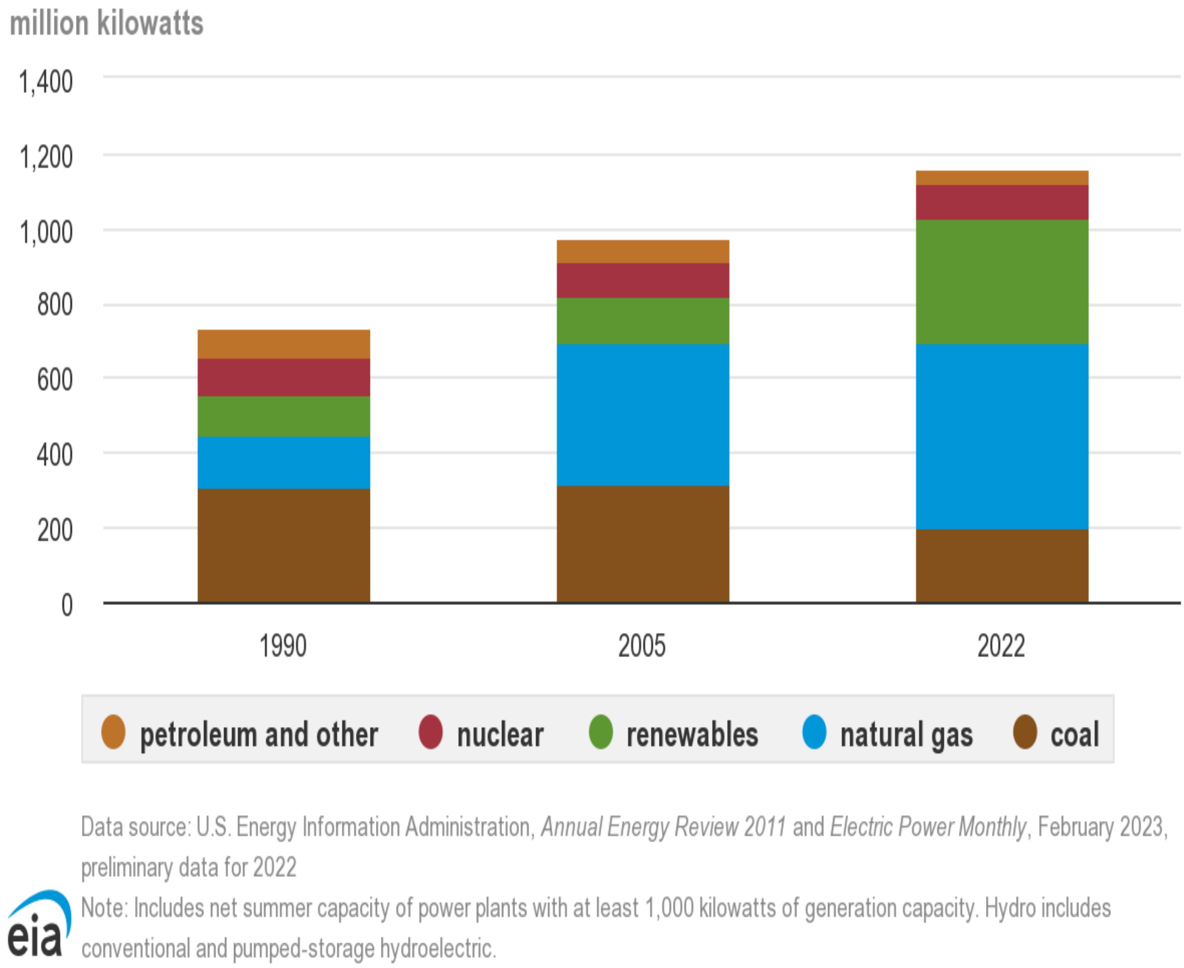
Source: Graph created by author, data from the International Energy Agency-IEA (Million USD at constant prices in 2021 using the GDP deflator). Note: The graph shows an initial lag in renewable energy R&D funding compared to fossil fuels. Post-1990, however, there's a reversal with declining fossil fuel funding and increasing renewable energy spending. Despite a shared decline post-2009, renewable energy R&D not only outpaced fossil fuels but also exceeded its 1990s' spending, signaling a substantial shift towards green energy.

Figure E.3: U.S. Renewable and Fossil Fuel Energy Patents and Knowledge Stock from 1978 to 2021



Source: Graph created by author, data from the International Energy Agency-IEA. Note: Both clean and fossil fuel energy patents increased from 1978 to 2021, but clean energy patents were higher than fossil fuel patents. The U.S. surge in clean energy patents, peaked at 3,959 in 2011, while dirty energy patents peaked later in 2013 at 2,384. Despite these peaks, both categories experienced significant declines since 2020.

Figure E.4: U.S. electricty generation capacity by major energy source, 1990, 2005, 2022



Source: U.S. Energy Information Administration. Note: the chart indicates a substantial rise in electricity generation capacity by renewable energy in 2022, compared to 1990 and 2005. In contrast, coal's capacity has recently seen a marked downturn. Simultaneously, natural gas's share of electricity generation capacity has consistently grown over the years.

Chapter 2

Evaluating Environmental Policy Instruments: A Dynamic General Equilibrium Perspective

2.1 Abstract

This paper evaluates the effects of various environmental policy instruments—carbon taxes, R&D subsidies, dirty investment taxes, and clean investment tax credits—within a DGE model inspired by the Directed Technical Change (DTC) framework. The model integrates a savings mechanism into the DTC framework, extending the analysis to capture investment behavior and its role in the transition to clean technology. This paper also extends the scope of policies examined to include, for instance, clean investment tax credits (ITCs), which have received considerable attention in recent policy debates. The findings show that policies targeting the dirty sector, such as carbon and dirty investment taxes, are particularly effective in reducing emissions. This is due to the sector's large market size. However, restricting this sector can impede economic prosperity. This indicates the need for complementary measures.

In our analysis, we also distinguish between supply- and demand-side policies. Demand-side measures, such as carbon taxes and clean input tax credits, facilitate substitution between clean and dirty goods. This encourages cleaner alternatives. By targeting both the clean sector and the demand side, such as through clean input tax credits, we can accelerate the transition to cleaner technologies and achieve emission reduction targets. The trade-off may include higher taxes, such as household lump-sum taxes, for financing such policies. Finally, we explore a clean "double dividend" approach, where revenues from dirty-sector taxes fund clean-sector incentives. This provides a more balanced path toward emissions reduction and economic per-

formance. Based on these findings, we recommend a policy mix that prioritizes dirty-sector initiatives, improves demand-side measures, and most importantly, adopts clean double dividend strategies to support both environmental and economic objectives.

2.2 Introduction

The threat of climate change, driven by the dependence on fossil fuels, remains a top global policy priority. In economic analysis, policies that attempt to mitigate these impacts could reveal trade-offs between environmental benefits, such as reducing emissions and preventing environmental degradation, and potential economic growth restrictions. Policymakers must carefully consider trade-offs to formulate policies that achieve sustainable goals while preserving economic prosperity. Climate scientists and policymakers agree that policies must encourage the development of clean technologies. Economists traditionally model technological change as an exogenous factor. It is often treated as an autonomous function of time. While this approach simplifies the analysis, it neglects the nuance of technological change, which is influenced by various other factors. The shift towards endogenous modeling of technological change reflects a growing recognition in the literature of these larger forces (Gillingham et al. 2008, Popp et al. 2010).

Endogenous technological change plays a crucial role in analyzing the evolution of technology driven by economic activities and policies. Furthermore, when technological change is endogenized, the impact of various environmental policies becomes more evident. The literature typically models this evolution through three primary approaches: direct price-induced, learning-induced, and R&D-induced technological change, with the latter being particularly prominent. The renewed focus on R&D-driven technological change, especially within the DTC framework, highlights its central importance in steering innovation towards environmental objectives.

The DTC literature primarily addresses issues related to energy and climate change. A key distinction between these models lies in whether they treat directed innovation as influencing two inputs that are complements or substitutes.The complementarity approach, beginning with Smulders and De Nooij (2003), focuses on innovations that preserve energy or fossil fuel resources, using them as complements to capital or labor. In contrast, the substitutability approach, introduced by Acemoglu et al. (2012) (hereafter referred to as AABH), examines the development of clean technologies designed to replace dirty ones, such as renewable inputs that replace fossil fuels. They promoted policies that include Pigouvian taxes and research subsidies to encourage the development of clean technologies. Since then, the DTC literature has expanded to explore various aspects. Mattauch et al. (2015) built on the AABH model by introducing learning spillover effects in the clean sector, focusing on the role of cumulative learning capacity. In their view, a mix of carbon taxes and learning subsidies would be the most effective policy.

Fried (2018) applied the DTC framework to include the impact of energy price shocks on innovation and the optimal design of carbon taxes with endogenous innovation. Maria and Smulders (2004), Maria and Van der Werf (2008), Van den Bijgaart (2017), Acemoglu et al. (2014), and Hémous (2016) extended and applied the DTC model to include international trade and technological spillovers between the 'North' and 'South,' illustrating the dynamics of unilateral environmental policies and carbon leakage.[1]

The DTC framework, as discussed in studies by Acemoglu et al. (2012); Mattauch et al. (2015); Acemoglu et al. (2014); Hémous (2016); Van den Bijgaart (2017); Fried (2018), has important implications for policy recommendations in environmental economics and climate change. First, based on history or initial conditions, DTC models draw attention to the path dependency of dirty technologies.[2] Consequently, they emphasize the role of government intervention in stimulating clean technologies and breaking the lock-in of the dirty economy. Second, DTC models emphasize the need for front-load policies. Specifically, they advocate for the early implementation of policies to promote clean innovation and reduce emissions. In general, DTC models recommend a policy mix that includes carbon pricing and clean research subsidies. The DTC literature may produce different results depending on the type of innovation modeled, the substitution elasticity between dirty and clean technologies, and international

[1]For a detailed review of the DTC literature, refer to Hémous and Olsen (2021) and Dechezleprêtre and Hémous (2022).

[2]In path dependency, the current state of a system is determined by its past evolution and starting conditions. In DTC, the path dependency implies that technology growth depends on technology stocks in the past. Since dirty technologies are currently dominant, path dependency implies that they can impede the adoption and advancement of clean technologies.

aspects, such as carbon leakage and trade.

While the DTC framework has greatly advanced our understanding of how environmental policies drive technological innovation, there is still room for further research and refinement. One common simplification in these models is the exclusion of savings mechanisms. As Fried (2018) notes when setting up her model, *"There is no mechanism through which the household can save, and thus it consumes its income"* (p.97). In a related footnote, she further explains that *"This is a standard simplification in the directed technical literature (e.g., Acemoglu 2002; AABH), which considerably simplifies the solution"* (p.97). However, this simplification could overlook critical dynamics that could significantly influence policy outcomes, particularly in the context of environmental economics.

This paper contributes to the DTC framework by incorporating a savings mechanism. First, taking into account the possibility of capital accumulation within the clean and dirty sectors extends the analysis. Specifically, in existing DTC models, environmental policies are perceived through changes in relative costs or prices between the clean and dirty sectors. By including savings, these policies also affect relative returns on investment in these sectors.[3] For example, a carbon tax may not only increase the relative costs of dirty sectors but also reduce their relative returns on investment. In turn, this may affect the allocation of capital investments between the two sectors. These twofold impacts (or changes in relative prices and relative returns on investments) could potentially enhance the incentives to switch from dirty to cleaner technologies. In doing so, environmental policies become more effective in terms of achieving their objectives. The inclusion of savings mechanisms, therefore, could reveal that the impact of environmental policies in DTC models depends not only on substitution elasticity and innovation modeling, but also on how investment dynamics are incorporated.

Second, by integrating a savings mechanism into DTC models, we could expand the range of environmental policies examined. We could explore the role of taxation on investments in

[3]In the current paper, households save to invest in physical capital. In this regard, Hassler et al. (2021)'s model also integrates capital investment within the DTC framework. However, it is important to clarify a key difference: whereas Hassler et al. (2021)'s model assumes that part of the output is directly allocated to capital investment, accumulating over time, our paper explicitly assumes that capital investment originates from household saving decisions. This distinction enables us to effectively analyze the impact of various relevant policies, such as clean investment tax credits. Additionally, Hassler et al. (2021) treat capital as an aggregate input that, combined with labor, acts as an imperfect substitute for energy. In contrast, our model considers distinct types of capital associated with clean and dirty intermediate inputs. Consequently, environmental policies in our framework can influence outcomes through their dynamic effects on the return to capital in each sector separately.

emissions reduction and the transition to cleaner technologies. The inclusion of this measure would extend the scope of policies examined in the DTC literature beyond carbon taxes and R&D subsidies. In this context, it is important to examine how clean ITCs can spur innovation in clean energy. In particular, the clean ITCs encourage capital investment in clean technology equipment, such as wind and solar power. Recent policy developments indicate that ITCs are gaining significant attention from policymakers in major economies such as the U.S. and Canada.

In Canada, for example, this incentive is one of the new federal clean ITCs introduced to promote clean technologies (Fulbright 2023).[4] In the US, the ITC outlined in Section 48 of the Internal Revenue Code significantly supports the progress of clean technology by providing financial incentives for a variety of energy properties. This tax credit is particularly relevant for facilities engaged in renewable energy sources, including solar, wind and energy storage systems (House 2023; Comello and Reichelstein 2016).[5] Thus, incorporating ITCs into DGE models within the DTC literature is crucial. It allows a comprehensive assessment of how these financial incentives influence the transition to clean technologies. This includes their effects on economic prosperity and welfare. By doing so, we can also better understand the comparative effectiveness of ITCs against other policy instruments (e.g. carbon taxes and R&D subsidies), potentially guiding more informed and impactful environmental policy decisions.

This paper examines the effects of several key environmental policies within the DTC framework, including carbon taxes, clean input tax credits, R&D subsidies, dirty investment taxes, and ITCs. These policies were chosen because they represent different approaches to tackling emissions. Demand-side policies, such as carbon taxes and clean goods tax incentives, attempt to increase the cost of dirty goods to increase the demand for clean alternatives. A supply-side policy, such as dirty investment taxes or clean ITCs, impacts investment incen-

[4]This credit is a 30% refundable tax credit for eligible clean technology properties. This includes equipment to generate electricity from solar, wind and water sources, as well as some types of storage and heating equipment. The 30% ITC began in March 2023 and will end in December 2033. By 2024, the credit rate will drop to 15% before being phased out (Fulbright 2023).

[5]The standard credit rate for eligible energy properties under the ITC is 30% for projects that initiate construction before January 1, 2025. Projects that begin after this date must comply with the prevailing wage and apprenticeship conditions to be eligible for the 30% credit rate; if these criteria are not met, the rate drops to 6%. The ITC covers various technologies, such as standalone energy storage, qualified biogas properties, and fuel cells (House 2023). The ITC was first established under the Energy Policy Act of 2005 and later extended until the end of 2016 by the Emergency Economic Stabilization Act of 2008 (for more details, refer to Comello and Reichelstein 2016).

tives. Additionally, R&D subsidies influence producers' decisions to spend on R&D to enhance productivity. This distinction between demand- and supply-side policies allows us to draw a generalized conclusion about potential policies that fit into one of these categories. Furthermore, the mentioned policies can also be grouped by their focus on either the dirty or clean sectors. For example, policies such as carbon taxes or dirty investment taxation directly target the dirty sector, whereas clean ITCs and clean R&D subsidies focus on promoting the clean sector. The distinction allows us to compare the impact of policies targeting dirty versus clean sectors on emissions reductions and economic outcomes.

Although previous studies (e.g. Acemoglu et al. 2012, 2014) have considered some or most of these policies individually, the existing literature has not explicitly categorized them by their targeted sector - clean or dirty - or by their function as demand or supply side interventions. This study fills this gap by evaluating policies based on their primary target sector (clean or dirty) and their initial impact, on the demand or supply side. Grouping policies in this way allows us to provide insights on a broader range of policies that are compatible with these categories.

In the second question, we compare the effectiveness of each policy in reaching environmental goals. The third question examines how these policies might be combined to reduce emissions and accelerate the transition to clean technologies, while also minimizing the negative impact on economic growth and welfare. A DTC framework is incorporated into the study in order not only to address the direct effects of these policies but also to examine how they can guide technological innovation towards more sustainable practices. In this study, the DGE model is used to simulate the effects of these policies under different budget conditions, revealing how fiscal constraints affect the effectiveness of policies in achieving environmental and economic objectives.

To address research questions, this paper develops a DGE model inspired by the DTC literature with two key distinctions. First, the model incorporates saving mechanisms that allow households to accumulate capital through their investment decisions in the clean or dirty sectors. Second, this paper models technological change as a flow variable, focusing on a single stock variable: capital, to ensure analytical simplicity and model tractability. This approach reduces complexity while still capturing the key dynamics of how R&D expenditures affect productivity. The relationship between R&D and productivity in this framework is inspired by the work of Montresor and Vezzani (2015), Aghion and Howitt (2008), and Wakelin (2001).[6] This paper develops a DGE model rooted in the DTC literature, incorporating a saving mechanism and set within an infinite-horizon discrete-time framework. The model involves a continuum of households and a continuum of firms engaged in the production of final goods and intermediate goods: clean and dirty.

The final good is produced using a combination of two substitutable intermediate inputs: one reliant on fossil fuels ("dirty") and the other on renewable and nuclear energy sources ("clean"). Within this context, the model incorporates endogenous innovation, enhancing productivity across sectors, alongside investment dynamics that expand the capital stock in each sector. The model integrates the effects of carbon taxes, which aim to curb the use of dirty inputs; R&D subsidies, designed to steer innovation towards clean technologies; and investment tax credits, which promote capital stock in clean sectors.

With a DGE model, we examine how different environmental policy instruments can assist in reducing emissions and transferring technologies to cleaner ones. These measures include taxing the use of dirty or clean goods, investment taxation in each sector, and R&D subsidies in each sector: clean and dirty. With a balanced budget constraint, our simulations explore how each policy instrument, when implemented independently, influences emissions, the transition to clean technology, and other macroeconomic implications. The findings suggest that policies targeting the dirty goods sector are particularly effective in reducing emissions. This is largely due to the large size of the market and the production capacity. However, this focus on the dirty sector introduces an obvious trade-off, as inhibiting such a significant part of the economy can hinder overall economic growth. By categorizing policies as demand-side (e.g. carbon taxes) or supply-side (e.g. clean ITCs), we observe distinct mechanisms through which each category influences emissions. Demand-side policies tend to shift consumption patterns more directly, supporting clean alternatives. In sectors where the substitution of clean and dirty goods is

[6] Aghion and Howitt (2008) argue that productivity growth is associated with R&D expenditure, but with diminishing returns, as the gains from R&D diminish when productivity increases and the scope for further advancements narrows. Wakelin (2001) treats the flow of R&D expenditure as a production factor that also determines productivity growth.

more feasible, policy instruments must incentivize demand-side participants to leverage their capacity to substitute between these goods.

Policies that target both the clean sector and the demand side, such as clean input tax credits, can significantly accelerate the transition to cleaner technologies. This can help to achieve emission reduction targets, especially when the elasticity of substitution between clean and dirty production is sufficient. However, these policies come with trade-offs, including a potential increase in household lump-sum taxes (or other types of distorting taxation), which may encounter practical challenges due to political resistance or social concerns. Finally, our examination of a "clean double dividend" approach reveals a promising strategy for emissions reductions along with favorable welfare impacts. By redirecting revenue from dirty-sector policies into clean goods incentives, this approach mitigates the economic burdens typically associated with policies like carbon taxes, providing a more balanced path toward sustainability.

The paper is organized as follows: the second section discusses the relevant literature and identifies the research gap we are attempting to fill with this study. In the third section, we present the DGE model used in the analysis. The fourth section outlines the calibration process and the selected parameters, while the fifth section summarizes the main findings related to different policy instruments. Finally, the sixth section concludes the paper.

2.3 Related Work

Technological change plays an important role in long-term environmental and economic well-being. Economists initially integrated technological change exogenously before shifting to the recent development of endogenous technical change. Exogenous technological change is often modeled as an autonomous function of time, implying that energy efficiency improves constantly across time. Exogenous models typically incorporate parameters such as autonomous energy efficiency improvement (AEEI) or backstop technologies.[7] Modeling technological change exogenously simplifies the process, but extensive literature recognizes that technologi-

[7] AEEI is a parameter representing productivity gains that enhance energy efficiency across the economy or within specific sectors by a fixed amount each year. Backstop technologies refer to carbon-free energy sources that are known but not yet widely used. These technologies, like advanced solar power or nuclear fusion, are available in large quantities but at a high marginal cost. They become viable when energy prices, including the impact of carbon policies, reach a level that makes these backstop technologies competitive.

cal change is complex and influenced by factors beyond the merely passage of time (Gillingham et al. 2008; Popp et al. 2010).

Endogenous technological change is crucial to understanding the dynamics of technological advances driven by economic activities and policies. There are three key approaches for modelling endogenous technological change: direct price-induced, learning-induced, and R&D-induced changes (Gillingham et al. 2008, Popp et al. 2010). Direct price-induced technological change suggests that changes in relative prices, such as higher energy prices, encourage innovations aimed at improving energy efficiency (Jakeman et al. 2004, Dowlatabadi 1998). Learning-induced technological change, or learning-by-doing (LBD), emphasizes how cumulative experience with technology reduces costs and improves efficiency, facilitating early investments in low-carbon technologies (Grübler and Messner 1998, Van der Zwaan et al. 2002). R&D-induced technological change—which is a more commonly used approach —- emphasizes the role of R&D investments in steering innovation towards specific clean technology options (Acemoglu 2002, Popp 2004). These approaches collectively underscore the significant role of policy and market incentives in driving technological change and achieving environmental goals.

The resurgence of R&D-induced technological change, particularly through Acemoglu's DTC framework, underscores its pivotal role in guiding innovation toward environmental objectives. Acemoglu (2002) offers a theoretical model illustrating how policies and economic incentives can channel technological advancements to reduce carbon emissions (Acemoglu 2002, Popp 2004). Recent models integrating DTC have shown substantial implications for climate policy, highlighting the importance of targeted R&D investments. Induced innovation in clean technology can occur through the knowledge stock or a continuum of intermediate inputs. Models integrating knowledge stocks in the production function, as in Buonanno et al. (2003), extend the RICE[8] model to enhance the productivity of all inputs equally but do not inherently direct innovation towards carbon-saving technologies.

On the other hand, Smulders and De Nooij (2003) and Van Zon and Yetkiner (2003) demon-

[8]The RICE model, which stands for Regional Integrated Climate-Economy model, is an influential framework in environmental economics. It was developed by William Nordhaus and is a variant of the DICE model (Dynamic Integrated Climate-Economy model). The RICE model is designed to evaluate the economic impact of climate change and to assess optimal policy responses by dividing the world into different regions. Each region in the model makes its own decisions about investments in reducing climate change, based on regional costs and benefits.

strate that improving the quality or quantity via R&D can shift technological change to energy saving innovations in response to rising energy prices. Sue Wing (2006) further explores these dynamics by incorporating externalities and environmental taxation into Acemoglu's model, revealing that environmental taxes can shift production towards cleaner goods but only promote clean R&D under high tax levels where clean inputs can adequately replace dirty ones.

Multisector general equilibrium models, like those of Goulder and Schneider (1999), highlight sector-specific interactions and spillovers, showing that endogenous technological change can reduce abatement costs while increasing gross carbon tax costs, thus underscoring the diverse impacts of policy-induced R&D on economic sectors (Goulder and Schneider 1999, Sue Wing 2003). These models provide a detailed examination of the interactions between sectors, such as R&D spillovers and crowding out. For example, the Goulder and Schneider model divides the knowledge stock into appropriable and non-excludable knowledge, illustrating how endogenous technological change can result in more elastic economic responses to policy shocks.

Sue Wing (2003) incorporates these insights within a DGE framework, demonstrating that carbon taxes can lead to a significant reallocation of knowledge services, allowing the economy to adapt more flexibly and thereby reducing overall costs. Arif (2012) builds a model that addresses the debate about equity efficiency for policy makers in a small open economy, using Canada as a case study. He introduces a new welfare ranking of four permit allocation policies that tackle the equity-efficiency trade-off. By incorporating induced technological change, the model treats knowledge stock accumulation similarly to physical capital accumulation. Additionally, it incorporates R&D subsidies to correct market imperfections in the knowledge accumulation process.

The primary variation among these models is whether they treat directed innovation as affecting two inputs that are either complements or substitutes. The complementarity case, starting with Smulders and De Nooij (2003), addresses innovations that save energy or fossil fuel resources, viewing these resources as complements to capital or labor. In contrast, the substitutability case, beginning with AABH, looks at the creation of clean technologies that can replace dirty ones, such as renewable energy sources versus fossil fuels in electricity production. We focus on the substitutability case initiated with AABH, given its close relation to the theoretical framework of the current paper. AABH provides a seminal work that integrates environmental constraints into a growth model, whereby a single final good is produced using two competing inputs: dirty inputs that depend on fossil fuels and clean inputs based on clean energy. With the CES function, these inputs are modeled as imperfect substitutes, and the degree of substitutability is highlighted. According to the AABH model, both dirty and clean inputs are produced by labor and a set mass of machines specific to each sector. These machines are different for each sector, and their productivity grows endogenously with innovation activity.

The AABH framework offers compelling insight into the dynamics of technological innovation. In their study, they demonstrate how robust and sustained policy interventions can effectively redirect innovation from dirty to clean technologies. In this way, clean technologies not only catch up but eventually surpass dirty ones, allowing market forces to naturally favor clean innovation. When inputs are highly substitutable, even a temporary intervention can be very effective in reducing emissions in the long run. Although these interventions are important, they are not cost-free. During the catch-up phase, productivity growth is slower because innovation is focused on less advanced clean technologies, which are initially less productive than dirty ones. This makes early intervention essential. Delaying intervention increases the gap between clean and dirty technologies, making it more expensive and time-consuming to bring clean technologies up to speed later.

In particular, the DTC framework allows examining situations where clean inputs can eventually replace dirty inputs. This framework applies to various scenarios, such as the transition from fossil fuels to renewable or nuclear energy. It is also applicable to the transition from fossil fuels to electric vehicles, and the substitution of traditional plastics for bioplastics. AABH - and the DTC literature in general - emphasizes the importance of substitution elasticity between dirty and clean inputs. Mattauch et al. (2015) integrated learning spillover effects into the AABH model, emphasizing cumulative learning capacity. They claim that costs per unit of clean production decrease as a result of increased experience, as clean technologies benefit from learning effects over time. Compared with mature clean technologies, mature dirty technologies are less likely to face declining innovation returns due to a lack of opportunities for improvement. As a result, they developed a cumulative learning capacity to enhance the productivity of clean total factors. Their findings suggest that with high substitution elasticity and learning spillovers, only moderate policy intervention is needed. However, without such an intervention, dirty technologies would dominate the market, leading to higher economic costs. Their recommendation is to implement a permanent carbon tax and a learning subsidy for clean technologies.

Fried (2018) applied the DTC framework to include the effects of energy price shocks on innovation and the optimal design of carbon taxes with endogenous innovation. When cross-sectoral knowledge spillovers are included, innovation can be directed toward domestic fossil fuel energy, green energy, or production inputs. When she compares this scenario to one without DTC, she finds that carbon taxes significantly influence innovation allocation. The carbon tax required to reduce emissions by 30% over two decades is 19.2% lower in an economy with DTC than in one without it. Maria and Smulders (2004), Maria and Van der Werf (2008), Van den Bijgaart (2017), Acemoglu et al. (2014), and Hémous (2016) expanded and applied the DTC model to include international aspects and technological spillovers. Their work demonstrates the dynamics of unilateral environmental policies and carbon leakage. It shows how international interactions and spillovers contribute to the effectiveness and efficiency of these policies.

This paper differs from the DTC framework by integrating ITCs for clean sectors and savings mechanisms into the model. This approach permits a more comprehensive examination of how various tax policies, such as ITCs for clean sectors and increased investment taxes on dirty sectors, impact emissions reduction targets and the transition to cleaner technologies. In this paper, we examine how clean technology ITCs, such as those implemented in Canada and the US, can stimulate innovation and capital investment. In addition, the model can be used to evaluate how savings amplify the effects of different policies, thus improving our understanding of how they work.

2.4 The Model

We consider an infinite-horizon, discrete-time economy with a continuum of households and firms. In this model, households supply labour, save, and invest in capital specific to either the clean or dirty sector. Firms exist in three different sectors: a final good producer and two firms producing substitutable intermediate inputs—clean and dirty goods. These inputs serve as the primary components in the production of the final good. Inspired by the DTC literature, the model includes the possibility of technological change, driven by R&D expenditures in each sector. In addition, a benevolent government uses environmental policies to guide innovation toward clean technologies and reduce emissions.

2.4.1 Households

Households provide their labor across all production sectors. The representative household maximizes intertemporal utility, which is derived from consumption and disutility from labor. The utility function, encompassing both consumption, C_t, and worked hours, H_t, is represented as follows:

$$\sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} U(C_t, H_t) \tag{2.4.1}$$

where C_t denotes the consumption level at time t and H_t represents the labor supply at time t. The parameter $\rho > 0$ is the discount rate, reflecting the time preference of households. We define the discount factor at time t as $\beta_t \equiv \frac{1}{(1+\rho)^t}$.

The revenue for households comes from multiple sources. Primarily, households earn wages from labor ($W_t H_t$), where W_t represents the wage rate. Rental income is another source of revenue, specifically from the rental of capital $R^x_{g,t}$ and $R^x_{d,t}$, reflecting the rental rate applicable to capital in clean and dirty sectors. In addition to these revenue streams, households are subject to a consumption tax and a labour income tax, and they receive a lump-sum transfer (or lump-sum tax), which is assumed to be a fixed amount per period.

The budget constraint for a single time period is given by:

$$(1-\tau_{h,t})W_t h_t + R^x_{g,t} X_{g,t} + R^x_{d,t} X_{d,t} + T_t = (1+\tau_{c,t})C_t + (1-\tau^x_g) I_{g,t} + (1+\tau^x_d) I_{d,t}$$

Households accumulate capital in the clean (g) and dirty (d) sectors. The terms $R^x_{g,t}$ and $R^x_{d,t}$ represent the price returns from holding capital in each sector. Households also earn profits derived from the ownership of capital in both sectors: clean and dirty. Specifically, households earn profits from the final goods producer and the operation of intermediate sectors. However, since these firms use constant returns to scale technology, their profits are zero and do not need to appear in the budget constraint. In addition, they may receive government transfers (T_t). On the expenditure side, households face a consumption tax $\tau_{c,t}$ and allocate their income to both consumption (C_t) and investment in machine production for both sectors: $I_{g,t}$ and $I_{d,t}$. Importantly, τ^x_g represents the rate at which clean investment purchases are subsidized, commonly referred to as clean ITCs. Conversely, τ^x_d denotes the tax rate imposed on dirty investments.

The law of motion for capital used in the clean sector is expressed as:

$$X_{g,t+1} = (1-\delta_x)X_{g,t} + I^x_{g,t}$$

With rearrangement,

$$I^x_{g,t} = X_{g,t+1} - (1-\delta_x)X_{g,t} \tag{2.4.2}$$

Similarly for the investment in the dirty sector:

$$I^x_{d,t} = X_{d,t+1} - (1-\delta_x)X_{d,t} \tag{2.4.3}$$

After incorporating the investments in both sectors into the household budget constraint, the household's Lagrangian is

$$L = \max_{C_t, H_t, X_{g,t+1}, X_{d,t+1}} \sum_{t=0}^{\infty} \beta_t \Bigg\{ U(C_t, H_t) + \mu^h_t \Bigg[(1-\tau_{h,t})W_t h_t + X_{g,t}\big[R^x_{g,t} + (1-\delta_x)(1-\tau^x_g)\big]$$
$$+ X_{d,t}\big[R^x_{d,t} + (1+\tau^x_d)(1-\delta_x)\big] + T_t - (1+\tau_{c,t})C_t - (1-\tau^x_g)X_{g,t+1} - (1+\tau^x_d)X_{d,t+1} \Bigg] \Bigg\}.$$

The first-order conditions of the household are:

$$U_H(C_t, H_t) + \frac{U_c(C_t, H_t)}{(1+\tau_{c,t})}(1-\tau_{h,t})W_t = 0 \tag{2.4.4}$$

$$(1-\tau^x_{g,t})\frac{U_c(C_t, H_t)}{(1+\tau_{c,t})} = \beta\frac{U_c(C_{t+1}, H_{t+1})}{(1+\tau_{c,t+1})}\Big[R_{g,t+1} + (1-\tau^x_{g,t+1})(1-\delta_x)\Big] \tag{2.4.5}$$

$$(1+\tau^x_{d,t})\frac{U_c(C_t, H_t)}{(1+\tau_{c,t})} = \beta\frac{U_c(C_{t+1}, H_{t+1})}{(1+\tau_{c,t+1})}\Big[R^x_{d,t+1} + (1+\tau^x_{d,t+1})(1-\delta_x)\Big] \tag{2.4.6}$$

The arbitrage condition governing the labor-leisure choice (equation 2.4.4) reflects the optimal trade-off between the utility derived from leisure and the utility gained from labor income. The first term, $U_H(C_t, H_t)$, represents the marginal disutility of labor (or the utility derived from leisure). The second term, $\frac{U_c(C_t,H_t)}{1+\tau_{c,t}}(1-\tau_{h,t})W_t$, captures the marginal utility of consumption from labor income, adjusted by both the consumption tax $\tau_{c,t}$ and the labor income tax $\tau_{h,t}$. At equilibrium, this equation balances the disutility of labor with the utility from the income it generates. If the marginal disutility of labor exceeds the utility from labor income, individuals will reduce their labor supply, opting for more leisure. Conversely, if the utility from labor income is greater, individuals will increase their labor supply. The interaction of these forces determines the optimal allocation of time between labor and leisure, taking into account the impact of taxes on both consumption and income.

The Euler equation provided in equation 2.4.5 can be interpreted as a condition balancing the marginal cost and marginal benefit of investment in capital within the clean sector. The left-hand side represents the marginal cost of allocating one additional unit of consumption towards investment in clean sector capital. This cost is expressed in terms of the marginal utility of consumption, adjusted for the consumption tax $\tau_{c,t}$ and the investment tax rate $\tau^x_{g,t}$. Essentially, it reflects the opportunity cost of consuming today versus investing in future productive capacity.

The right-hand side captures the marginal benefit of this investment. It represents the discounted expected future returns from the additional unit of investment, which include the gross rental income from the capital $R^x_{g,t+1}$. In equilibrium, marginal cost equals marginal benefit. If there is any deviation—such as if marginal cost is less than marginal benefit—it signals that there are unexploited gains from investment. This incentivizes individuals to increase their investment until the equality is restored. Conversely, if marginal cost exceeds marginal benefit, it would prompt a reduction in investment. Thus, the equilibrium condition ensures that resources are allocated efficiently, balancing the present cost of investment with its expected future benefits. The role of an investment tax credit, represented by $\tau^x_{g,t}$, is crucial in shaping the investment decisions in the clean sector. In this context, the tax credit acts as a positive adjustment to the cost of investment, effectively lowering the net cost of giving up consumption toward investment in clean sector capital.

The Euler equation governing investment in the dirty sector (equation 2.4.6), mirrors the structure of the equation for the clean sector, with a key difference in the role of the tax term $\tau^x_{d,t}$, which now represents a tax imposed on investment rather than a tax credit. While the tax credit in the clean sector lowers net costs of investing in capital, the tax in the dirty sector raises net investment costs. This dynamic serves to shift resources away from the dirty sector and towards the clean sector.

It is also worth mentioning that, in this context, the consumer has two investment options: one in green sector capital and the other in dirty sector capital. The presence of these different investment opportunities establishes an arbitrage condition, under which the consumer compares the relative returns of both sectors. In the absence of investment taxation, this condition ensures that the returns on green capital R_g and dirty capital R_d are equal, as the consumer seeks to maximize utility across both investments. When assessing these options, the consumer must consider the after-tax returns associated with each type of capital. The differential taxation creates a significant incentive for the consumer to direct investment toward the sustainable sector, as the net returns from clean investments become comparatively more favourable.

2.4.2 Production Sector

In the production sector, a single final product is generated within a competitive market framework. To simplify the analysis, I assume that the producer of the final good uses two sets of intermediate inputs. First, dirty inputs rely on fossil fuel energy sources that emit CO_2 and cause environmental degradation, such as coal, oil, and natural gas. Second, clean inputs rely on clean energy sources such as solar, wind, geothermal, hydropower, and nuclear energy.

These dirty and clean inputs have separate production functions that depend on both labour and machinery, which we will elaborate on shortly.

Final Good Producer:

The final good producer utilizes a CES function to illustrate the imperfect substitutability between these two types of intermediate goods.[9] The production of the final good, Y_t, is represented as follows:

$$Y_t = [1 - D(t)] \left[\; Y_{t,d}^{\frac{\epsilon-1}{\epsilon}} \; + \; Y_{t,g}^{\frac{\epsilon-1}{\epsilon}} \; \right]^{\frac{\epsilon}{\epsilon-1}} \tag{2.4.7}$$

where $Y_{t,d}$ and $Y_{t,g}$ are intermediate inputs from both dirty and clean sources, respectively. The approach of modeling intermediate inputs as imperfect substitutes using a CES function is inspired by the work of Acemoglu et al. (2012, 2014).[10] The elasticity of substitution between the two sectors can be expressed as $\epsilon \in (0, \infty)$, with $\epsilon > 1$ indicating that both inputs are substitutes, with the level of substitutability increasing as ϵ rises. The term $[1 - D(t)]$ refers to the damage function, which will be discussed later. The final good firm operates in a perfectly competitive market and faces the following profit maximization problem:

$$\max_{Y_d, Y_g} \quad \Pi_t = P_t Y_t - (1 + \tau_{d,t})\, P_{t,d}\, Y_{d,t} - (1 - \tau_{t,g})\, P_{g,t}\, Y_{g,t} \tag{2.4.8}$$

P_t represents the price of the final good (normalized to one). $P_{d,t}$ and $P_{g,t}$ are the prices of dirty and clean inputs. The final good firm pays a tax $\tau_{d,t}$ and receives a tax credit $\tau_{g,t}$.

In equilibrium, the quantities of both clean and dirty intermediate goods are presented below (refer to Appendix A for more details).

$$Y_{d,t} = \left(\frac{1}{(1 + \tau_{d,t})\, P_{d,t}} \right)^{\epsilon} Y_t$$

[9]Dirty and clean intermediate goods describe scenarios where production is based on imperfect substitutes. In the automotive industry, clean intermediates are components used in electric vehicles, whereas dirty intermediates are parts used in internal combustion engines. Clean intermediates in industrial manufacturing could be green steel made with hydrogen, while dirty intermediates are conventional steel made with coal in blast furnaces.

[10]Following Acemoglu et al. (2012) and Acemoglu et al. (2014), we exclude the share of dirty and clean intermediate goods from the CES function to allow this share to endogenously change over time in response to different environmental policies. The initial level of this share is determined by the difference in the initial productivity levels of the clean and dirty sectors, as will be discussed later in this section.

$$Y_{g,t} = \left(\frac{1}{(1-\tau_{g,t})\,P_{g,t}}\right)^{\epsilon} Y_t$$

With some rearrangement, the prices of both clean and dirty intermediate goods are given by:

$$P_{d,t} = \frac{1}{(1+\tau_d)}\left(\frac{Y_t}{Y_{d,t}}\right)^{\frac{1}{\epsilon}} \tag{2.4.9}$$

$$P_{g,t} = \frac{1}{(1-\tau_g)}\left(\frac{Y_t}{Y_{g,t}}\right)^{\frac{1}{\epsilon}} \tag{2.4.10}$$

The quantities of clean and dirty intermediate goods, denoted by $Y_{g,t}$ and $Y_{d,t}$ respectively, are influenced by several key factors, including the elasticity of substitution (ϵ), the aggregate economic output Y_t, and the relative prices of the inputs, which are influenced by taxation policies. The elasticity of substitution plays a crucial role in determining how easily producers can substitute between clean and dirty intermediate goods. A higher elasticity means that producers are more responsive to changes in the relative prices of these goods, making it easier for them to switch between clean and dirty inputs depending on cost considerations. This implies that if the price of dirty goods increases due to a carbon tax, producers with a high ϵ will readily substitute dirty goods with clean ones, thus decreasing $Y_{d,t}$ and increasing $Y_{g,t}$.

The aggregate output, Y_t, which represents the demand for the final good directly influences the demand for both clean and dirty intermediate goods. As Y_t increases, so does the demand for these intermediate goods, assuming the relative prices and the elasticity of substitution remain constant. Taxation plays a pivotal role in shaping the relative prices of clean and dirty inputs, and consequently, in determining the quantities of $Y_{g,t}$ and $Y_{d,t}$. A carbon tax, $\tau_{d,t}$, effectively raises the price of dirty intermediate goods, making them less attractive to producers. This results in a decrease in $Y_{d,t}$, as producers either reduce their reliance on dirty inputs or shift towards cleaner alternatives. On the other hand, a tax credit for clean input, $\tau_{g,t}$, lowers the effective price of clean intermediate goods, thereby encouraging producers to increase their use of clean input. This leads to an increase in $Y_{g,t}$ as clean inputs becomes more cost-competitive relative to dirty ones. Overall, the determination of $Y_{g,t}$ and $Y_{d,t}$ is influenced by the interplay between substitution elasticity, economic output, and tax policies.

It is also worth noting that reducing dirty inputs (by taxation, for example) can have two opposite effects on the final output. First, it can lower final output if clean substitutes cannot fully replace the reduction in dirty inputs. This is the case in our model, since the clean and dirty sectors are imperfect substitutes. Second, reducing dirty input can improve the final output by lowering environmental damage, as captured by the term $[1 - Dt]$. The net impact of dirty input reduction on final output depends on which effect dominates. The first effect will likely dominate, since the second effect usually takes longer to make a significant difference. In contrast, the first effect is more immediate, especially in the short and medium term, as economies still face challenges in making clean sectors perfectly substitutable, as achieving that requires significant investments in infrastructure, machinery, and technological advancements.

Intermediate Good Producers:

We utilize separate production functions for each type of intermediate input. Particularly, we propose that the production function can be represented by a Cobb-Douglas function unique to each type—clean and dirty—given by the equations:

$$Y_{g,t} = A_{g0}\ RD_{g,t}^{\theta}\ X_t^{\alpha}\ h_{g,t}^{1-\alpha-\theta} \tag{2.4.11}$$

$$Y_{d,t} = A_{d0}\ RD_{d,t}^{\theta}\ X_t^{\alpha}\ h_{d,t}^{1-\alpha-\theta} \tag{2.4.12}$$

where $\alpha \in (0, 1)$. To simplify the algebra, α and θ are assumed to be the same across both sectors. In addition to labor inputs ($h_{g,t}$ and $h_{d,t}$), intermediate input production ($Y_{g,t}$ and $Y_{d,t}$) in both sectors is facilitated by physical capital. $A_{i,t} = A_{i0}\ RD_{i,t}^{\theta}$, where $i \in \{g, d\}$, denotes the flow of technological change or productivity in either the clean or dirty sector. The association between R&D and productivity in this analysis is based on the work of Montresor and Vezzani (2015), Aghion and Howitt (2008) and Wakelin (2001).[11]

We assume that the initial level of productivity of dirty technology ($A_{d,0}$) is higher than that of clean technology ($A_{g,0}$) due to the historical context of technological development. Since

[11] Aghion and Howitt (2008) assert that productivity growth is associated with R&D expenditure, but with diminishing returns, as the gains from R&D diminish when productivity increases and the scope for further advancements shrinks. Wakelin (2001) treats the flow of R&D expenditure as a production factor that also determines productivity growth.

dirty technologies, such as fossil fuels, have existed for decades, they have benefited from extensive research, investment, and infrastructure. This results in greater efficiency and productivity than newer clean technologies. This assumption aligns with insights from the DTC literature, such as Acemoglu et al. (2012), which suggest that established sectors have higher productivity due to the accumulated knowledge stock. By presuming $A_{d,0} > A_{g,0}$, we create a realistic baseline for analyzing the transition from dirty to clean technologies.

Productivity changes every period, either in the clean or dirty sector, through conducting R&D expenditure by the producers of clean or dirty inputs. The return of such investments in R&D is diminishing as $0 < \theta < 1$. When technologies mature, innovation and productivity exhibit diminishing returns.[12] For producers of clean and dirty intermediate inputs, it is assumed that the cost of R&D is assumed to be fixed at one unit of the final good.[13] The return or reward for investing in R&D is the technological enhancement or the improvement of productivity that occurs in either sector, conditional on successful innovation. This improvement improves the efficiency of the labor and capital used in the corresponding sector.

Intermediate input producers operate in a perfectly competitive market[14] and optimize their profits according to the following profit function:[15]

$$\Pi_{i,t} = \max_{X_{i,t},h_{i,t}} \left\{ P_{i,t}Y_{i,t} - R^x_{i,t}X_{i,t} - W_t h_{i,t} - \left(1 - R^s_{i,t}\right) RD_{i,t} \right\} \tag{2.4.13}$$

Here, $R^x_{i,t}$ denotes the rental price of capital in the clean and dirty sectors, $i \in \{g, d\}$, respectively.[16] W_t represents the wage rate for labor, which is assumed to be uniform across both

[12] Popp (2002) and subsequent works by Popp et al. (2022) illustrate that innovation activities are subject to diminishing returns to scale, implying that as research within a field progresses, the most promising opportunities are exploited first, leading to a gradual decrease in the rate of further advancements. Specifically, Popp (2002) shows, through productivity estimates derived from citation data from U.S. patent filings between 1970 and 1994, a declining trend over time in returns to energy research. This finding suggests that innovation in well-established dirty technologies yields lower marginal returns compared to newer clean technologies, which still have considerable potential for novel advancements and improvements.

[13] The cost of R&D is subtracted from the final output in the feasibility constraint (equation F.2.17), reflecting R&D as an expenditure that reduces available resources for consumption or investment.

[14] This paper is also inspired by the work of Hassler et al. (2021) on innovation behavior within a perfect competition framework. Hassler et al. (2021) consider innovation and productivity under the assumption of perfect competition in the input markets. This is evident from the formulation of the aggregate production function and the assumption that technology levels can be derived from firm demand given data on inputs and their prices in perfect competition.

[15] Since this is a constant returns to scale technology, as shown in the Cobb-Douglas function for each intermediate sector, no excess profits beyond the normal returns on labour h and capital, X, can be achieved in a perfectly competitive framework.

[16] The rental rate $R^x_{i,t}$ is sector-specific, unlike the uniform wage rate. However, under a no-arbitrage condition and in the absence of frictions, $R^x_{i,t}$ for each sector $i \in \{g, d\}$ converges in equilibrium.

sectors. The cost of R&D is represented in equation 2.4.13 as one $\times$ $RD_{i,t}$, as the cost of R&D is assumed to be one unit of the final good. $R^s_{i,t}$ refers to the portion of R&D costs subsidized by the government.

The first-order conditions yield the following equations for the demand of labor and capital in both sectors, where $i \in \{g, d\}$:

$$X_{i,t} = \frac{\alpha P_{i,t} \cdot Y_{i,t}}{R^x_{i,t}} \tag{2.4.14}$$

$$h_{i,t} = \frac{(1-\alpha-\theta)P_{i,t} \cdot Y_{i,t}}{W_{i,t}} \tag{2.4.15}$$

Furthermore, the first-order condition related to R&D expenditure is as follows. Refer to Appendix G for more details on the model solution:

$$1 - R^s_{i,t} = P_{i,t} \cdot \theta \cdot A_{i0} \cdot RD^{\theta-1}_{i,t} \cdot h^{1-\alpha-\theta}_{i,t} \cdot X^{\alpha}_{i,t} \tag{2.4.16}$$

The optimal $RD_{i,t}$ will then be as follows:

$$RD_{i,t} = \frac{\theta P_{i,t} Y_{i,t}}{1 - R^s_{i,t}} \tag{2.4.17}$$

In equation 2.4.16, the left-hand side represents the effective marginal cost of investing in R&D, adjusted for any government-provided R&D subsidies ($R^s_{i,t}$). These subsidies effectively lower the cost of R&D expenditures, incentivizing producers in the clean or dirty sector to allocate more resources toward innovation. The right-hand side represents the marginal benefit or return from R&D expenditures. This return is measured by the incremental improvement in productivity ($A_{i,t}$) in the respective sector, weighted by the price of the output in that sector ($P_{i,t}$). It captures how an additional unit of R&D investment enhances the efficiency of labor input ($h_{i,t}$) and capital ($X_{i,t}$) input. In general, this framework highlights the dynamic trade-off faced by intermediate goods producers: balancing the subsidized marginal cost of R&D against expected productivity gains that drive sectoral growth.

The R&D subsidies in this model directly affect the cost of R&D expenditures, as shown also in Equation 2.4.17. When the government provides an R&D subsidy ($R^s_{g,t}$ for the clean sector and $R^s_{d,t}$ for the dirty sector), it effectively reduces the cost burden on firms, making it more attractive for them to invest in R&D. The equations for $RD_{g,t}$ and $RD_{d,t}$ show that these subsidies lower the effective cost of innovation (given that $0 < \theta < 1$), which in turn increases the amount of R&D expenditure in the respective sector. This implies that substantial increases in R&D subsidies can lead to significant reallocations of innovation efforts between sectors. If the subsidy for the clean sector is larger in relation to that for the dirty sector, it creates a stronger incentive for firms to invest in clean innovation. In contrast, if the subsidy is higher in the dirty sector, resources can continue to flow into dirty technology R&D. Therefore, the government can strategically use R&D subsidies to steer innovation towards the clean sector, promoting technological advancements that contribute to environmental sustainability.

2.4.3 Economic Impact of Environmental and Climate Damage

In our model, we follow Golosov et al. (2014), Nordhaus (2014), and Acemoglu et al. (2016) in considering how climate variables influence output, with the possibility of aggregate production being negatively (or positively) impacted by climate change. We refer to this impact as "damage." We focus on various types of damage, all of which are incorporated into the production function. The specifics of the damage function will be discussed later.

In this model, S_t represents the amount of carbon in the atmosphere. We link this carbon concentration to the climate, represented by the global mean temperature. Then we map the climate to the resulting damages (denoted by D_t), which ultimately affect aggregate production. To this end, we follow Golosov et al. (2014) and Nordhaus (2014) in incorporating the damage function into the production function of the final good to consider these environmental aspects.

Specifically, the damage function, as shown in Equation 2.4.7, is the term $[1 - D_t(S_t)]$, which represents the percentage reduction in final output attributed to climate change. $D(S)$ involves a two-step mapping: first, from carbon concentration to climate (usually represented by global mean temperature) and second, from climate to damages. Nordhaus explicitly modeled both steps in this mapping from carbon concentration to damages. In our current model, we use an exponential specification for $D(S)$, following Golosov et al. (2014), since this exponential specification closely approximates Nordhaus's formulation. More specifically,

$$[1 - D_t(S_t)] = \exp\left(-\gamma_t(S_t - \bar{S})\right) \tag{2.4.18}$$

where $\bar{S}$ is the pre-industrial CO_2 concentration in the atmosphere, and the parameter γ_t refers to the scale of the damage function. This parameter indicates how changes in the climate (compared to the pre-industrial level) affect productivity.

To model the carbon concentration, we use the following simplified carbon cycle:

$$S_t - \bar{S} = \sum_{s=0}^{t+T} (1 - d_s) Y_{d,t-s}, \tag{2.4.19}$$

where $1 - d_s$ is the fraction of carbon emissions that remain in the atmosphere s periods after being emitted. To quantify this carbon depreciation schedule, we follow the approach outlined by Golosov et al. (2014), which involves a three-parameter system. First, ϕ_L represents the fraction of carbon emissions that remain in the atmosphere indefinitely. Second, $1 - \phi_0$ denotes the fraction of emissions that are immediately removed from the atmosphere and absorbed by the biosphere and surface oceans. Lastly, Φ is the geometric decay rate of the remaining emissions. Thus, the formula used is:

$$1 - d_s = \phi_L + (1 - \phi_L)\phi_0(1 - \Phi)^s. \tag{2.4.20}$$

We will show how these formulas and their parameters are quantitatively determined in the calibration section.

2.4.4 Government

The government's fiscal operations are governed by a comprehensive budget equation that ensures a balance between collected revenues through various taxation mechanisms and the expenditures incurred. The budget identity is formulated as follows:

$$G_t+T_t = \tau_{c,t}C_t+\tau_{h,t}W_tH_t+\tau^x_{d,t}I^x_{d,t}-\tau^x_{g,t}I^x_{g,t}+\tau_{d,t}P^e_{d,t}Y_{d,t}-\tau_{g,t}P^e_{g,t}Y_{g,t}-R^s_{d,t}RD_{d,t}-R^s_{g,t}RD_{g,t} \tag{2.4.21}$$

This equation balances the government's total expenditures, G_t, and transfers to households, T_t, against its income from various taxes. These include taxes on consumption ($\tau_{c,t}C_t$) and labor income ($\tau_{h,t}W_tH_t$), reflecting direct contributions to fiscal resources. Investment taxes are sector-specific, with $\tau^x_{d,t}I^x_{d,t}$ indicating a higher tax burden on investments in the dirty sector and $\tau^x_{g,t}I^x_{g,t}$ representing tax credits for investments in clean technologies.

Additionally, the government levies taxes on intermediate inputs, $\tau_{d,t}P^e_{d,t}Y_{d,t}$ and $\tau_{g,t}P^e_{g,t}Y_{g,t}$, to align fiscal incentives with energy policy goals, imposing higher costs on the use of dirty inputs while providing relief for clean initiatives. Subsidies for R&D are also crucial, with $R^s_dRD_d$ and $R^s_gRD_g$ representing targeted fiscal tools designed to support R&D activities in the dirty and clean sectors, respectively. These subsidies are provided as contributions to the respective sectors' expenditures on R&D, thereby fostering innovation and adaptation in technologies critical to sectoral adjustments in response to evolving environmental and economic landscapes.

Our framework incorporates two different taxes on dirty inputs: an investment tax and a tax on dirty intermediate goods. Each tax aims to reduce emissions through a different channel. Therefore, it is necessary to discover which approach is most effective while minimizing adverse economic impacts. Investment taxes discourage future capital investments in polluting technologies. Alternatively, a tax on dirty inputs raises production costs, causing final good firms (i.e., the demand side) to reconsider their fossil fuel use. Furthermore, we include two types of subsidies: one for R&D activities and one for clean production output. Subsidies play a crucial role in reducing emissions. The R&D subsidy encourages innovation and cleaner technologies, while the output tax credit incentivizes the adoption of these technologies. Meanwhile, output tax credits (or subsidies) drive the demand for clean technologies to the surface.

2.4.5 Equilibrium Conditions

Within our economic framework, a competitive equilibrium is established when all markets clear and all economic agents maximize their objectives subject to their constraints, from the initial period $t = 0$ extending indefinitely into the future ($t \to \infty$). This dynamic equilibrium is characterized by the following comprehensive set of conditions:

- **Optimization of Agents:** Households and firms determine their optimal levels of consumption, labor supply, investment, and production based on prices $\{P_t, W_t, R^x_{d,t}, R^x_{g,t}, P_{d,t}, P_{g,t}, P^x_{d,t}, P^x_{g,t}\}$ and government policies $\{\tau_{c,t}, \tau_{h,t}, \tau_{d,t}, \tau_{g,t}, \tau^x_{d,t}, \tau^x_{g,t}, R^s_{d,t}, R^s_{g,t}, G_t, T_t\}$. These conditions ensure that the equilibrium quantities for households $\{C_t, H_t, X_{d,t}, X_{g,t}\}$ and firms $\{Y_t, Y_{g,t}, Y_{d,t}, X_{d,t}, X_{g,t}, h_{g,t}, h_{d,t}, A_{g,t}, A_{d,t}, RD_{g,t}, RD_{d,t}\}$ are sustained over time from $t = 0$ to infinity.

- **Market Clearing Conditions:** Equilibrium in the markets for goods, labor, and capital is continuously maintained as follows:

$$C_t + G_t + I^x_{d,t} + I^x_{g,t} = Y_t - (RD_{d,t} + RD_{g,t}), \tag{2.4.22}$$

$$H_t = h_{d,t} + h_{g,t} \tag{2.4.23}$$

The clearing condition of the goods market ensures that the output Y_t in each period from $t = 0$ to infinity is allocated to consumption, investment, government spending, and R&D expenditures in both sectors. The total labor supplied by the workers' households H_t corresponds to the aggregate labor demand of the intermediate goods producers in both sectors. Appendix G contains the list of equations used to derive the equilibrium solution for the endogenous variables in this model.

In the model presented, we have conducted a concise analysis of the effects of three key policy instruments: investment taxation (whether in the form of incentives for clean investments or burdens on dirty investments), input taxation (such as carbon taxes or clean tax credits), and R&D subsidies for clean and dirty technologies. Each of these policy approaches aims to reduce emissions and facilitate the transition to clean technologies, but they operate through distinct channels.

Investment taxation primarily influences households by shaping their decisions on whether to invest in the clean or dirty sectors for future returns. Taxation, particularly carbon taxes and clean tax credits, directly impacts the demand for either clean or dirty intermediate goods, thereby steering consumption and production choices. R&D subsidies, on the other hand, guide the allocation of R&D expenditure, directing innovation toward the clean sector. This directly improves productivity and ultimately enhances production levels in the clean sector. In essence, while these policies share the common objective of reducing emissions and promoting clean technologies, they differ fundamentally in their initial points of impact. Investment taxation initially alters investors' decisions to allocate capital toward machinery and assets in clean production. Demand-side taxation, such as carbon taxes, initially reduces the consumption of dirty goods by demand-side participants. R&D subsidies initially influence innovators by making the development of clean technologies more attractive.

Although the initial channels through which these policies operate may differ, all are expected to impact other key variables, such as technology, investment allocation, and output. For example, a carbon tax initially increases the relative cost of fossil fuel use compared to clean alternatives on the demand side. However, this also changes the relative returns on capital in both sectors, redirecting investment and capital accumulation toward clean sectors. As a result, the carbon tax ultimately increases the profitability of capital in the clean sector, boosting clean R&D expenditure and productivity. Similarly, clean ITCs reduce the cost of clean investments, encouraging capital accumulation in the clean sector. This, in turn, supports clean R&D expenditure and, ultimately, raises clean goods production.

Given the differing initial channels through which these policies operate, we can expect that their DGE effects will vary, leading to diverse outcomes for key economic variables such as emissions reduction, technological advancement, clean production, GDP, consumption, and welfare. In the following sections, we will conduct a numerical analysis with various policy simulations over time to explore these differential impacts on the economy. This approach will allow us to compare policies and identify a policy mix that effectively achieves the dual goals of reducing emissions and promoting clean technologies while minimizing adverse economic impacts and enhancing individual welfare.

2.5 Calibration and Parameter Selection

The utility of the representative agent is derived from consumption and leisure, with each period offering a fixed amount of time to allocate between work (H_t) and leisure. Preferences are modeled using a time-separable utility function. The period utility function follows a constant relative risk aversion (CRRA) specification:

$$u(c, 1-H) = \frac{c^{1-\sigma_u}}{1-\sigma_u} + \psi_u \cdot \frac{(1-H)^{1-\eta_u}}{1-\eta_u}.$$

Following Cogan et al. (2010), we set σ_u — which represents the inverse of the intertemporal elasticity of substitution — to 1.5. This reflects a moderate elasticity of intertemporal substitution, implying that the agent has a somewhat balanced willingness to smooth consumption over time. η_u, a parameter linked to the elasticity of the Frisch labor supply, is set to 2 following Cogan et al. (2010). ψ_u refers to leisure weight in the utility function. Using the first-order condition for the trade-off between consumption and leisure, and targeting labor supply at one-third of the available time allocation (as is standard in macroeconomic models), we calibrate the leisure weight ψ_u in the utility function to 2.4. The discount rate is set at 1.5%, which corresponds to a discount factor $\beta = 0.985$, consistent with standard values in the literature, such as in Golosov et al. (2014).

The final good production function is modeled as a CES production function, as illustrated in equation 2.4.7. For the elasticity of substitution ϵ, the empirical estimation began with Papageorgiou et al. (2017), who estimated it between 2 and 3 using macroeconomic data. Jo (2020) found similar results to microeconomic data. Stöckl and Zerrahn (2023) provided a bottom-up perspective, identifying this elasticity as greater than 3. In our estimation in the first chapter, the implied elasticity of substitution is also between 2 and 3, using different specifications and methods. In this paper, we set the value of this elasticity to 3 to align with the approximations of these various works.

For the intermediate goods sectors—clean and dirty—we employ Cobb-Douglas production functions, as illustrated in equations 2.4.11 and 2.4.12. Following Acemoglu et al. (2012), we assume $\alpha = \frac{1}{3}$, ensuring that the share of national income allocated to machinery corresponds to the share of capital. Subsequently, we compute the initial values of A_g and A_d to align the implied initial values and ratio of Y_g and Y_d. The production levels of non-fossil and fossil fuels in the U.S. primary energy supply are derived from data provided by the EIA. According to the EIA's International Energy Outlook 2023, in 2022, non-fossil fuel sources accounted for approximately 21% of global primary energy consumption, while fossil fuels made up the remaining 79%. Accordingly, we set the initial values of $A_{g,t}$ and $A_{d,t}$ to produce the initial levels of $Y_{g,t}$ and $Y_{d,t}$ that maintain these proportions. For the depreciation rate of capital, δ, we apply a 5% rate, which is a standard assumption in macroeconomic models. Regarding innovation elasticity with respect to R&D expenditure, to the best of our knowledge, no previous study has estimated this parameter. Our analysis in the first chapter provides an approximation using data from the U.S. electricity sector, where we estimate the value of θ to be approximately 0.16.

In calibrating the environmental components of our model, we closely follow the approach outlined by Golosov et al. (2014). The calibration focuses on three primary sets of parameters: those related to the damage function (γ_t), the carbon cycle's depreciation structure (the ϕ parameters), and the initial carbon concentration levels. The damage function in our model, denoted as $D(S_t)$, quantifies the negative impact of climate change on economic output. This function is crucial as it translates changes in carbon concentration into productivity losses. We adopt an exponential form for the damage function, similar to Golosov et al. (2014) where the damage is expressed in equation 2.4.18. This exponential specification is chosen because it provides a close approximation to the more complex damage functions used in other studies, such as those of Nordhaus (2007). The parameter γ_t is calibrated to match the observed economic impacts of different levels of increase in temperature, ensuring that our model reflects the current scientific understanding of climate damage. γ_t is calibrated in Golosov et al. (2014) to have an average value of 2.379×10^{-5}.

The carbon cycle depreciation is modeled to account for the decay of carbon emissions over time. We adopt a three-parameter system, as proposed by Golosov et al. (2014), to describe the dynamics of carbon in the atmosphere, as previously shown in equation 2.4.20. The parameters ϕ_L, ϕ_0, and Φ are calibrated as follows: ϕ_L represents the fraction of carbon that remains in the atmosphere indefinitely, which is set at 0.2 based on estimates from Eggleston et al.

(2006), indicating that about 20% of emitted carbon will stay in the atmosphere for thousands of years. ϕ_0 is the fraction of carbon that is quickly absorbed by the biosphere and surface oceans, calibrated to 0.393 to reflect that approximately half of the carbon pulse is removed within 30 years. Φ is the geometric decay rate of the remaining emissions, set at 0.0228 to match the average lifetime of the carbon that does not stay in the atmosphere indefinitely.[17] For the initial carbon concentration, we assume a pre-industrial carbon concentration ($\bar{S}$) of 581 GtC (gigatonnes of carbon), consistent with historical data. This level serves as the baseline against which all subsequent changes in carbon concentration are measured (Golosov et al. 2014).

Finally, the model calibrates tax rates on consumption and labor income using U.S. economic data as a benchmark. The average labor income tax, measured by the tax wedge, is around 30%. Notably, the tax wedge for the average single worker in the U.S. declined from 30.5% in 2022 to 29.9% in 2023 (OECD 2023). For the consumption tax rate, the model applies the average combined sales tax rate, which includes both state and local taxes across the country. Recent data suggest that this combined rate averages 6.61% (Walczak 2024). In the baseline scenario, taxes on the carbon-intensive (dirty) sector, green sectors, clean investment tax credits, and R&D subsidies are initially set to zero. This configuration facilitates policy experiments designed to assess the impact of these fiscal instruments on emissions reduction and the transition to clean sectors.

Table 2.1 below summarizes the parameter values used in the calibration. This calibration sets the stage for running simulations to evaluate the effectiveness of different environmental tax policies in achieving the emission reduction targets set by international agreements such as the Paris Accord. The following section presents the results of these simulations.

2.6 Results and Scenarios of Policy Options

In this section, the baseline scenario of the model represents the steady-state levels of the variables in a laissez-faire environment without government intervention. In the baseline, the clean input share is calculated as:

[17] For more details on calibrating this carbon cycle depreciation, refer to Golosov et al. (2014)).

Table 2.1: Calibration Parameters for the Model

Parameter	Value	Description	Source
σ_u	1.5	Inverse of the intertemporal elasticity of substitution	Cogan et al. (2010)
ψ_u	2	Parameter linked to Frisch labor supply elasticity	Cogan et al. (2010)
ψ	2.4	Leisure weight in utility function	Calibrated based on target labor supply
β	0.985	Discount factor	Golosov et al. (2014)
ϵ	3	Elasticity of substitution in final goods production	Papageorgiou et al. (2017), Jo (2020), Stöckl and Zerrahn (2023)
α	0.333	Capital share in production	Acemoglu et al. (2012)
δ	0.05	Depreciation rate of capital	Standard assumption
θ	0.16	Elasticity of innovation with respect to R&D expenditure	Chapter 1 analysis
A_{g0}	0.60	Initial level of clean technology	EIA International Energy Outlook 2023
A_{d0}	1	Initial level of dirty technology	EIA International Energy Outlook 2023
ϕ_L	0.2	Fraction of carbon that remains in atmosphere indefinitely	Eggleston et al. (2006)
ϕ_0	0.393	Fraction of carbon absorbed quickly by biosphere and surface oceans	Golosov et al. (2014)
Φ	0.0228	Geometric decay rate of remaining emissions	Golosov et al. (2014)
γ_t	2.379×10^{-5}	Scale of the damage function	Golosov et al. (2014)
τ_h	0.299	Labor income tax rate	OECD (2023)
τ_c	0.0661	Consumption tax rate	Walczak (2024)
τ_d, τ_g	0	Dirty goods tax and clean goods tax credits	Baseline level
τ_d^x, τ_g^x	0	Dirty investment tax and clean investment tax credits	Baseline level
R_d^s, R_g^s	0	Dirty R&D and clean R&D subsidies	Baseline level

Note: All parameters are calibrated based on empirical data and established literature.

$$\text{Clean Input Share} = \left(\frac{Y_{g,t}}{Y_{g,t} + Y_{d,t}} \right) \times 100$$

This formula represents the proportion of clean intermediate inputs ($Y_{g,t}$) relative to the total intermediate inputs used ($Y_{g,t} + Y_{d,t}$) in the production process, expressed as a percentage. It serves as a key indicator of the economy's transition towards cleaner production practices. The value of this share is 20% in the steady state, consistent with data from the EIA regarding the shares of clean and fossil fuel energy. This implies that the majority of production relies predominantly on dirty energy.

This reliance underscores the need for government interventions to reduce dependency on dirty inputs and lower CO_2 emissions. The analysis focuses on the effects of various policy instruments on emission reduction targets, the clean input share, and their broader macroeconomic implications.[18]

2.6.1 Scenarios of Policy Options

In this section, we analyze the effects of various policy instruments on emission reduction targets, the shift from dirty to clean sectors, and implications for economic growth and other key economic variables. Each policy instrument is adjusted from its steady-state level set in the initial period. We assume a balanced government budget with constant government spending. To account for the connections between policies and the economy, we modify the lump-sum transfer to respond to changes in each policy instrument. For instance, an increase in the carbon tax would raise the lump-sum transfer through a carbon tax rebate. In contrast, introducing clean tax credits requires a decrease in this transfer to maintain fiscal balance.

The paper computes the percentage deviation from the baseline, which is the steady state level. In analyzing these scenarios, it is useful to categorize the policy instruments into demand-side and supply-side policies. This classification facilitates the identification of common outcomes within each category. Demand-side policies are those that exert a direct or initial influence on the demand side of both the clean and dirty sectors. For example, the carbon tax and the clean input tax credit primarily impact the optimal decisions made by final goods producers, representing the demand side of our economy.

Supply-side policies directly affect the production dynamics of both sectors. These include the clean investment tax credit and R&D subsidies. The distinction between these two categories allows us to better understand how policies affect economic behavior and equilibrium outcomes and draw a generalized conclusion about any potential policy that falls into either category. Another useful way to categorize these policies is by whether they directly target the dirty sector (e.g., carbon taxes and dirty investment taxes) or the clean sector (e.g., clean ITCs,

[18]The model is solved in two steps using MATLAB. First, I compute the steady state by solving the nonlinear equilibrium conditions. Second, I simulate the transition dynamics by iteratively solving the model forward over time under perfect foresight. This approach captures the economy's response to policy shocks.

clean input tax credits, and R&D subsidies). This classification helps identify common effects within each group and allows for more generalized findings that apply to policies targeting either sector.

We divide our analysis of these policy instruments into two subsections. In the first subsection, we simulate various scenarios where each policy is independently adjusted by 10% to assess its impact on emissions reduction and its economic implications. In the second subsection, we directly compare these policies by imposing a 20% emissions reduction target over the next 26 years, in alignment with the 2050 emissions reduction commitments under the Paris Agreement. Finally, we simulate and evaluate the effectiveness of each policy or policy mix in achieving this goal.

Before proceeding into a detailed analysis of alternative policy options, we summarize the key findings across different scenarios. First, policies targeting the dirty sector have the potential to achieve emission reduction targets more efficiently. The downside is that these dirty-sector policies adversely affect economic growth and prosperity. This is largely due to the fact that the dirty energy sector has a larger capacity and market size than the clean energy sector. Consequently, policies that constrain the dirty sector naturally result in greater emissions reductions but at the cost of slower economic growth.

Furthermore, demand-side policies typically result in greater emissions reductions than supply-side policies. Taxing the use of dirty goods (for example, a carbon tax) has a greater impact on emissions than taxing dirty-sector investments. Tax incentives for using clean goods (or inputs) have a greater impact than clean ITCs. This is largely due to the substitutability between clean and dirty goods in the market. When the elasticity of substitution is high, demand-side policies become more effective because consumers and firms can more easily switch from dirty to clean alternatives.

When a policy targets both the clean sector and the demand side at the same time, such as clean input tax credits, it can play a major role in speeding up the transition to cleaner sectors and meeting emission reduction goals. However, the success of this approach depends on having a reasonably high degree of substitution between clean and dirty production. Also, there is a trade-off: funding this kind of policy often means significantly increasing household lump-sum taxes or introducing other taxes, which can be a challenge. Political or social factors, such as household opposition or concerns, can make implementing these policies at a substantial scale particularly difficult.

Tax credits for clean inputs (i.e., policies aimed at both the clean sector and the demand side) can accelerate the move toward cleaner technologies. These policies have trade-offs, including an increase in household lump-sum taxes (or other forms of distortionary taxation), which may be met with political resistance or social opposition. More importantly, there is the possibility to adopt what we call a clean double dividend approach by using revenue generated by carbon taxes and/or dirty investment taxes to finance clean incentives, such as clean input tax incentives and clean ITCs. Policymakers can use this strategy to leverage the effectiveness of dirty-sector policies while simultaneously mitigating their negative economic implications by redirecting revenues to growth-promoting clean-sector policies. For example, individuals who purchase clean alternatives, such as hybrid or electric vehicles, could receive tax credits, while those purchasing fossil-fuel-powered vehicles would incur a carbon tax.

In an industrial context, a system similar to Canada's Output-Based Pricing System (OBPS) could be applied, where carbon pricing revenue is returned to sectors that adopt cleaner technologies and processes. Our analysis suggests that redirecting carbon tax revenues to clean initiatives is more effective than allocating these revenues as lump-sum carbon rebates to households. The clean double dividend approach more effectively achieves emission reduction targets while mitigating the adverse economic effects of carbon pricing. This is further supported by our welfare analysis in Section 2.6.2, which shows that the clean double dividend approach results in a favorable welfare impact compared to policies like the carbon tax when revenues are returned to households as lump sum rebates.

The Impact of Alternative policy Options

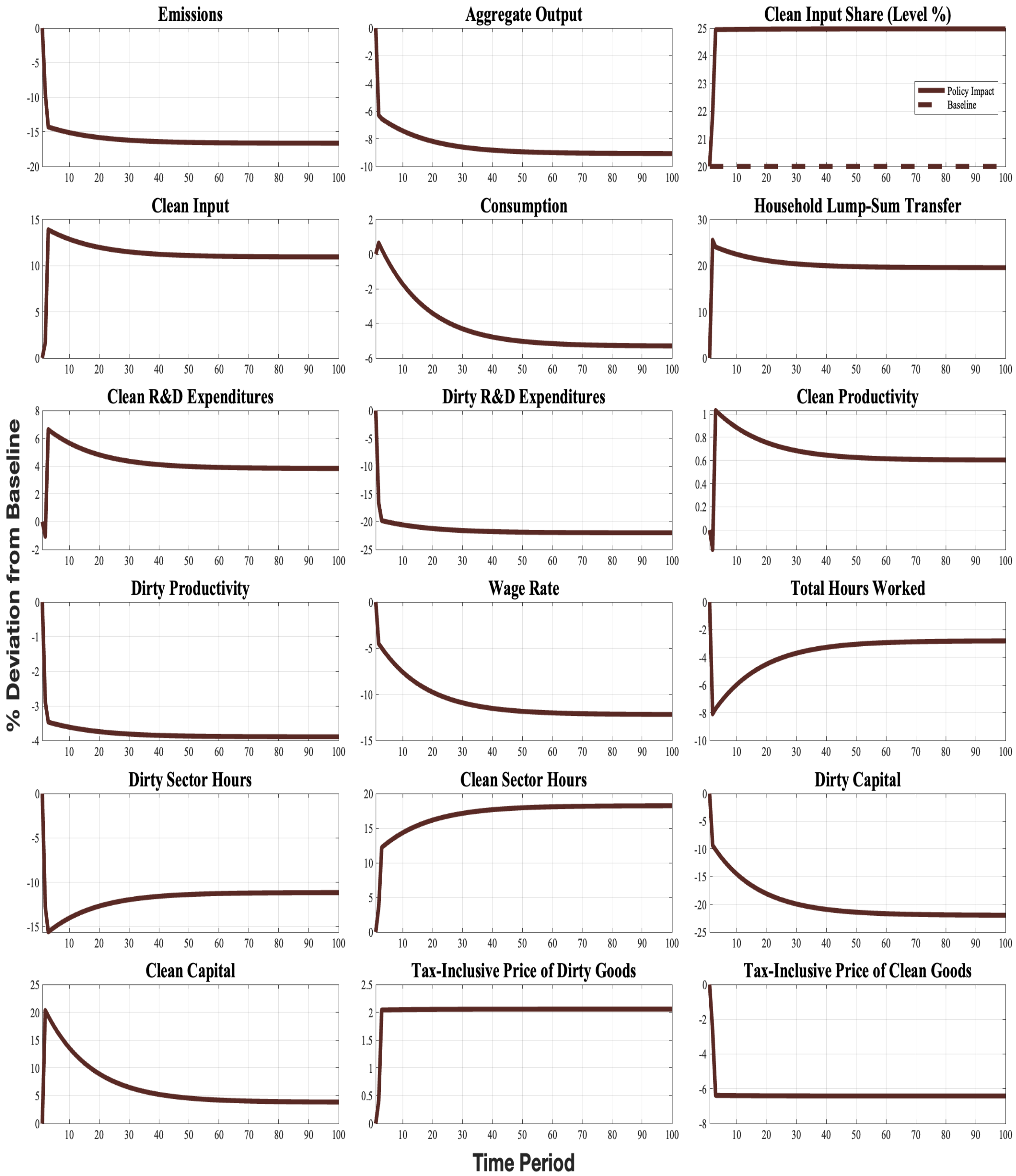
Dirty Input Taxation

The introduction of a 10% tax on dirty input use (i.e., carbon tax), τ_d, drives several key economic changes, including shifts in relative prices, output levels, and other effects. The increase in the carbon tax leads to a significant rise in government revenue, enabling household transfers to increase by approximately 20% compared to the baseline case, as the carbon tax revenue is redistributed as tax rebates to households. Emissions decrease by 9.40% after two periods, with this reduction reaching 16.20% in the long run. This highlights the effectiveness of the carbon tax in incentivizing economic agents to adjust their behavior toward achieving emission reductions. The decrease in dirty production (and consequently emissions) occurs through two channels: the transition to cleaner alternatives and the reduction in aggregate output due to the imperfect substitutability between dirty and clean goods.

As presented in Figure 2.1 and Table 2.2, the carbon tax alters the relative prices of clean and dirty goods. Specifically, the after-tax price of dirty goods increases by 2.05% from its baseline case, while the price of clean goods decreases by approximately 6.40% over 10 years. This shift incentivizes demand-side actors, particularly final good producers in our model, to reconsider their choices as the cost of dirty goods increases while clean goods become more competitively priced. Consequently, the change in relative prices makes clean goods more attractive, facilitating a substitution effect. As a result, clean output increases by 12.88%, highlighting a strong transition towards cleaner alternatives. This shift confirms the effectiveness of the carbon tax in influencing consumer behavior and promoting sustainable production practices. The magnitude of this substitution effect depends on the elasticity of substitution; in our calibration, the elasticity ϵ is set to 3. Industries with a higher substitution elasticity are expected to experience a more significant substitution effect, while those with a lower degree of substitution will see comparatively smaller impacts.

Furthermore, carbon pricing increases the return on capital accumulation in the clean energy sector. For example, the accumulation of clean capital increases significantly, by 13.62% within the first 10 years, while the capital in the dirty sector declines by 14.50% during the same period. This decline in dirty capital continues, reaching a reduction of around 20% after 30 years. This reallocation of household savings toward clean capital amplifies the overall impact of a carbon tax. The reason is that clean capital is a key input for producing clean goods. As a result, the effectiveness of the carbon tax extends beyond simply altering the relative price between clean and dirty sectors; it also drives capital reallocation across sectors. This

Figure 2.1: Effects of a Carbon Tax Increase



Note: The graph illustrates the impact of a 10% increase in dirty input taxation (i.e., carbon tax) on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show that this increase in the carbon tax raises the relative price of dirty inputs and reallocates investment toward clean inputs. This makes clean substitutable inputs more favorable, thereby reducing the use of dirty inputs and associated emissions. It also increases the share of clean inputs in the production process and accelerates the transition to clean technology.

dual effect, through both pricing and capital redistribution, increases the impact of policy in promoting clean energy production.

The carbon tax also influences technological change in favor of clean sectors. By increasing

Table 2.2: Effects of Dirty Input Taxation: Baseline Deviations (%)

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	-9.40	-15.10	-16.20
Aggregate Output (%)	-6.30	-7.42	-8.60
Clean Input Share (%)	9.55	24.74	24.81
Clean Input (%)	1.68	12.88	11.50
Consumption (%)	0.65	-1.72	-4.31
Wage Rate (%)	-4.55	-7.58	-10.92
Dirty Labor (%)	-12.74	-14.04	-11.97
Clean Labor (%)	3.66	14.33	17.15
Total Hours (%)	-8.08	-5.98	-3.70
Dirty Capital (%)	-9.34	-14.50	-19.94
Clean Capital (%)	20.34	13.62	6.51
Clean R&D Expenditures (%)	-1.05	5.66	4.35
Dirty R&D Expenditures (%)	-16.71	-20.56	-21.58
Dirty Technology (%)	-2.88	-3.62	-3.82
Clean Technology (%)	-0.17	0.89	0.68
After-tax Dirty Price (%)	0.41	2.05	2.05
After-tax Clean Price (%)	-2.69	-6.40	-6.41

the profitability of clean sectors, it incentivizes producers to invest more in R&D for clean technologies. This ultimately accelerates the transition to clean technology in relation to dirty technology, as demonstrated in the table and figure referred to. For example, the adoption of clean technology increases by 1.1% compared to the baseline scenario, while the adoption of dirty technology decreases by 2.23%.

Although positive changes in clean output are evident, the overall implications for economic growth are mixed. Aggregate output decreases by approximately 15% after 10 years and by 16.20% over 30 years, indicating a contraction as the economy adjusts to the new tax regime. Consumption also declines by 1.7% over 10 years and by 4.42% over 30 years, reflecting the reduced disposable income resulting from tax adjustments and their impact on total income. Figure 2.1 and Table 2.2 also illustrate an expansion in both labor demand and capital stock in the clean sector relative to the dirty sector. Overall, the introduction of a carbon tax effectively alters economic incentives, promoting emission reduction and cleaner production. However, it has adverse effects on production, consumption, and welfare.

Clean Input Tax Incentive

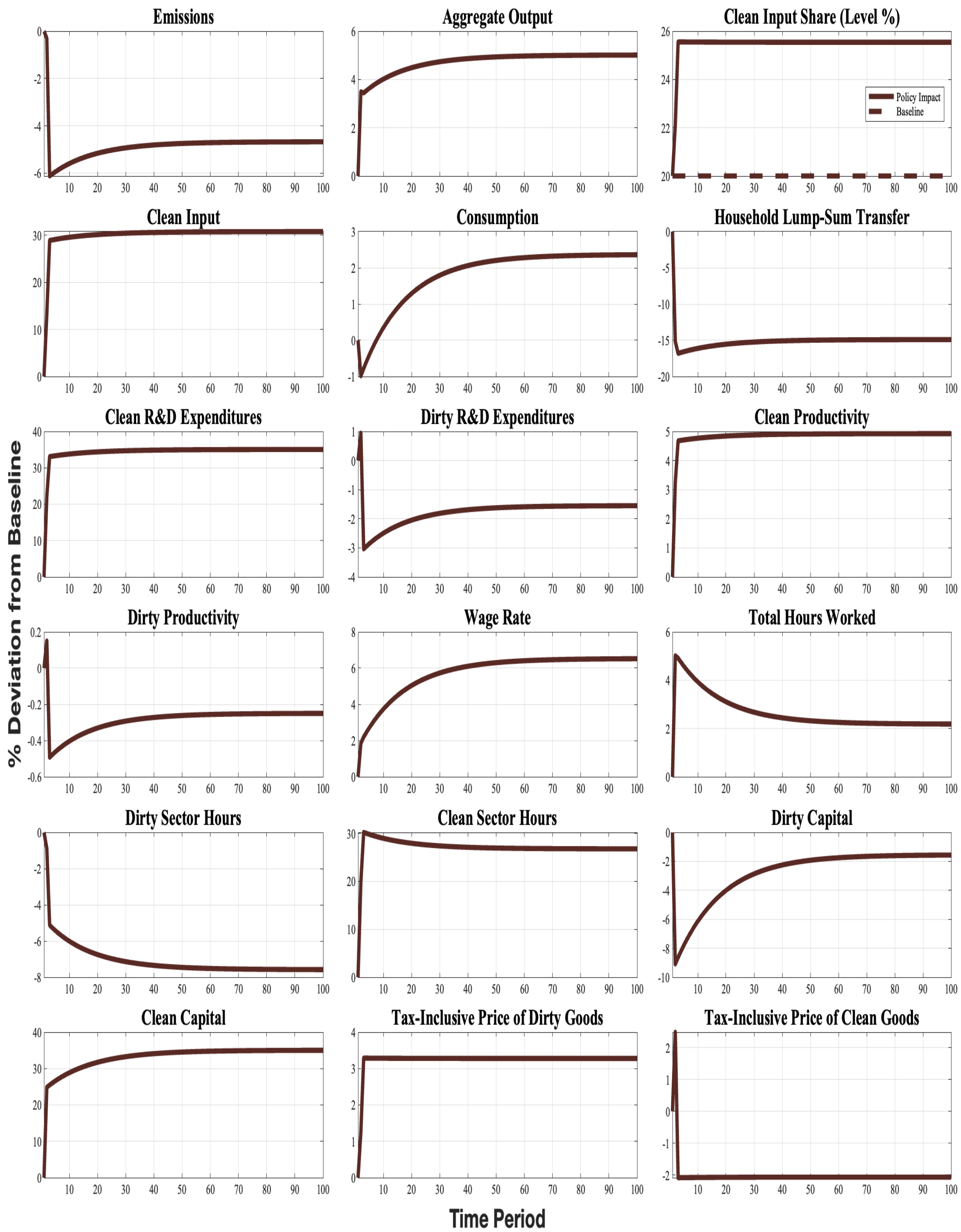
By adopting a clean Input tax credit (τ_g), several economic changes are initiated, affecting relative prices, capital reallocation, output levels, and other macroeconomic implications. A 10 percent increase in the clean input tax credit reduces emissions, cutting them by around 5% over time. This outcome highlights the effectiveness of the tax credit in promoting cleaner production practices and lowering emissions.

Ideally, this policy would result in cleaner goods being made cheaper and a substitution effect occurring. Table 2.3 and Figure 2.2 show that the after-tax price of dirty goods increases by 5.94%, while the price of clean goods decreases by 5%. Clean goods are now more competitively priced, causing demand-side actors, such as final goods producers, to prioritize clean inputs in their production processes. By incentivizing clean production, this policy increases the share of clean production by approximately 37% over time compared to the baseline scenario. This suggests a shift towards cleaner alternatives. Furthermore, clean input tax credits directly impact return, the demand for clean capital, and consequently. This leads to a greater reallocation to clean capital. This policy also incentivice the clean R&D and then clean technology compared to dirty technology, as shown in the table and figure.

Table 2.3: Effects of Clean Input Tax Credits: Baseline Deviations (%)

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	-0.31	-5.60	-4.93
Aggregate Output (%)	3.49	4.01	4.73
Clean Input Share (%)	10.60	27.73	27.69
Clean Input (%)	13.26	29.57	30.43
Consumption (%)	-0.98	0.35	1.79
Wage Rate (%)	1.85	3.74	5.73
Dirty Labor (%)	-0.89	-6.01	-7.14
Clean Labor (%)	19.89	28.97	27.39
Total Hours (%)	5.01	3.93	2.67
Dirty Capital (%)	-9.09	-6.14	-2.87
Clean Capital (%)	24.88	28.86	33.27
Clean R&D Expenditures (%)	22.11	33.80	34.70
Dirty R&D Expenditures (%)	0.94	-2.50	-1.81
Dirty Technology (%)	0.15	-0.40	-0.29
Clean Technology (%)	3.25	4.77	4.88
After-tax Dirty Price (%)	1.25	3.28	3.28
After-tax Clean Price (%)	2.48	-2.07	-2.06

Figure 2.2: Effects of Clean Input Tax Credits



The graph illustrates the impact of a 10% increase in clean input tax credits on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show that this increase in clean tax credits reduces the effective relative price of clean inputs compared to dirty inputs. It also encourages investment reallocation toward clean inputs, making clean substitutable inputs more favorable. This, in turn, reduces the use of dirty inputs and associated emissions. Furthermore, it increases the share of clean inputs in the production process and accelerates the transition to clean technology.

The general implications for economic growth are positive, with aggregate output steadily increasing to 5.81% after 30 years. This shows that the clean input tax credit not only promotes cleaner production, but also supports long-term economic growth. By shifting economic incentives, the policy encourages cleaner production and contributes to emission reductions. The positive effects on production, labor, and wages highlight the potential of the policy as an effective tool to achieve both environmental and economic objectives. However, the magnitude of these favorable impacts is largely dependent on the substitution elasticity between clean and dirty production. If the degree of substitutability is lower, the effects of the policy are expected to be less pronounced.

Clean Investment Tax Credit

The introduction of a 10% clean Investment Tax Credit (ITC), τ_g^x, (as illustrated in Figure 2.3 and Table 2.4) leads to a steady reduction in emissions, reaching a decrease of 1.35% after 10 years, while this reduction become 0.9% over the long run.[19] Clean ITC effectively increases the share of clean energy by approximately 8.64% compared to the baseline scenario. Clean ITC lowers the cost of accumulating clean capital, making investments in clean capital more attractive and affordable for households relative to dirty capital. Consequently, this policy drives a significant increase in clean capital stock, which increases by 15.82% after 10 years, with continued growth in the longer term. In contrast, the stock of dirty capital initially decreases by 4.83% after 2 periods. However, this reduction decreases with time, falling to just 0.60% after 30 periods.

Generally, a clean ITC policy generates two opposing economic effects—**the substitution effect** and **the income effect**—a dynamic observed with other policies. The substitution effect arises because clean ITCs lower the effective cost of clean capital, ultimately substituting dirty capital for clean capital. The income effect arises, on the other hand, because clean ITCs lower the overall production costs for final goods producers. With reduced costs, producers are

[19]The initial increase in emissions (as shown in Figure 2.3) following a 10% clean (ITC) can be explained within a DGE framework as follows: initially, the clean ITC reduces the overall production cost for final good producers, stimulating economic activity and temporarily raising total energy use—including both clean and dirty sources. However, as producers observe a decrease in the relative cost of investment in clean capital compared to dirty capital, they increasingly shift their investments toward clean energy. Over subsequent periods, this shift reduces reliance on dirty capital, eventually lowering emissions as the economy transitions to cleaner production methods. The same logic explains the initial rise observed in related variables such as dirty production and labour hours.

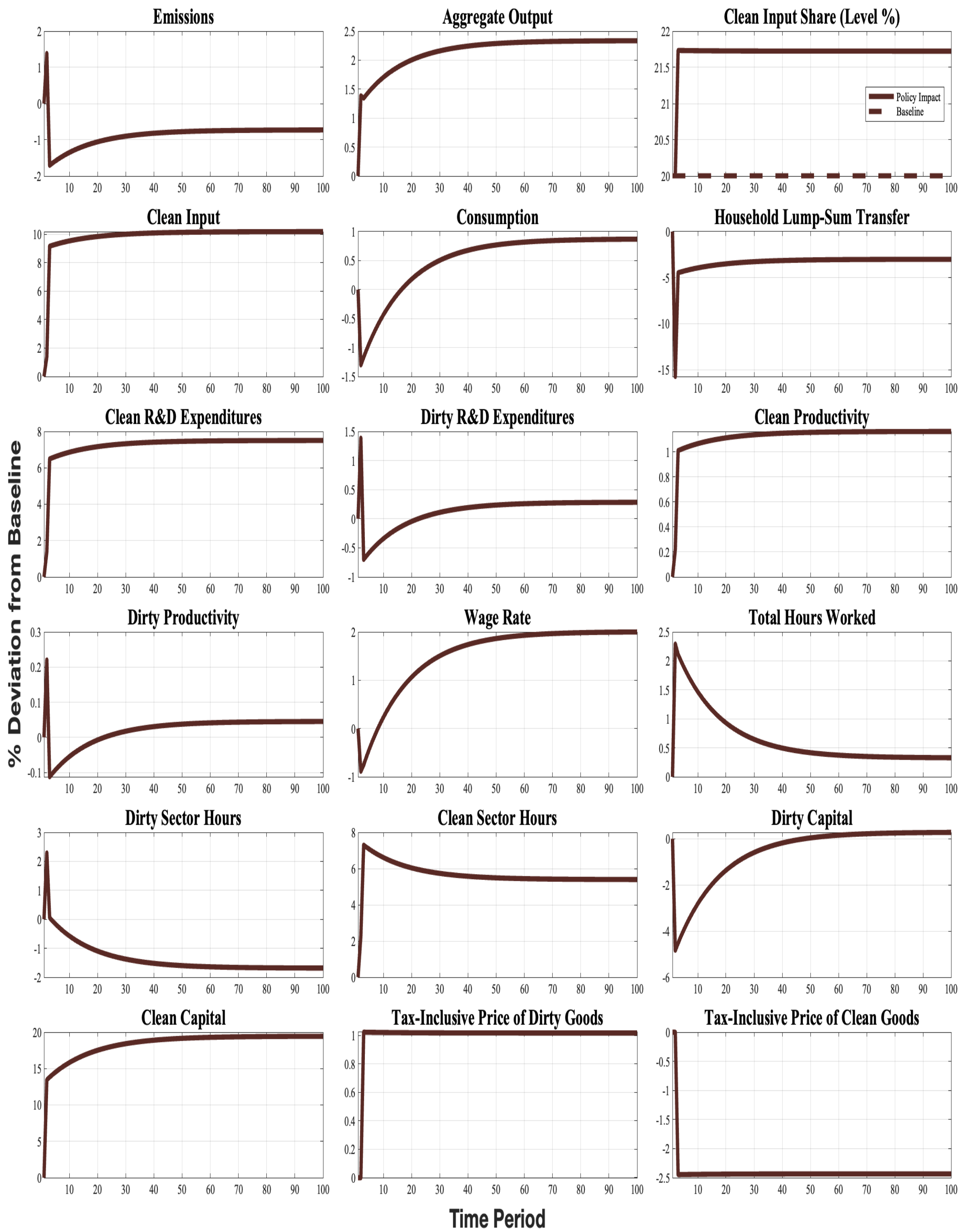
incentivized to increase total production. As shown in the referenced table, the output increases by 2.16% over time. However, this expanded production increases the demand for inputs from both the clean and dirty sectors. In the short and medium term, since dirty production still holds a larger share of the economy, the income effect tends to favor dirty production more than clean production. The net impact of the clean ITC policy depends on which of these two effects, substitution or income, dominates. In this scenario, the income effect appears to dominate, leading to a weaker reduction in emissions and a slower transition to cleaner production. In summary, while clean ITCs contribute significantly to economic growth, their impact on emissions reduction is more limited because of the dominance of the income effect over the substitution effect in the short and medium term.

Dirty Investment Taxation

Figure F.1 and Table F.2 illustrate the effects of implementing a dirty investment tax. This policy leads to a substantial reduction in emissions, with a decrease of 5.72% in the short term that increases to 6.86% in the long term. The tax imposes a significant constraint on the dirty sector, as evidenced by a sharp decline in dirty output, which closely aligns with the observed emissions reductions. However, aggregate output declines by 3.26% over time, indicating a notable economic slowdown primarily driven by the contraction of dirty sector activity. The clean output share increases by approximately 7.7% over time. Although the tax effectively encourages cleaner production, it also reduces the dirty capital stock by about 13.30% over time. In contrast, the clean sector capital stock experiences notable short-term growth of 10.82%, but this gain fades over time, resulting in a long-term increase of 1.56%.

Analyzing this policy through the lens of substitution and income effects, as previously done with clean ITCs, reveals important dynamics. The income effect of dirty investment taxation operates by constraining total production, as the dirty sector faces higher costs. This reduction in production affects both the dirty and clean sectors, leading to a lower overall output. At the same time, the substitution effect arises because the policy makes dirty production more expensive, incentivizing producers to shift toward cleaner production.

Figure 2.3: Effects of Clean Investment Tax Credits



Note: The graph illustrates the impact of a 10% increase in clean ITCs on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show that this increase in clean ITCs reduces the effective cost of investing in the clean sector, encouraging investment reallocation toward clean inputs and making clean substitutable inputs more favorable. However, this policy has a growth effect as it also stimulates output, which expands the demand for both the clean and dirty sectors. The net effect of this policy is a slight reduction in emissions initially, followed by a return to the baseline level over time as the growth effect takes hold. Additionally, the share of clean inputs slightly increases compared to the baseline level.

Table 2.4: **Effects of Clean Investment Tax Credits: Baseline Deviations (%)**

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	1.38	-1.35	-0.90
Aggregate Output (%)	1.38	1.70	2.16
Clean Input Share (%)	0.00	8.64	8.61
Clean Input (%)	1.38	9.53	10.01
Consumption (%)	-1.30	-0.44	0.50
Wage Rate (%)	-0.89	0.23	1.50
Dirty Labor (%)	2.29	-0.57	-1.37
Clean Labor (%)	2.29	6.61	5.74
Total Hours (%)	2.29	1.47	0.65
Dirty Capital (%)	-4.83	-2.82	-0.60
Clean Capital (%)	13.46	15.82	18.42
Clean R&D Expenditures (%)	1.38	6.86	7.33
Dirty R&D Expenditures (%)	1.38	-0.34	0.11
Dirty Technology (%)	0.22	-0.05	0.02
Clean Technology (%)	0.22	1.07	1.14
After-tax Dirty Price (%)	-0.00	1.02	1.02
After-tax Clean Price (%)	-0.00	-2.44	-2.44

In this case, the income effect and the substitution effect work in the same direction by reducing dirty production, which explains the substantial emission reductions observed. However, the increase in clean production remains modest because the income effect, which restricts total production, also limits the expansion of the clean sector alongside the dirty sector.

R&D Subsidy

A 10 percent increase in clean R&D subsidies leads to only minor changes in emissions and other economic variables, as shown in Table F.3 and Figure F.2, with emissions decreasing only by 0.35% over 10 years. Similarly, reducing dirty R&D subsidies has a moderate effect on emission reduction, as illustrated in Table F.4 and Figure F.3. While increasing clean R&D or reducing dirty R&D boosts the relative productivity of the clean sector, making its prices more competitive compared to fossil fuels, this change promotes only a modest transition from emissions-intensive inputs to cleaner alternatives.

This limited effect is due to the probabilistic nature of innovation and the time needed for the technological change to take effect. In our model, R&D subsidies primarily encourage entrepreneurs to invest more in R&D, yet this goal could potentially be achieved more effectively through indirect policy instruments, such as carbon taxes or investment taxes. These policies can serve as an instrumental means to drive technological change toward clean technologies.

Policy Mix: Taxation and Clean Incentives

In our previous analysis, we balanced the government budget through lump-sum taxes or transfers to households. For instance, when we introduced a tax on dirty goods, such as a carbon tax, the revenue generated was redistributed to households in the form of lump-sum rebates. Similarly, when we implemented green sector policies, like clean ITCs, these were treated as a lump-sum tax or a reduction in household transfers. This method of using environmental taxes to finance household transfers is known as the double dividend approach.[20] However, using lump-sum transfers is not the only way to apply this approach. In this part, in addition to the 10 percent carbon tax increase, we also exogenously include other clean incentives. The latter takes from the household lump-sum transfer while the carbon tax adds to it. Specifically, beside the 10% increase in carbon tax, we add a 9.5% increase with each policy: clean input tax credits, clean ITCs, and R&D subsidies.[21] As seen in Figure 2.4 and Table 2.5, the policy was designed to ensure that the net effect on household lump-sum transfers eventually approaches zero. Initially, household transfers increase due to the carbon tax, but over time, the introduction of green incentives reduce these transfers.

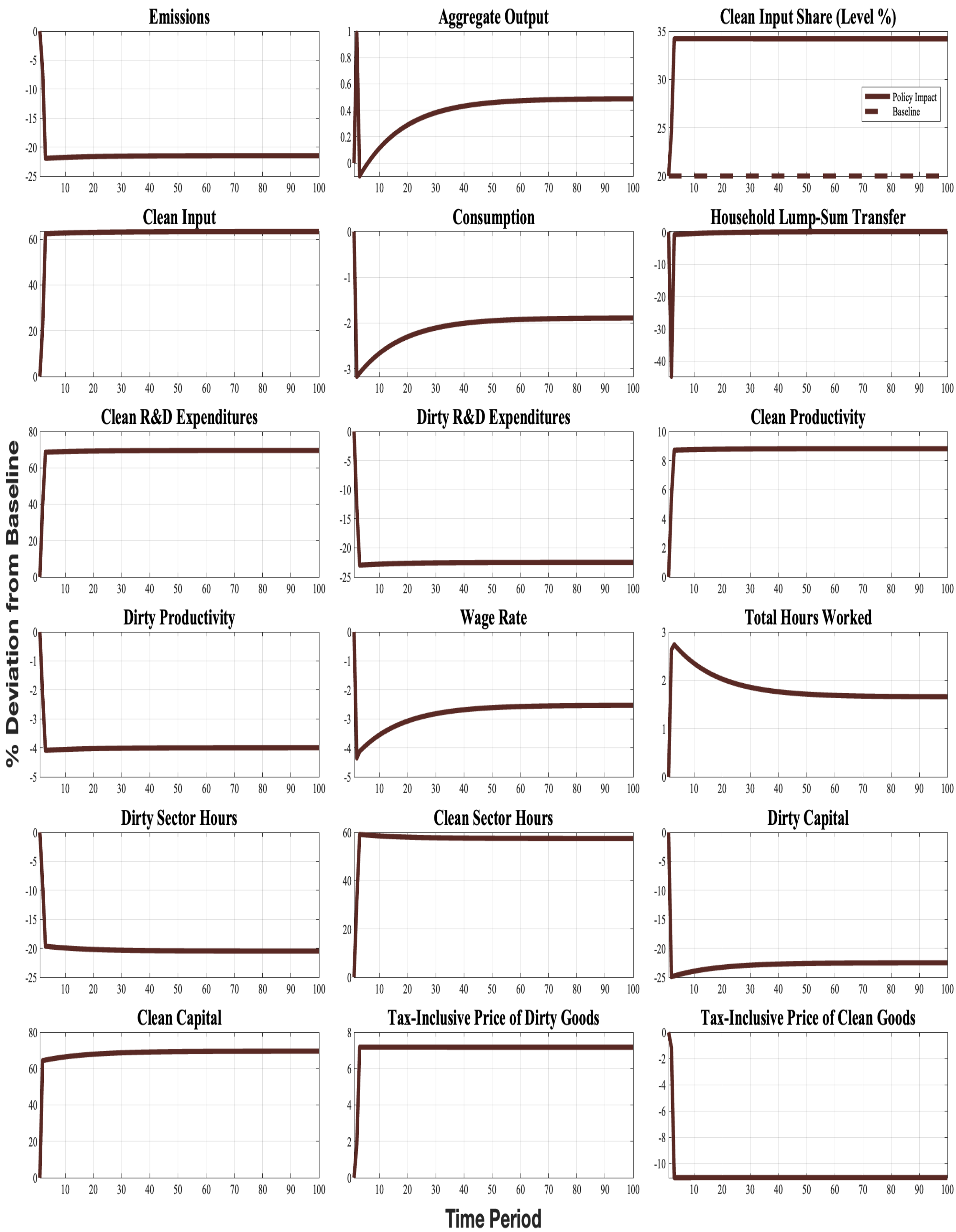
This strategy leads to substantial effects on emissions reduction and economic growth acceleration. Using this approach shows the greatest reduction in emissions, with short-term reductions of 6.80% and reductions of 21.78% over 10 years. The pronounced decrease in emissions is much greater than that of any other policy analyzed, as the combined emphasis on the dirty sector tax and substantial clean energy incentives amplify the overall impact.

The adverse effect of the carbon tax on aggregate production is mitigated by implementing clean incentives simultaneously. Aggregate output increases by 0.98% after two periods and stabilizes at 0.38% in the long term. This indicates that the expansion of the clean sector ultimately offsets the initial contraction caused by the carbon tax. This recovery is driven by a significant increase in the share of clean production, which grows to approximately 71% in

[20] For more details regarding the the double dividend hypothesis, refer to Jaeger (2013) and Freire-González (2018).

[21] We chose the value of the clean incentives such that the net effect on the household transfer approach zero in the long run

Figure 2.4: Effects of Policy Mix: Taxation and Clean Incentives



Note: The graph illustrates the impact of a policy mix: a 10% increase in the carbon tax and a 5% increase in each clean incentive, including clean ITCs, clean input tax credits, and clean R&D subsidies. The mix is designed to ensure household transfers stabilize in the long run. The results show that this policy has a significant impact on emission reduction, the clean input share, and clean technology transition, while also having a favorable effect on aggregate output. This policy leverages the substantial impact of the carbon tax on emission reduction while mitigating its adverse effects on output by incorporating clean sector initiatives.

Table 2.5: Effects of Policy Mix: Carbon Tax and Clean Incentives: Baseline Deviations (%)

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	-6.80	-21.78	-21.57
Aggregate Output (%)	0.98	0.11	0.38
Clean Input Share (%)	22.90	71.04	71.03
Clean Input (%)	21.50	62.69	63.11
Consumption (%)	-3.17	-2.66	-2.11
Wage Rate (%)	-4.35	-3.56	-2.82
Dirty Labor (%)	-9.01	-19.95	-20.34
Clean Labor (%)	31.97	58.54	57.76
Total Hours (%)	2.63	2.35	1.85
Dirty Capital (%)	-24.91	-23.96	-22.92
Clean Capital (%)	64.40	66.44	68.68
Clean R&D Expenditures (%)	39.48	68.95	69.40
Dirty R&D Expenditures (%)	-12.98	-22.80	-22.58
Dirty Technology (%)	-2.20	-4.06	-4.01
Clean Technology (%)	5.47	8.75	8.80
After-tax Dirty Price (%)	1.85	7.18	7.18
After-tax Clean Price (%)	-1.18	-11.09	-11.08

the long term compared to its trajectory in the baseline scenario. This outcome is attributed to clean initiatives that stimulate investment, innovation, and production. Part of the shift from dirty to clean output is due to changes in their relative prices. The price dynamics reveal an increasing cost of dirty goods, with after-tax dirty prices increasing by 12.13% in the long term, further discouraging their use. Meanwhile, the after-tax price of clean goods decreases significantly by about 11% after 10 years, making clean goods more affordable and competitive, thus accelerating the transition to clean production and consumption.

The decline in dirty labor and capital further confirms this shift, with both shrinking in the short and long term. However, the reallocation of labor and capital to the clean sector is substantial, with clean labor and capital expanding significantly. In terms of technological change, this mix of policies has a pronounced impact on the direction of innovation toward the clean sector. The growth of clean technology has accelerated by approximately 4.7% (after 30 periods) compared to the baseline scenario without government intervention. With this policy mix, the capital stock in the clean sector has expanded significantly, boosting the profitability of clean sector capital.

These trends underscore the ability of a policy mix that includes both taxation and clean incentives to redirect resources toward cleaner, more sustainable economic growth. This approach is highly effective in reducing emissions while supporting long-term economic growth. The use of carbon tax revenues to fund clean initiatives, even indirectly, not only mitigates the negative economic effects of dirty-sector taxes but also promotes substantial expansion in the clean sector. Therefore, this strategy addresses both environmental and economic concerns in a balanced and sustainable way.

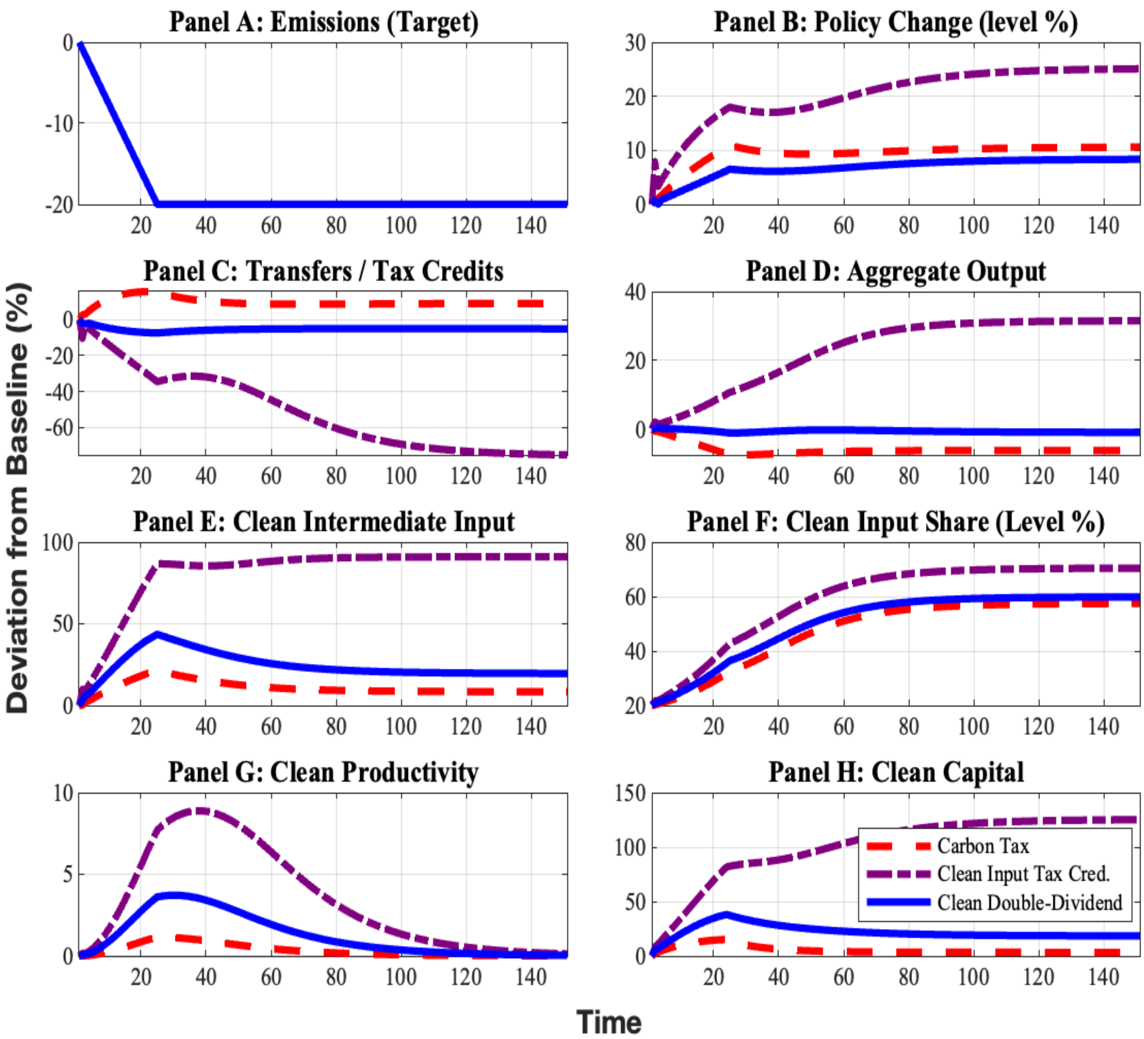
Achieving Emission Targets: A Comparison of Policy Options

In this section, we conduct a direct comparison of different policy options to achieve an emission reduction target. We set a target of 20% emission reduction to be achieved over a 25-year span in the future. To reach this goal, we consider three policy alternatives: a carbon tax, a clean input tax credits, and a clean double dividend policy. For the carbon tax, we determine the level of the tax, τ_d, required to meet the target emission over time. This approach assumes a balanced budget, where a lump-sum transfer to households balances the tax revenue. Consequently, the carbon tax revenue is redistributed to households as a carbon tax rebate. On the other hand, clean input tax credits will be derived from the household transfer.

For the clean double dividend policy, we again implement a carbon tax but allocate the revenue to fund clean input tax credits, maintaining a balanced government budget. In this setup, carbon tax revenue is redirected as an incentive to promote clean input usage. This scenario mirrors a situation where consumers who use dirty goods pay a carbon tax, while those opting for clean alternatives receive tax credits. For example, a consumer purchasing a hybrid or electric vehicle may receive a tax credit, whereas those buying vehicles relying on fossil fuels incur a carbon tax. When the industrial sector is the main demand driver, we can imagine a system similar to Canada's OBPS, where carbon pricing revenue is returned to jurisdictions or sectors that adopt cleaner technologies and processes.

To assess the impact of the three policy options, Figure 2.5 and Table 2.6 illustrate that achieving a 20% reduction in emissions requires the carbon tax rate to stabilize at approximately 13.18%. In comparison, the clean tax credit must increase steadily from 21.4% over a 10-year period to 35% in the long run. Clean input tax credits outperform the carbon tax in stimulating capital accumulation, productivity, and investment in the clean sector. Both policy options directly alter the relative prices of clean and dirty inputs, improving the profitability of the clean sector and redirecting innovation, productivity, and investment toward clean technologies.

Figure 2.5: Policies Targeting a 20% Emission Reduction



Note: The red dashed line represents the changes in economic variables following the carbon tax policy aimed at achieving a 20% emission reduction target. The mauve dotted line corresponds to the clean input tax credits policy, while the blue line reflects the clean double dividend policy option. Note that Panels B and C illustrate specific changes in policy options. Specifically, in Panel A, the red dashed line indicates the increase in the carbon tax. In contrast, in Panel C, the same line represents the change in household transfers resulting from the rebate associated with this policy. Additionally, the mauve dotted line in Panel C shows the reduction in household transfers (or the imposition of a lump-sum tax) to finance the clean input tax credit policy. Finally, the blue line in Panel B reflects the carbon tax, while in Panel C, the same line represents the clean tax credit financed by the carbon tax revenue.

The clean double dividend policy appears to be a promising approach, effectively achieving

Table 2.6: **Comparison of Policy Instruments for Emission Reduction Target**

Policy Instrument	After 2 Periods	After 10 Periods	After 30 Periods
Carbon Tax Policy			
Emissions (%)	-0.80	-7.20	-20.00
Carbon Tax rate (Level %)	9.08	4.17	13.18
Aggregate Output (%)	-0.77	-3.70	-10.22
Clean Input (%)	-0.69	5.29	16.04
Clean Input Share (%)	0.09	10.49	33.06
Clean Capital (%)	1.35	7.65	12.57
Clean R&D Expenditures (%)	-0.72	2.21	6.53
Clean Technology (%)	-0.12	0.35	1.02
Clean Input Tax Cred.			
Emissions (%)	-0.80	-7.20	-20.00
Clean Input Tax Cred. (level %)	-9.08	21.41	35.05
Aggregate Output (%)	15.28	18.68	31.10
Clean Input Share (%)	43.16	70.80	138.70
Clean Input (%)	59.20	92.60	192.35
Clean Capital (%)	32.78	95.48	219.94
Clean R&D Expenditures (%)	111.29	108.53	244.48
Clean Technology (%)	12.71	12.48	21.88
Clean Double Dividend			
Emissions (%)	-0.80	-7.20	-20.00
Carbon Tax rate (Level %)	9.08	2.43	9.04
Clean Input Tax Credits (Level %)	-12.04	5.00	11.27
Aggregate Output (%)	0.28	0.27	-2.00
Clean Input (%)	3.03	19.92	48.43
Clean Capital (%)	5.17	22.30	47.94
Clean R&D Expenditures (%)	4.44	19.56	45.66
Clean Technology (%)	0.70	2.90	6.20

environmental goals while mitigating the adverse impact on economic growth. With a lower increase in the carbon tax rate (approximately 9% compared to the first option), the revenue generated is used to provide a clean input tax credit of around 11%, which is sufficient to meet the goal of reducing emissions. This policy results in a small but negative effect on aggregate output while driving a substantial shift toward the clean sector. Specifically, aggregate output is slightly positive at around 0.30% after 10 years but turns negative, reaching a decline of 2% after 30 years. This outcome is significant compared to the first option, where the use of a carbon tax alone led to a 10% reduction in output over time. This suggests that when the clean double dividend approach is implemented, the adverse economic effects associated with the carbon tax are mitigated by using its revenue to finance clean production incentives. In sum, the clean double dividend policy not only alleviates the negative impacts of carbon taxation, but also fosters favorable economic outcomes, creating a strong incentive for growth within the clean sector.

One could argue that clean tax credits alone can achieve the emission reduction target while having a more favorable impact on economic growth, as shown in Figure 2.5 and Table 2.6. However, this policy comes with significant trade-offs. Relying solely on clean tax credits places a substantial burden on households, as lump sum transfers to households decrease significantly by approximately 170% compared to the baseline scenario. An important consideration when evaluating policy options is finding a way to balance the budget without disproportionately burdening households. In this case, financing clean production incentives requires much higher lump-sum taxes from households. This radical shift in lump-sum taxation could lead to broader issues, such as political resistance or equity concerns, which, while beyond the scope of this paper, are important to acknowledge. Furthermore, the favorable economic impact of clean tax credits may be less pronounced in scenarios where the elasticity of substitution between clean and dirty sectors is low. In such cases, households and firms are less responsive to incentives favoring cleaner production, limiting the policy's effectiveness.

We selected a 26-year timeframe to achieve the emission reduction target, aligning with the governmental goals to reduce emissions by 2025. This approach allows us to evaluate various policy options to achieve partial emission reductions within this period. We focus on partial reductions because attaining net zero emissions by 2050, which is a relatively short period, cannot be achieved solely through one or two fiscal policy measures. Comprehensive macroeconomic efforts are essential, including investments in infrastructure, technological innovation, regulatory frameworks, and international cooperation.

To further explore these dynamics, we conducted an additional exercise by setting an emission target of a reduction of 90% relative to the baseline by 2050. Notably, we did not simulate a 100% reduction (i.e., zero emissions) due to computational infeasibility. As shown in Figure

F.4, achieving this ambitious emission reduction target leads to a radical decline in economic output and household consumption, both of which drop approximately 48%. This occurs despite achieving significant increases in the share of clean inputs, which increases to nearly 85%.

These results underscore a key point: Fiscal policies alone, while effective at reducing emissions, are insufficient to achieve net zero targets by 2050. The substantial economic trade-offs observed confirm that broader structural changes, such as investments in infrastructure, technological advancements, and regulatory support, are essential. Fiscal policies should therefore be viewed as complementary tools within a broader strategy to meet emissions targets while maintaining economic stability and growth.

2.6.2 Welfare Analysis

This section summarizes the welfare effects of different policy options. As the baseline scenario, we use the case without government intervention, where no taxes or subsidies are applied. We then compare the welfare implications of alternative policy interventions, such as taxing dirty goods or introducing subsidies for clean goods, to this baseline. We compute a Hicksian equivalent variation (EV).[22] Based on this analysis, we determine the value of ζ, such that:

$$\underbrace{\sum_{0}^{\infty} \beta_t U((1-\zeta)\,C_t,\ H_t)}_{\text{Policy option}} = \underbrace{\sum_{0}^{\infty} \beta_t U(\tilde{C}_t,\ \tilde{H}_t)}_{\text{Baseline without intervention}}$$

On the right-hand side, the equation represents the lifetime utility of the representative household under the alternative policy. ζ is the constant fraction of consumption that can be taken from the household in the baseline scenario (without government intervention), leaving it just as well-off as it would be under the alternative policy.

Table 2.7 presents the welfare impact of the policies analyzed in Section 2.6.1. It should be noted that our goal is not to directly compare the welfare effects of these policies; rather, our objective is to evaluate the welfare impact of each policy relative to the baseline case. As shown in Table 2.7, implementing a 10% increase in carbon pricing on dirty goods (that is, increasing

[22] A Hicksian EV quantifies changes in welfare caused by policy interventions (such as tax changes, subsidies, etc.). Specifically, the EV can be viewed as the amount of compensation (or payment) required to make an individual or household as well-off under the new scenario (like a new tax or subsidy) as they were under the baseline one, without changing policy.

Table 2.7: Welfare Benefits of Alternative Policies (as a percentage of consumption)

Policy Scenario	Welfare Impact
Carbon Pricing	-4.21%
Clean Input Tax Credits	1.58%
Clean ITCs	0.43%
Dirty Investment tax	-1.18%
Clean R&D Subsidies	0.26%
Dirty R&D Subsidies	-0.67%
Policy Mix	-2.22%

τ_d) results in a welfare loss of 4.21%, measured as a reduction in consumption relative to the baseline scenario. This indicates that while taxing dirty goods significantly reduces emissions, it also imposes a notable welfare cost. These results are consistent with previous analyses, in which such taxation successfully curbs emissions but adversely affects key macroeconomic variables, including economic growth and consumption. In the second scenario, introducing tax credits for the use of clean goods (that is, increasing τ_g by 10%) results in a modest welfare gain of 1.58% compared to the baseline. This gain is driven by positive effects on economic output and household consumption.

In the third policy option, increasing clean ITCs (raising τ_{gx} by 10%) results in a welfare gain of 0.43% compared to the baseline scenario. This gain is driven by the positive effects on economic output and consumption. Furthermore, the welfare impact of R&D subsidies is relatively minor for both clean and dirty technologies. However, it is positive when it is directed toward clean technologies and negative when applied to dirty ones. This limited effect arises from the modest immediate impact of these subsidies on economic activity, as their success depends on probabilistic innovation outcomes. Consequently, the benefits of innovation and productivity gains from R&D subsidies are not immediate and require a longer period to fully materialize.

Finally, the policy mix (raising τ_d and increasing clean incentives—τ_g, τ_{gx}, and R_g^s) demonstrates a negative welfare impact of -1.64%. However, this negative impact is significantly lower compared to using carbon taxes for household carbon rebates, where the welfare impact is -4.21%, as shown in Table 2.7. This result is primarily driven by the fact that clean goods incentives effectively offset much of the negative implications of dirty goods taxation. The growth-promoting effects of clean energy initiatives mitigate the distortions caused by taxes on dirty goods. These findings strongly support the clean dividend approach as superior to other policy options.

Table 2.8: Comparing Welfare Impact of Policies Targeting 10% Emissions Reduction

Policy Scenario	**Welfare Impact**
Carbon Pricing	-4.54%
Clean Input Tax Credits	2.52%
Green Dividend	-1.57%

Table 2.8 presents the welfare impact of the policies analyzed in Section 2.6.1. Here, we aim to directly compare the welfare effects of these policy options, as each policy is adjusted to achieve a uniform emission reduction target. This alignment allows for a straightforward comparison of the magnitude of welfare impacts across the different policies. Table 2.8 shows that carbon pricing results in a welfare loss of 4.54%, indicating that while this demand-side policy effectively reduces emissions, it also imposes economic costs, particularly through its impact on consumption and economic output. Clean input tax credits result in a considerable welfare gain of 2.52%. This suggests that this policy contributes significantly to welfare compared to carbon pricing. The clean dividend approach stands out with a lower welfare loss of 1.57% compared to the case of using the carbon tax as a household tax rebate. By allocating carbon tax revenue to clean sector incentives, the clean dividend mitigates the economic drawbacks of carbon pricing, supporting both emissions reduction and economic growth. This approach can compensate for most welfare losses associated with the carbon tax. This makes it an attractive policy option to achieve emissions targets with minimal economic disruption.

2.7 Conclusion

This paper explores the effects of several key environmental policy instruments—carbon taxes, R&D subsidies, dirty investment taxes, and clean ITCs within a DGE model rooted in the DTC framework. Our findings highlight the significant role of policy implementation in guiding emission reduction and economic outcomes. Policies directly targeting dirty energy sectors, such as carbon taxes and dirty investment taxes, are found to be the most effective at reducing emissions. Interventions in the dirty sector are more effective due to its larger market size and capacity, at least in the short and medium term. However, there are notable trade-offs associated with these policies. By constraining a dominant sector, they slow down economic growth and increase the economic burden. In addition, when we categorize such policies into supply- and demand-side policies, we find that demand-side measures, such as carbon taxes and clean goods tax incentives, are more effective at reducing emissions. This is primarily due to the evident substitution between clean and dirty goods. This allows individuals and firms to switch from dirty to clean alternatives.

Furthermore, when a policy simultaneously targets the clean sector and the demand side, such as through clean input tax credits, it can significantly accelerate the transition to clean sectors and help achieve emission reduction targets, provided that the degree of substitution between clean and dirty production is reasonably high. However, this policy entails a trade-off, as it leads to a substantial increase in household lump-sum taxes. This can be practically infeasible due to political or social considerations, such as resistance from households or equity concerns, which may hinder its implementation. Finally, we find that a clean "double dividend" strategy, in which revenues from policies targeting the dirty sector are reinvested into clean energy incentives, could be a promising approach. This strategy takes advantage of the strength of dirty sector targeted policies while mitigating their negative implications for economic growth by using the funds to promote clean sector development. In such a scenario, a sustainable and reliable transition to a low-carbon economy can be facilitated.

The policy recommendations of this paper can be summarized as follows. First, policymakers could focus on interventions in the dirty sector. Policies such as carbon taxes and dirty investment taxes should play a central role in emissions reduction strategies. These measures are both immediate and effective in curbing emissions, but their implementation must be carefully managed to avoid significant economic disruptions. Second, demand-side policies are particularly important. Carbon taxes and clean input tax credits, for example, are well-suited to accelerating the substitution of fossil fuels with cleaner alternatives. By stimulating demand for clean technologies, these policies drive the transition to sustainable energy more effectively than many supply-side measures. Finally, policymakers should adopt a "clean double dividend" strategy. Rather than rebating carbon tax revenues directly to individuals, these funds could be reinvested in clean-energy incentives. This approach not only offsets the economic costs of carbon pricing, but also fosters long-term growth in the clean sector, paving the way for a more sustainable future.

Appendix F

Model Equations: Solving for Equilibrium

In this section, we present a comprehensive equilibrium solution for the entire model. Only the equations used to solve the endogenous variables in the model are numbered.

F.1 Households

The representative household maximizes the intertemporal utility, which depends on consumption and the disutility of labor. The utility function, which encompasses both consumption C_t and working hours H_t, is represented as follows:

$$\sum_{t=0}^{\infty} \beta_t U(C_t, H_t)$$

The budget constraint for a single time period is given by:

$$(1 - \tau_{h,t})W_t h_t + R^x_{g,t} X_{g,t} + R^x_{d,t} X_{d,t} + T_t = (1 + \tau_{c,t})C_t + (1 - \tau^x_g) I_{g,t} + (1 + \tau^x_d) I_{d,t}$$

Households accumulate capital in the clean (g) and dirty (d) sectors. The term $R^x_{i,t}$ represents the returns from holding capital in each sector. Households also earn profits from the production of the final good (Π_t), and the operation of intermediate sectors ($\Pi_{i,t}$). Additionally, they may receive government transfers (T_t). On the expenditure side, households face a consumption tax rate $\tau_{c,t}$ and allocate their income to both consumption (C_t) and investment in machine production for both sectors: green and dirty, denoted by $I_{g,t}$, and $I_{d,t}$ respectively. Importantly, τ^x_g represents the rate at which clean investment purchases are subsidized. In other words, this rate refers to the investment tax credit in the clean sector.

The law of motion for capital used in the clean sector is expressed as:

$$X_{g,t+1} = (1-\delta_x)X_{g,t} + I^x_{g,t}$$

With rearrangement,

$$I^x_{g,t} = X_{g,t+1} - (1-\delta_x)X_{g,t} \tag{F.1.1}$$

Similarly for the investment in the dirty sector:

$$I^x_{d,t} = X_{d,t+1} - (1-\delta_x)X_{d,t} \tag{F.1.2}$$

By incorporating the investments in both sectors into the household budget constraint, we can get the following:

$$\begin{aligned}(1-\tau_{h,t})W_t h_t + X_{gt}\left[R^x_{g,t} + (1-\delta_x)(1-\tau^x_g)\right] + X_{dt}\left[R^x_{d,t} + (1-\delta_x)\right] \\ +\Pi_t + \Pi_{g,t} + \Pi_{d,t} + T_t = (1+\tau_{c,t})C_t + (1-\tau^x_g)X_{g,t+1} + X_{d,t+1}\end{aligned}$$

The household's Lagrangian is

$$\begin{aligned}L = \max_{C_t,H_t,X_{g,t+1},X_{d,t+1}} \sum_{t=0}^{\infty} \beta_t \Bigg\{ U(C_t,H_t) + \mu^h_t \Bigg[1 - \tau_{h,t})W_t h_t + X_{gt}\left[R^x_{g,t} + (1-\delta_x)(1-\tau^x_g)\right] \\ +X_{dt}\left[R^x_{d,t} + (1-\delta_x)\right] + T_t - (1+\tau_{c,t})C_t - (1-\tau^x_g)X_{g,t+1} - X_{d,t+1} \Bigg] \Bigg\}\end{aligned}$$

The first-order conditions of the household are:

$$U_c(C_t,H_t) = \mu^h_t(1+\tau_{c,t})$$

$$U_H(C_t,H_t) + \mu^h_t(1-\tau_{h,t})W_t = 0$$

$$(1-\tau^x_{g,t})\mu^h_t = \beta\mu^h_{t+1}\Big[R^x_{g,t+1} - (1-\tau^x_{g,t})(1-\delta_x)\Big]$$

$$(1+\tau_{dx,t})\mu^h_t = \beta\mu^h_{t+1}\Big[R_{d,t+1} - (1+\tau_{dx,t})(1-\delta_x)\Big]$$

By substituting the value of μ_t^h from the first equation into the remaining Euler equations, we derive the following refined forms of the Euler equations.

$$U_H(C_t, H_t) + \frac{U_c(C_t, H_t)}{(1+\tau_{c,t})}(1-\tau_{h,t})W_t = 0 \tag{F.1.3}$$

$$(1-\tau^x_{g,t})\frac{U_c(C_t, H_t)}{(1+\tau_{c,t})} = \beta\frac{U_c(C_{t+1}, H_{t+1})}{(1+\tau_{c,t+1})}\Big[R_{g,t+1} - (1-\tau^x_{g,t+1})(1-\delta_x)\Big] \tag{F.1.4}$$

$$(1+\tau_{dx,t})\frac{U_c(C_t, H_t)}{(1+\tau_{c,t})} = \beta\frac{U_c(C_{t+1}, H_{t+1})}{(1+\tau_{c,t+1})}\Big[R^x_{d,t+1} - (1+\tau_{dx,t})(1-\delta_x)\Big] \tag{F.1.5}$$

F.2 Production Sector

The Final good Sector

The final good producer uses a CES production function:

$$Y_t = [1-D(t)]\left[\ Y_{t,d}^{\frac{\epsilon-1}{\epsilon}} + \ Y_{t,g}^{\frac{\epsilon-1}{\epsilon}}\ \right]^{\frac{\epsilon}{\epsilon-1}} \tag{F.2.1}$$

In this equation, $Y_{d,t}$ and $Y_{g,t}$ represent the intermediates of dirty and clean inputs, respectively. The substitution elasticity between the two input types is denoted as ϵ, where $\epsilon \in (0,\infty)$. The objective of the final good firm is to solve the following profit maximization problem:

$$\max_{Y_{d,t}, Y_{g,t}} \quad \Pi_t = P_tY_t - (1+\tau_{d,t})\ P_{d,t}\ Y_{d,t} - (1-\tau_{g,t})\ P_{g,t}\ Y_{g,t}$$

Here, $P_{d,t}$ and $P_{g,t}$ are the prices of dirty and clean inputs, respectively. The final good firm incurs a tax on dirty inputs ($\tau_{d,t}$) and a tax credit for clean inputs ($\tau_{g,t}$). To find the optimal solution, the first order conditions are derived as follows:

$$\frac{\partial \Pi_t}{\partial Y_{d,t}} = P_t\ [1-D(S_t)]\ \left[\ Y_{d,t}^{\frac{\epsilon-1}{\epsilon}} + \ Y_{g,t}^{\frac{\epsilon-1}{\epsilon}}\ \right]^{\frac{1}{\epsilon-1}} Y_{d,t}^{-\frac{1}{\epsilon}} - (1+\tau_{d,t})\ P_{d,t} = 0$$

$$\frac{\partial \Pi_t}{\partial Y_{g,t}} = P_t\ [1-D(S_t)]\ \left[\ Y_{d,t}^{\frac{\epsilon-1}{\epsilon}} + \ Y_{g,t}^{\frac{\epsilon-1}{\epsilon}}\ \right]^{\frac{1}{\epsilon-1}} Y_{g,t}^{-\frac{1}{\epsilon}} - (1-\tau_{g,t})\ P_{g,t} = 0$$

The necessary rearrangement of the first-order condition with respect to $Y_{d,t}$ yields the optimal value of Y_d:

$$Y_{d,t}^{-\frac{1}{\epsilon}} = \frac{(1+\tau_{d,t})\ P_{d,t}}{P_t[1-D(S_t)]}\ \left[\ Y_{d,t}^{\frac{\epsilon-1}{\epsilon}}\ +\ Y_{g,t}^{\frac{\epsilon-1}{\epsilon}}\ \right]^{\frac{-1}{\epsilon-1}}$$

With some rearrangement:

$$Y_{d,t} = \left(\frac{P_t}{(1+\tau_{d,t})\ P_{d,t}[1-D(S_t)]}\right)^{\epsilon}\ Y_t$$

With further rearrangement, and given P_t is normalized to one:

$$(1+\tau_d)P_{d,t} = \left(\frac{Y_t}{Y_{d,t}}\right)^{\frac{1}{\epsilon}} \tag{F.2.2}$$

Similarly, we find $P_{g,t}$:

$$(1-\tau_g)P_{g,t} = \left(\frac{Y_t}{Y_{g,t}}\right)^{\frac{1}{\epsilon}} \tag{F.2.3}$$

The Clean and Dirty intermediate firms

We model each input type—clean (g) and dirty (d)—with a specific Cobb-Douglas production function. Starting with the clean energy sector, the function is given by:

$$Y_{g,t} = A_{g,t}h_{g,t}^{1-\alpha-\theta}X_{g,t}^{\alpha} \tag{F.2.4}$$

where:

$$A_{g,t} = A_{g0}RD_{g,t}^{\theta}. \tag{F.2.5}$$

$$A_{d,t} = A_{d0}RD_{d,t}^{\theta}. \tag{F.2.6}$$

In this model, clean input $Y_{g,t}$ is produced using labor (h_g) and capital ($X_{g,t}$). The profit maximization objective for producers of clean energy is encapsulated by the following:

$$\Pi_{g,t} = \max_{X_{g,t},h_{g,t},RD_{g,t}} \{P_{g,t}Y_{g,t} - R^x_{g,t}X_{g,t} - W_t\ h_{g,t} - (1 - R^s_{g,t})\ RD_{g,t}\}$$

Here, P^x_g denotes the cost of capital specific to the clean energy sector, and W is the wage rate, consistent in all sectors. The optimization leads to the following first order conditions:

$$\frac{\partial \Pi_{g,t}}{\partial X_{g,t}} = \alpha P_{g,t} h^{1-\alpha}_{g,t} A_{g,t} X^{\alpha-1}_{g,t} - R^x_{g,t} = 0$$

Reorganizing, we find:

$$R^x_{g,t} = \alpha P_{g,t} h^{1-\alpha-\theta}_{g,t} A_{g,t} X^{\alpha-1}_{g,t} \tag{F.2.7}$$

Similarly for $h_{g,t}$:

$$\frac{\partial \Pi_{g,t}}{\partial h_{g,t}} = (1-\alpha-\theta) P_{g,t} h^{-\alpha-\theta}_{g,t} A_{g,t} X^{\alpha}_{g,t} - W_t = 0$$

Rearranging to obtain:

$$W_t = (1-\alpha-\theta) P_{g,t} h^{-\alpha-\theta}_{g,t} A_{g,t} X^{\alpha}_{g,t} \tag{F.2.8}$$

FOC with R&D expenditure:

$$1 - R^s_{g,t} = P_{g,t} \cdot \theta \cdot A_{g0} \cdot RD^{\theta-1}_{g,t} \cdot h^{1-\alpha-\theta}_{g,t} \cdot X^{\alpha}_{g,t}$$

The optimal $RD_{g,t}$ will then be as follows:

$$RD_{g,t} = \frac{\theta P_{g,t} Y_{g,t}}{1 - R^s_{g,t}} \tag{F.2.9}$$

These equations dictate the optimal input quantities $X_{g,t}$ and $h_{g,t}$ to maximize profits in the clean input sector under competitive market conditions.

By applying similar logic and analogous parameters, we can get the relevant equations in the dirty sector, represented by:

$$Y_{d,t} = A_{d,t} h^{1-\alpha}_{d,t} X^{\alpha}_{d,t} \tag{F.2.10}$$

$$R^x_{d,t} = \alpha P_{d,t} h^{1-\alpha}_{d,t} A_{d,t} X^{\alpha-1}_{d,t} \tag{F.2.11}$$

$$W_t = (1-\alpha)P_{d,t}h_{d,t}^{-\alpha}A_{d,t}X_{d,t}^{\alpha} \tag{F.2.12}$$

$$RD_{d,t} = \frac{\theta P_{d,t}Y_{d,t}}{1-R_{d,t}^{s}} \tag{F.2.13}$$

Economic Impact of Environmental and Climate Damage

This model incorporates climate variables into the aggregate production function, following the approach of Golosov et al. (2014), Nordhaus (2014), and Acemoglu et al. (2016). The climate's influence on output is captured by a damage function, $D_t(S_t)$, where S_t represents atmospheric carbon concentration. The damage function is modeled as:

$$[1 - D_t(S_t)] = \exp\left(-\gamma_t(S_t - \bar{S})\right), \tag{F.2.14}$$

where $\bar{S}$ is the pre-industrial carbon level, and γ_t reflects the sensitivity of productivity to climate change.

Carbon concentration, S_t, is determined by a simplified carbon cycle:

$$S_t - \bar{S} = \sum_{s=0}^{t+T}(1-d_s)Y_{d,t-s}, \tag{F.2.15}$$

with carbon depreciation modeled as:

$$1 - d_s = \phi_L + (1-\phi_L)\phi_0(1-\Phi)^s.$$

The parameters ϕ_L, ϕ_0, and Φ are calibrated based on the methodology of Golosov et al. (2014). Further details on these parameters and their calibration are provided in Section 2.5.

Government

The government's fiscal operations are defined by a budget identity that balances revenues and expenditures.

$$G+T_t = \tau_{c,t}C_t+\tau_{h,t}W_tH_t+\tau^x_{d,t}I^x_{d,t}-\tau^x_{g,t}I^x_{g,t}+\tau_{d,t}P^e_{d,t}Y_{d,t}-\tau_{g,t}P^e_{g,t}Y_{g,t}-R^s_{d,t}RD_{d,t}-R^s_{g,t}RD_{g,t} \tag{F.2.16}$$

This equation accounts for government expenditures (G) and household transfers (T_t) against revenues from taxes on consumption ($\tau_{c,t}C_t$), labor income ($\tau_{h,t}W_tH_t$), and carbon or dirty energy taxes ($\tau_{d,t}P_{d,t}Y_{d,t}$). The government also spends on clean ITCs ($\tau^x_{g,t}I^x_{g,t}$) and R&D subsidies ($R^s_dRD_d$ and $R^s_gRD_g$) to promote innovation in both the clean and dirty sectors.

Equilibrium Conditions

The equilibrium is defined by market clearing and optimization of agents:

$$C_t + G + I^x_{d,t} + I^x_{g,t} = Y_t - (RD_{d,t} + RD_{g,t}), \tag{F.2.17}$$

$$H_t = h_{d,t} + h_{g,t}. \tag{F.2.18}$$

Optimization across all agents and continuous market clearing ensure the economy's stable progression from $t = 0$ to infinity. With the above model, we use equations from A.1 to A.23 to find the following 23 endogenous variables shown in Table F.1.

F.3 Tables

Table F.1: Model Variables

Endogenous Variables	
I_g: Investment in dirty sector	I_d: Investment in clean sector
W: Wage rate	X_d: Capital stock in dirty sector
X_g: Capital stock in clean sector	Y: Final output
P_d: Price of dirty input	P_g: Price of clean input
Y_g: Clean output	R_g: Capital return rate in clean sector
h_g: Worked hours in clean sector	Y_d: Dirty output
R_d: Capital return rate in dirty sector	h_d: Worked hours in dirty sector
A_g: Productivity in clean sector	A_d: Productivity in dirty sector
RD_g: Clean R&D expenditure	RD_d: Dirty R&D expenditure
$D(S)$: Damage	S: Carbon concentration
T: Household transfer	C: Consumption
H: Total worked hours	
Exogenous Variables	
τ_c: Consumption tax rate	τ_g^x: Clean investment tax credit
τ_d^x: Dirty investment tax rate	τ_h: Labor income tax
τ_d: Tax on dirty output (carbon tax)	τ_g: Tax credit to clean output
R_g^s: Clean R&D subsidies	R_d^s: Dirty R&D subsidies
$\bar{S}$: Pre-industrial CO_2 concentration	G: Government expenditure

Table F.2: Effects of Dirty Investment Taxation: Baseline Deviations (%)

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	-2.50	-5.97	-6.86
Aggregate Output (%)	-2.50	-3.37	-4.27
Clean Input Share (%)	0.00	7.70	7.75
Clean Input (%)	-2.50	3.26	2.34
Consumption (%)	2.36	0.62	-1.28
Wage Rate (%)	1.65	-0.74	-3.29
Dirty Labor (%)	-4.08	-4.41	-2.80
Clean Labor (%)	-4.08	1.75	3.49
Total Hours (%)	-4.08	-2.66	-1.02
Dirty Capital (%)	-5.22	-9.11	-13.28
Clean Capital (%)	10.82	6.35	1.56
Clean R&D Expenditures (%)	-2.50	1.00	0.09
Dirty R&D Expenditures (%)	-2.50	-5.11	-6.00
Dirty Technology (%)	-0.40	-0.84	-0.99
Clean Technology (%)	-0.40	0.16	0.01
After-tax Dirty Price (%)	0.00	0.91	0.92
After-tax Clean Price (%)	0.00	-2.19	-2.20

Table F.3: Effects of Clean R&D Subsidies: Baseline Deviations (%)

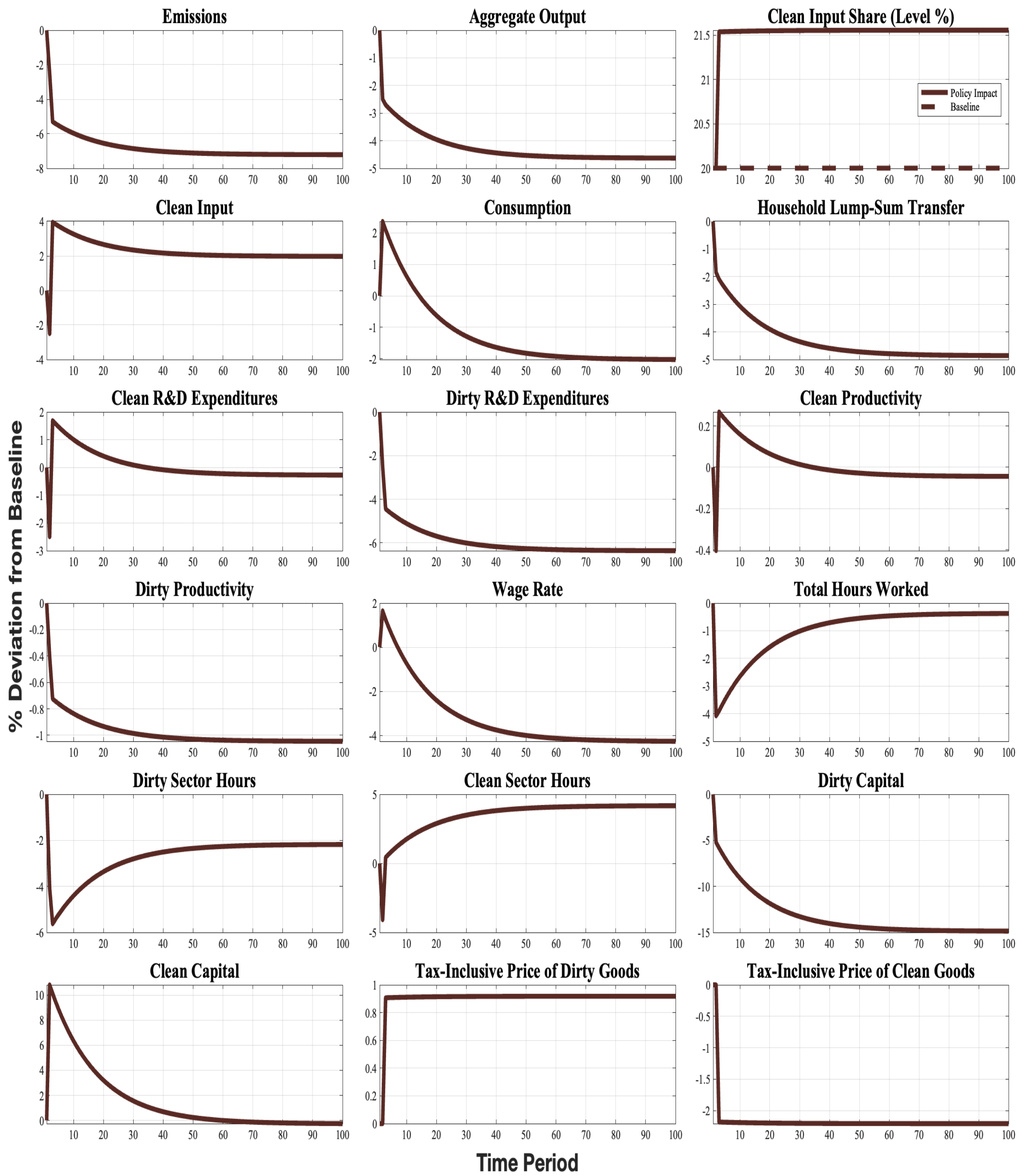
Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	0.13	-0.35	-0.25
Aggregate Output (%)	1.01	1.11	1.21
Clean Input Share (%)	2.46	4.11	4.11
Clean Input (%)	3.23	4.82	4.93
Consumption (%)	-0.12	0.07	0.28
Wage Rate (%)	0.30	0.56	0.84
Dirty Labor (%)	0.13	-0.42	-0.60
Clean Labor (%)	2.18	3.00	2.81
Total Hours (%)	0.71	0.55	0.37
Dirty Capital (%)	-0.89	-0.43	0.08
Clean Capital (%)	2.52	3.00	3.51
Clean R&D Expenditures (%)	13.87	15.08	15.19
Dirty R&D Expenditures (%)	0.43	0.13	0.23
Dirty Technology (%)	0.07	0.02	0.04
Clean Technology (%)	2.10	2.27	2.29
After-tax Dirty Price (%)	0.29	0.49	0.49
After-tax Clean Price (%)	-0.72	-1.20	-1.19

Table F.4: Effects of Reducing Dirty R&D Subsidies: Baseline Deviations (%)

Variable	After 2 Periods	After 10 Periods	After 30 Periods
Emissions (%)	-2.87	-3.56	-3.77
Aggregate Output (%)	-2.10	-2.29	-2.49
Clean Input Share (%)	2.22	3.70	3.71
Clean Input (%)	-0.16	0.94	0.73
Consumption (%)	0.13	-0.27	-0.71
Wage Rate (%)	-0.76	-1.29	-1.88
Dirty Labor (%)	-1.87	-1.87	-1.49
Clean Labor (%)	-0.06	1.16	1.56
Total Hours (%)	-1.36	-1.01	-0.63
Dirty Capital (%)	-1.02	-1.98	-3.02
Clean Capital (%)	2.00	1.03	-0.02
Clean R&D Expenditures (%)	-0.81	-0.15	-0.35
Dirty R&D Expenditures (%)	-11.47	-11.94	-12.13
Dirty Technology (%)	-1.93	-2.01	-2.05
Clean Technology (%)	-0.13	-0.02	-0.06
After-tax Dirty Price (%)	0.26	0.44	0.44
After-tax Clean Price (%)	-0.65	-1.08	-1.08

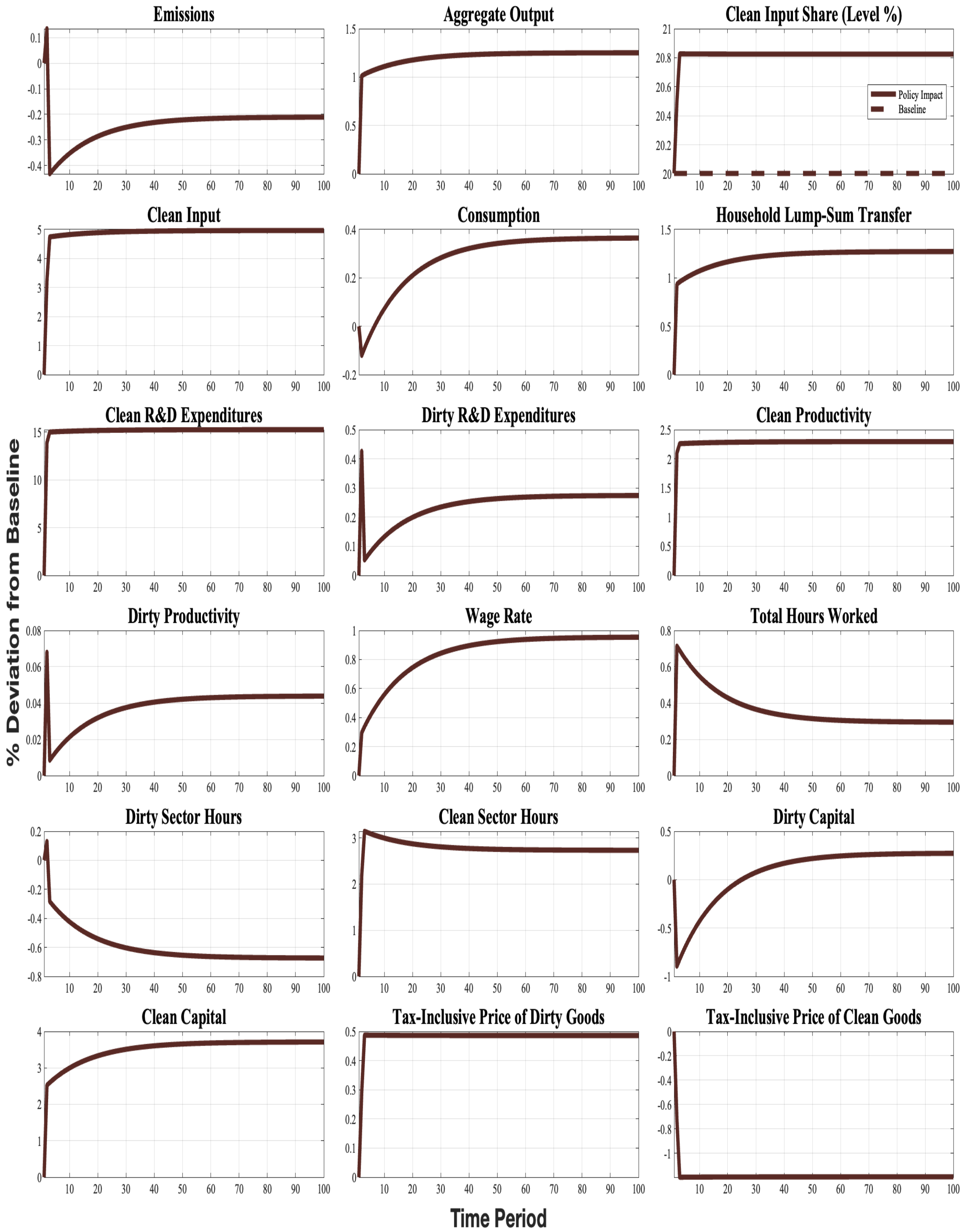
F.4 Figures

Figure F.1: Effects of Dirty Investment Tax



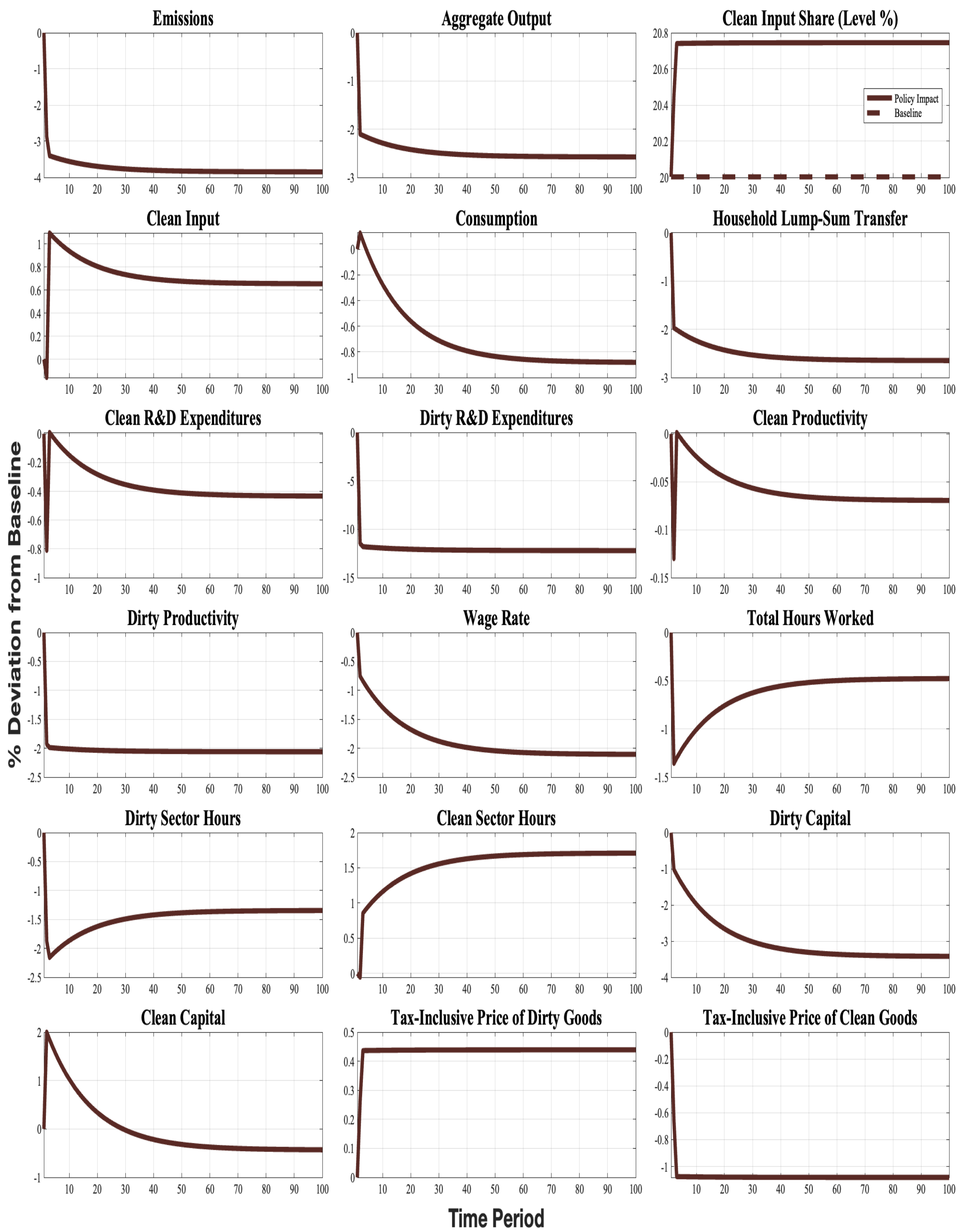
Note: The graph illustrates the impact of a 10% increase in dirty investment taxation on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show an increase in the effective cost of investing in the dirty sector, which is primarily reflected in the adverse growth effect, as output is significantly reduced compared to the benchmark. Consequently, emissions decrease considerably due to constraining on the dirty sector. However, the share of clean inputs does not significantly increase, as the substitution effect of this policy is modest. For additional information, please see Section 2.6.1.

Figure F.2: Effects of Increasing Clean R&D Subsidies



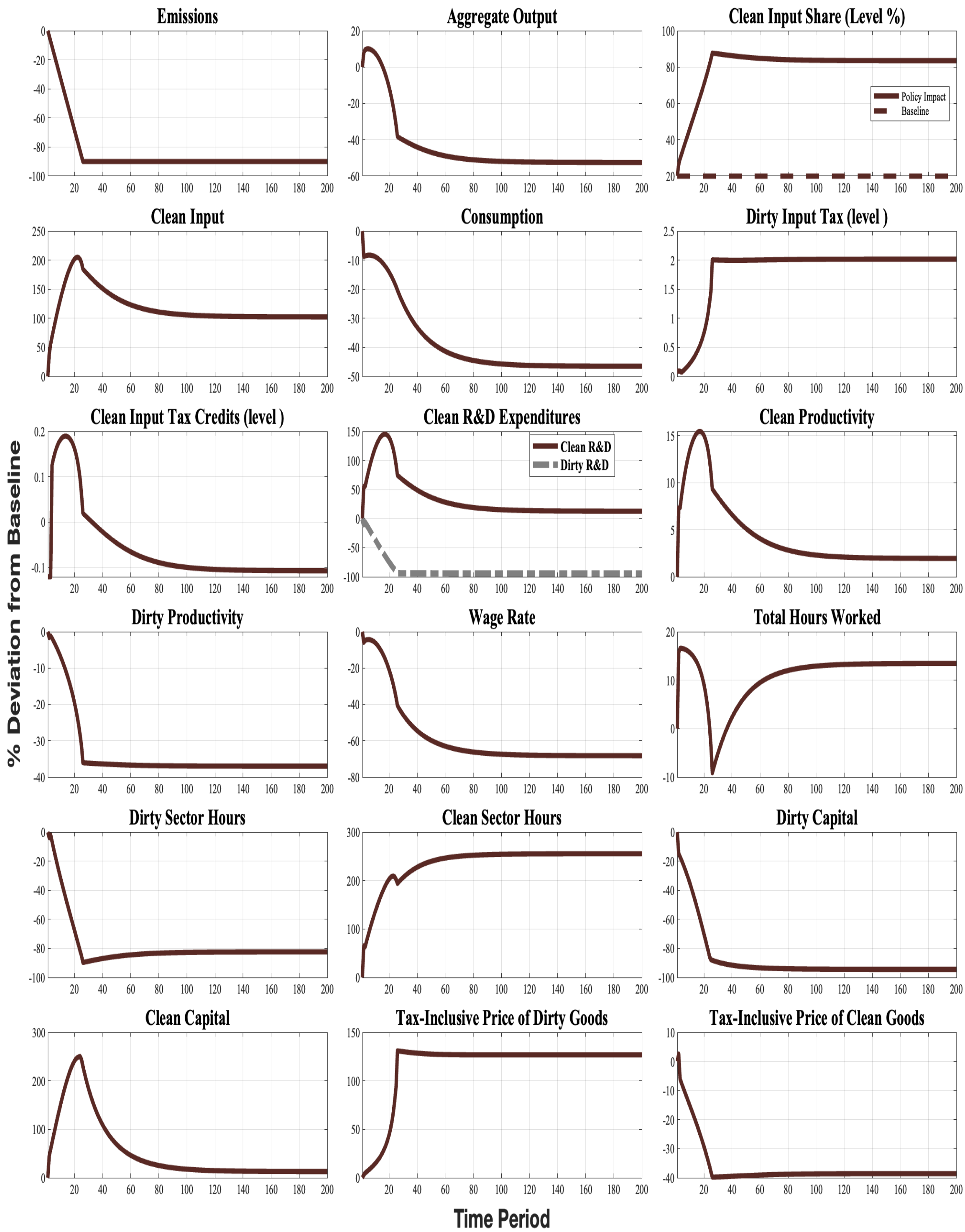
Note: The graph illustrates the impact of a 10% increase in R&D subsidies to the clean sector on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show an increase in clean R&D expenditure, which fosters clean technology development compared to dirty technology. This leads to a slight reduction in emissions for approximately 70 years before returning to the baseline level, as we impose an upper bound on technology levels. Additionally, this policy primarily has a growth effect, with output increasing before stabilizing once productivity reaches its maximum level. The combined effects result in only a minor impact on the share of clean inputs. For additional information, please see Section 2.6.1.

Figure F.3: Effects of Reducing Dirty R&D Subsidies



Note: The graph illustrates the impact of a 10% reduction in R&D subsidies to the dirty sector on emission reduction, the share of clean inputs, technology transition, and other macroeconomic implications. The results show that this policy restricts R&D expenditure, slowing down dirty technology development while allowing clean technology to expand. The policy also reduces the demand for dirty inputs, which is primarily reflected in its adverse impact on output and emission reduction. However, the share of clean inputs does not increase significantly, as the substitution effect of this policy is minor. Additionally, the effects on emissions and output stabilize in the long run due to the imposition of an upper bound on productivity. For more details, please see Section 2.6.1.

Figure F.4: Achieving a 90% Emission Reduction: Impact of Dirty Input Taxes and Clean Energy Credits



Note: The graph illustrates the impact of setting an emission reduction target of 90%, approaching the net-zero target by 2050. The policy employed is dirty input taxation, while stabilizing the government budget with clean input tax credits. The results show that achieving this radical reduction in emissions within a short period requires significantly constraining the dirty sector, necessitating an increase in the dirty input tax by more than 200 percent. This leads to a considerable rise in the price of dirty inputs relative to clean inputs, resulting in a substantial substitution effect, with the clean sector's share increasing to 90%. However, this policy also has a considerable adverse impact on economic prosperity, as the drastic reduction in dirty inputs and the short timeframe do not allow for significant substitution with clean inputs. For more information, please refer to Section 2.6.1.

Chapter 3

Exploring the Environmental Impact of Monetary Policy

3.1 Abstract

As climate change risks escalate, central banks are increasingly called upon to address this global challenge. Yet, estimates of the environmental impact of monetary policy are limited, leaving a significant gap in understanding how monetary policy interacts with climate change. In this paper, we aim to fill this gap by providing new evidence based on U.S. data. We identify monetary policy shocks using the recursiveness assumption and estimate their effects on domestic carbon dioxide emissions. Three key findings emerge from our analysis. First, an unexpected monetary policy tightening produces a persistent yet transitory negative effect on total CO_2 emissions. This finding holds consistently across different model specifications, periods, and monetary policy indicators, underscoring its robustness. Second, the effects of monetary policy vary significantly across major polluter types. Emissions in the industrial sector, closely tied to production activities, show the strongest response. In contrast, emissions in the residential and commercial sectors are weakly affected, likely due to the essential nature of energy services. Finally, the contribution of U.S. monetary policy shocks to explaining domestic CO_2 emissions fluctuations has been modest. Since central banks have limited capacity to directly influence environmental outcomes, monetary policy should be viewed as complementary to fiscal policy and environmental regulation in addressing climate change.

3.2 Introduction

In 2015, Mark Carney, then Governor of the Bank of England, delivered a speech highlighting the financial stability risks posed by climate change (Carney 2015). Since that pivotal moment, climate change considerations have gained growing recognition among central banks.[1] In response, theoretical monetary policy models have been adapted to integrate pollution and environmental policy.[2] Moreover, scholars have advocated for proactive central bank interventions to support desired environmental outcomes.[3] Despite the surge in theoretical literature, empirical research on the environmental impact of monetary policy remains limited, constraining the validation of theoretical models on an environmental dimension. In this paper, we provide new estimates of the impact of U.S. monetary policy on domestic CO_2 emissions.

According to the interest rate transmission channel, an unexpected monetary policy tightening raises real borrowing costs, reducing aggregate demand and ultimately leading to a decline in aggregate output and income. Emissions are often characterized as a by-product of production. Given this premise, we expect monetary policy tightening to reduce emissions alongside output via the interest rate channel. This prediction, however, receives mixed empirical support. While Khan et al. (2019) and Attílio et al. (2023) find that contractionary monetary policy actions reduce U.S. emissions, Halkos and Paizanos (2016) suggest that such policies trigger an increase in emissions.[4] These contrasting results motivate us to re-examine the existing evidence.

We build on the extensive literature aimed at estimating exogenous changes in U.S. monetary policy, or monetary policy shocks (e.g., Christiano et al. 1999; Ramey 2016). Our research centers on conventional interest rate shocks, identified with the recursiveness assumption in vector autoregressive (VAR) models. In addition to standard macroeconomic variables, our VARs include environmental indicators. We use data up to the end of 2005 in our estimation. This cut-off date avoids the zero lower bound periods when the Federal Reserve (the

[1] E.g., Rudebusch (2019), Boneva and Ferruci (2022), Hansen (2022), ECB (2024).

[2] E.g., Annicchiarico and Di Dio (2015, 2017), McKibbin et al. (2020), Chan (2020).

[3] E.g., Chan (2020), Böser and Senni (2020), Chen et al. (2021), Ramlall (2023), Ferrari and Nispi Landi (2024).

[4] Halkos and Paizanos (2016) and Khan et al. (2019) report emissions responses to a monetary expansion. However, their empirical models are linear, meaning the responses to a monetary contraction merely invert the signs.

Fed) resorted to unconventional monetary policy tools. Furthermore, environmental regulation can restrict how the economy responds to monetary policy shocks (e.g., Annicchiarico and Di Dio 2015). Without federal climate change regulation, several U.S. states have implemented CO_2 emissions reduction requirements in the power sector. By ending our sample before these measures took effect, we achieve a more accurate assessment of the environmental impact of monetary policy.[5]

Our baseline model integrates total CO_2 emissions into a monetary VAR model. We find that a contractionary monetary policy shock exerts a statistically significant negative impact on total emissions. The emissions response is delayed, persistent but transitory. This result is robust to several modifications, including controlling for weather and energy price changes. In terms of magnitude, the trough response of total emissions to a typical one-standard-deviation contractionary monetary policy shock centers around -0.11% to -0.13% across all monthly specifications, and occurs between five and eighteen months after the shock. For comparison, the standard deviation of the monthly growth rate of total emissions in our full sample is 0.28%. Furthermore, the trough effect of the same contractionary policy shock on industrial production centers around -0.22% to -0.19%. The contribution of the monetary policy shock to the forecast error variance of total emissions is modest. In most specifications, the peak contribution is around 10%.

We extend our analysis to major types of polluters, classified as energy end-use sectors by the EIA. Together, these sectors encompass CO_2 emissions of the entire U.S. economy. However, they vary in their energy needs and sources, and options for emissions reductions. We find that the environmental impact of monetary policy differs across the polluters. In response to monetary tightening, emissions fall sharply in the industrial sector and moderately in the transportation sector. By contrast, the policy effect on CO_2 emissions in the residential and commercial sectors is minimal.

The observed heterogeneity in sectoral responses helps us understand the dynamics of total emissions. In particular, the muted responses of residential and commercial emissions can

[5] An important robustness consideration is the choice to restrict our sample to the period before 2005. This cutoff is motivated by the timing of major U.S. climate and energy policy interventions. In essence, we avoid periods where dedicated greenhouse gas mitigation policies could confound the relationship between monetary policy and emissions. By focusing on data up to 2005, we leverage a timeframe in which nationwide climate-focused policies were minimal, thereby isolating macroeconomic drivers of emissions from regulatory shocks.

explain why total emissions fall less than aggregate output after a contractionary monetary policy shock. An immediate implication of our findings is the importance of distinguishing between different polluting sectors in both theoretical models and policy analyses. Ignoring sectoral differences may lead to an overestimation of the environmental impact of monetary policy.

Our research broadens the empirical evidence on the link between monetary policy and environmental outcomes. Qingquan et al. (2020) and Chishti et al. (2021) document a negative relationship between real interest rate changes and CO_2 emissions using panel regressions based on data from Asian and BRICS economies. These authors associate a contractionary (expansionary) monetary policy with an increase (decline) in the real interest rate. However, this approach does not account for the potential endogenous reactions of central banks to economic shocks. Attílio et al. (2023) conduct a structural analysis using a global VAR model. They find that a contractionary monetary policy shock in the U.S., the Eurozone or Japan reduces CO_2 emissions domestically but does not spill over to other regions. The impact of U.K. monetary policy shocks on emissions in their study is not statistically significant. In contrast to Attílio et al. (2023), we focus exclusively on U.S. monetary policy and apply a standard framework. Our estimated responses of U.S. macroeconomic variables to monetary policy shocks align with findings from prior U.S.-centered recursive VAR studies (e.g. Christiano et al. 1999; Ramey 2016) and conform to theoretical predictions in monetary theory.

Our paper is closely related to the work of Khan et al. (2019), who also employ a recursive scheme to identify U.S. monetary policy shocks. However, we focus solely on monetary policy shocks, rather than a variety of macroeconomic shocks, and conduct a sensitivity analysis of their effects. In addition, we estimate the impact of monetary policy shocks on major polluters. Halkos and Paizanos (2016) is the only other study that uses disaggregated data. They classify emissions from the EIA's sectors into consumption- and production-generated,[6] and identify monetary policy shocks via sign restrictions. Contrary to our estimates, their results imply an increase in both types of emissions after a contractionary monetary policy shock.

Another notable feature that distinguishes our research from the other studies is the end-

[6]These authors define emissions from the residential and transportation sectors as consumption-generated and label those from the industrial and commercial sectors as production-generated.

ing date of our estimation. Our sample restriction allows us to circumvent the challenges of identifying monetary policy shocks during zero lower bound episodes and avoids the effects of environmental regulation. It also helps us address potential concerns regarding the endogeneity of monetary policy responses to climate change. Our baseline model assumes that the Fed does not react to contemporaneous changes in emissions. We found no evidence to contradict this assumption in the pre-2005 period.[7] However, it may be more challenging to support this assumption in recent years.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Sections 3.1 and 3.2 analyze the impact of monetary policy shocks on total emissions in the baseline and alternative models. Section 3.3 focuses on major types of polluters. Section 4 concludes.

3.3 Methodology and Data

We identify monetary policy shocks using the recursiveness assumption in a VAR model. This methodology is well-established, widely used and reviewed in detail by Christiano et al. (1999) and Ramey (2016). In this section, we describe how this methodology is employed in our application.

Most economists would agree that a significant variation in the federal funds rate (FFR), the key policy instrument, can be attributed to the Fed's responses to the state of the economy. Such responses can be represented by a feedback rule $f(\Omega_t)$ defined on the Fed's information set Ω_t. For example, according to the interest rate rule proposed by Taylor (1993), the Fed reacts to changes in aggregate output and prices.[8] In practice, the policy rate may diverge from the path specified by the policy rule due to potential revisions in preliminary data or shifts in the Fed's policy priorities. Following Christiano et al. (1999), we describe the actual interest rate behaviour by an equation

$$FFR_t = f(\Omega_t) + \sigma_m \varepsilon_t^m, \tag{3.3.1}$$

[7] Rudebusch (2019) may be the earliest reference on the importance of climate change considerations for the Fed.

[8] A Taylor-type rule is a popular way to model monetary policy in theoretical models. Recently, several researchers have investigated the macroeconomic implications of augmenting a Taylor-type rule with environmental variables, such as CO_2 emissions, in theoretical models (see the references in footnote 2).

and define a *monetary policy shock* as the random variable $\sigma_m \varepsilon_t^m$. The parameter σ_m represents the standard deviation of the monetary policy shock, and ε_t^m is normalized to have unit variance.

The *recursiveness* assumption requires monetary policy shocks to be orthogonal to the information set of the monetary authority (Christiano et al. 1999, p.68). This assumption is based on the timing restrictions. It effectively imposes that all variables in the Fed's information set remain unaffected by a monetary policy shock within the period it occurs. Under the recursiveness assumption, monetary policy shocks and their effects on economic variables can be estimated using a VAR model. This approach assumes that $f(.)$ is a linear function and the information set Ω_t is characterized by the variables included in a VAR.

A reduced-form VAR describes the evolution of a vector of endogenous variables y_t:

$$y_t = B_0 + B_1 y_{t-1} + B_2 y_{t-2} + ... + B_n y_{t-n} + u_t,\ u_t \sim N(0, \Sigma_u). \tag{3.3.2}$$

We assume that y_t includes k variables. Then B_0 represents a k-dimensional vector of constants and B_j are $(k\text{x}k)$ matrices of the VAR coefficients $(j = 1, ..., n)$. The residuals u_t are the one-step-ahead forecast errors in y_t, and Σ_u is their variance-covariance matrix.

Let ε_t denote a vector of fundamental economic shocks, including the monetary policy shock. The fundamental economic shocks are mutually uncorrelated structural disturbances, with zero means and the variance-covariance matrix $E\varepsilon_t\varepsilon_t' = I$. We assume a linear relationship between the fundamental economic shocks and the VAR residuals,

$$Au_t = \varepsilon_t, \tag{3.3.3}$$

where A is an invertible matrix. The identification problem arises because an infinite number of solutions for A satisfy the equation $\Sigma_u = A^{-1}(A^{-1})'$. The recursiveness assumption imposes zero restrictions on the elements of A. Christiano et al. (1999) demonstrate that these restrictions are sufficient to identify the responses of y_t to a monetary policy shock.

To convey the intuition behind the monetary policy shock identification, we partition the endogenous variables y_t according to the assumed timing of their responses to monetary policy shocks. The k_1 slow-moving variables $X_{1,t}$ appear in the Fed's information set Ω_t and react to monetary policy actions only with a lag. The k_2 fast-moving variables $X_{2,t}$ are allowed to respond to monetary policy shocks contemporaneously. However, they enter the Fed's information set with a lag. The policy rate is also included in the VAR, so that

$$y_t = \begin{pmatrix} X_{1,t} \\ FFR_t \\ X_{2,t} \end{pmatrix} \text{ and } k = k_1 + 1 + k_2. \tag{3.3.4}$$

A monetary policy shock is identified from the FFR equation in the linear system (3.3.3). This equation excludes current movements in the $X_{2,t}$ variables, imposing k_2 restrictions on the matrix A. Additionally, k_1x(k_2+1) zero restrictions on the elements of A arise from excluding both direct and indirect contemporaneous effects of monetary actions on the variables $X_{1,t}$. In practice, the parameters in A are estimated by applying the Cholesky factorization to the variance-covariance matrix Σ_u. We refer the reader to Christiano et al. (1999) for technical details.

Our monetary VAR consists of the macroeconomic variables and abstracts from environmental indicators. We use the monthly average of the daily effective federal funds rate for FFR. As in Coibion (2012), the slow-moving variables $X_{1,t}$ include the log of industrial production (IP), the unemployment rate (UR), the log of the consumer price index and the log of a commodity price index. We add the log of the M1 monetary aggregate in $X_{2,t}$. This variable should help us isolate the effects of money demand changes on the policy rate. Appendix I describes the data sources.

Belongia and Ireland (2016, p. 1246) highlight the resemblance of the monetary policy shock identification equation to the Taylor rule. In our application, the Fed reacts to contemporaneous movements in output and prices, as in Taylor (1993). It also reacts to current changes in the unemployment rate and commodity prices. The unemployment rate provides additional information about real economic activity, while commodity prices are expected to capture anticipatory effects.

Our goal is to understand how monetary policy affects environmental outcomes. In this paper, we analyze the data on CO_2 emissions from energy consumption published by the EIA.

We work with total CO_2 emissions for the U.S. economy and sector-specific emissions from the residential, commercial, industrial, and transportation sectors. The data are available monthly, starting in January 1973. We adjust the log of the monthly series for seasonality using the X13 ARIMA-SEATS procedure.

Our analysis mainly focuses on two periods. Our primary sample period, from January 1973 to December 1996, closely aligns with those studied by Christiano et al. (1999) and Coibion (2012). However, our starting date is restricted by the availability of the environmental statistics. According to Ramey (2016, p.111), earlier periods tend to offer the most compelling evidence regarding the effects of conventional monetary policy shocks. Our extended sample period continues through December 2005. The ending date helps us address two potential threats to identifying monetary policy shocks and, hence, achieve a more accurate assessment of their effects on emissions.

First, the traditional recursive identification is ineffective during zero lower bound episodes, when a central bank cannot reduce the policy rate further to stimulate the economy. The methods fail to work for statistical and economic reasons (Rossi 2021). In response to the financial crisis, the Fed kept the federal funds rate close to zero between December 2008 and December 2015. Estimating a VAR model with an endogenous variable that remains constant over an extended time period poses significant statistical challenges, and may result in unreliable parameter estimates. Unconventional monetary policy tools, such as quantitative easing and forward guidance, introduce further challenges for identification in samples from the post-2007 period. When a central bank employs multiple tools to achieve similar objectives, it becomes difficult to capture the overall stance of monetary policy and to disentangle the individual effects of each policy tool. Although various solutions to these challenges have been proposed in the literature (Rossi 2021), we focus on the traditional approach in this paper and leave the alternative strategies for future work.

Second, environmental regulation may confound the VAR parameter estimates, potentially distorting inferences regarding the effects of monetary policy on emissions. The Regional Greenhouse Gas Initiative (RGGI) is the first market-based U.S. regional initiative to reduce

CO_2 emissions.[9] It operates as a mandatory cap-and-trade program for the power sector. The RGGI agreement was signed on December 20, 2005. Although the first auction of CO_2 emissions allowances occurred in 2008, some adjustments in the power sector could have occurred in anticipation of this event. By ending the estimation in 2005, we aim to exclude any potential anticipatory effects of RGGI on our estimates. U.S. state renewable portfolio and clean electricity standards are additional factors that may affect how emissions respond to monetary policy shocks. These policies aim to limit the use of fossil fuels, thereby reducing emissions. Although some policies were in place before 2005, their number and stringency took a notable uptake starting in 2007 (Barbose 2024). Our sample restriction mitigates the confounding influence of these factors on the VAR parameter estimates.

To estimate the effect of monetary policy shocks on emissions, we augment the standard monetary VAR with environmental indicators. Our key results are derived from specifications that include emissions in the block of fast-moving variables X_2, after M1. By placing emissions last, we assume that the Fed does not respond to contemporaneous movements in the environmental indicators. This approach is consistent with the view that climate change was not a factor influencing monetary policy decisions before 2005. However, we explore the implications of placing emissions first in the sensitivity analysis.

We estimate VAR models with a constant term and twelve lags of the endogenous variables, using ordinary least squares. The parameter estimates in the “level" specification are asymptotically consistent, even in the presence of cointegration. They are minimally affected if a linear trend is included in our models. Throughout the paper, we focus on the effects of a contractionary monetary policy shock. However, the linear structure of a VAR model implies symmetric effects of contractionary and expansionary monetary policy shocks. We follow Coibion (2012) in estimating the confidence bands for the impulse response functions. Specifically, we take 1,000 repeated draws from the asymptotic distribution of the VAR parameters to generate a distribution of impulse responses and compute one-standard-error bands.

[9] Eleven Northeastern states currently participate in RGGI: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. Detailed information can be found on the RGGI website at https://www.rggi.org/.

3.4 Results

We assess the environmental impact of monetary policy shocks using impulse response functions (IRFs), forecast error variance (FEV) decompositions, and historical decompositions. Sections 3.4.1 and 3.4.2 discuss the results for total CO_2 emissions in the baseline model and alternative specifications. Section 3.4.3 extends the analysis to emissions from different polluters.

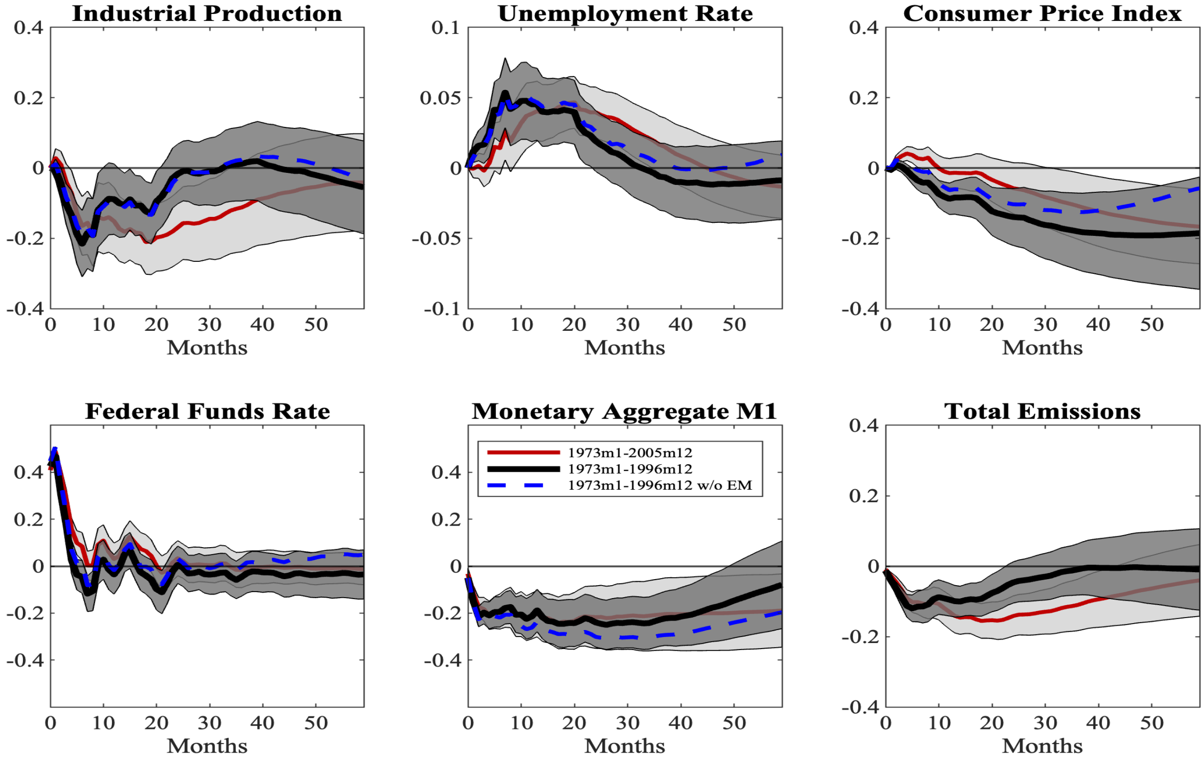
3.4.1 The Impact of Monetary Contraction on Total Emissions: Baseline

Figure 3.1 reports the results from our baseline: a monetary VAR augmented with total CO_2 emissions. The size of the monetary policy shock is set to its estimated standard deviation, σ_m. In our baseline VAR, such shock raises the federal funds rate by 42.5 basis points in the primary period and 40.5 basis points in the extended period. Thick black lines and darker shaded areas represent the IRF point estimates and confidence bands for the primary period, while thin red lines and lighter bands indicate the results for the extended period. Dashed blue lines depict the IRF point estimates from the monetary VAR model without emissions.

We first note that adding emissions to the monetary VAR has a limited impact on the responses of the macroeconomic variables. The IRF point estimates from the monetary VAR closely track those from our baseline and fall within the confidence bands. Second, the dynamic paths of the macroeconomic variables in both periods are consistent with the conventional theoretical predictions and empirical results in Christiano et al. (1999), Coibion (2012), and Ramey (2016). A contractionary monetary policy shock induces a short-lived increase in FFR and a persistent decline in M1. Output contracts and the unemployment rate surges, with the peak impacts at around twenty months. The monetary policy impacts on the real activity measures (IP and UR) dissipate over time. Finally, prices fall, although a short-lived price puzzle is present in the extended period. As noted by Ramey (2016), the price puzzle is a recurrent result in monetary VAR models.

The bottom right chart in Figure 3.1 depicts our first key finding: a contractionary monetary policy shock has a statistically significant negative impact on total CO_2 emissions. The emissions' response is hump-shaped, reaching its trough of -0.12% five months after the shock and becoming insignificant in two years in the primary period. This response is more persistent in the extended period, with the trough of -0.16% eighteen months after the shock.

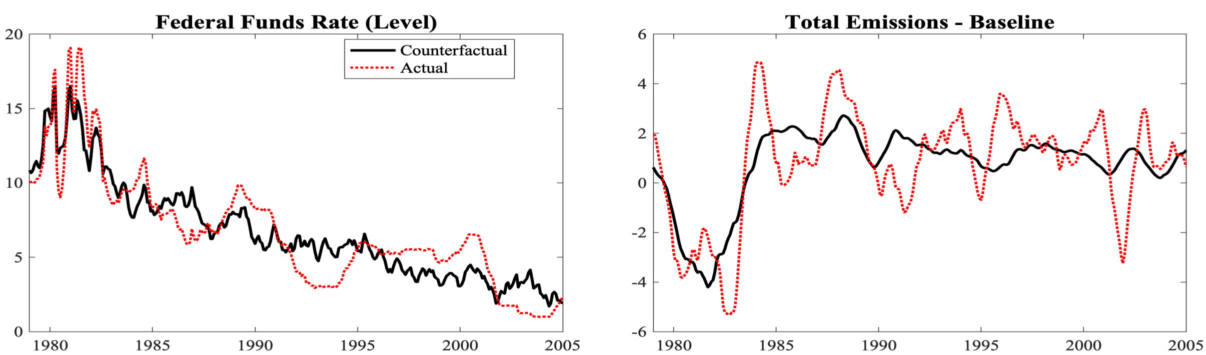
Figure 3.1: Effects of Monetary Policy Tightening (%)
Baseline Model



Notes: Responses to a one-standard-deviation contractionary monetary policy shock. Monetary VAR 1973m1–1996m12: *dashed blue lines*. Baseline VAR with total emissions, 1973m1–1996m12: *thick black lines*; 1973m1–2006m12: *thin red lines*. Darker and lighter shaded areas are the one-standard-error bootstrap confidence bands.

Figure 3.2 provides another perspective on the quantitative relevance of monetary policy shocks. Solid black lines depict the counterfactual paths of the federal funds rate and emissions

Figure 3.2: Historical Contribution of Monetary Policy Shocks in the Baseline Model (%)



Notes: *Dotted lines* are the historical values of FFR and total CO_2 emissions. *Solid lines* represent the counterfactuals attributed solely to the U.S. monetary policy shocks. Emissions are expressed as the year-over-year growth rates.

that would have prevailed if monetary policy shocks were the only shocks hitting the U.S. economy in the extended sample. Note that the counterfactual series start in January 1978 to remove the dependence of the simulations on the initial conditions.[10] Red dotted lines in Figure 3.2 denote the actual realized FFR and emissions. Emissions are reported as the year-over-year growth rates for visibility.

The historical decomposition relies on the estimated monetary policy shocks, which include both positive and negative values. Recall that a positive monetary policy shock raises FFR and contracts the money supply, thus indicating a tightening of monetary policy. A negative shock, with opposite effects, signals a monetary policy easing. The left chart in Figure 3.2 reveals large differences between the actual and counterfactual paths for the federal funds rate. These differences illustrate the importance of separating the feedback responses of the Fed to the state of the economy from exogenous changes in monetary policy in evaluating the policy effects. The right chart illustrates that monetary policy tightening during the Volcker disinflation period was a key factor in the emissions decline observed in the early 1980s. The contribution of monetary policy shocks at other points within this sample period was moderate, with other factors either offsetting or amplifying the effects of monetary policy actions.

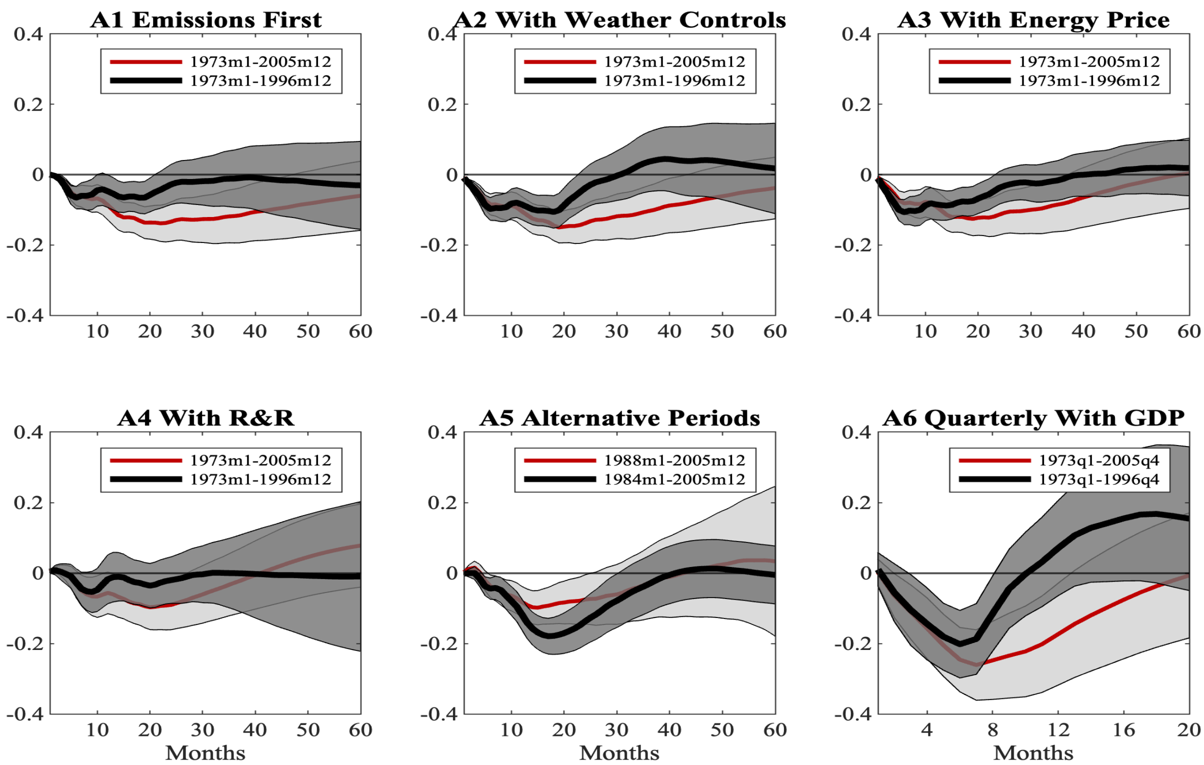
3.4.2 The Impact of Monetary Contraction on Total Emissions: Alternatives

Our first key finding - that a monetary policy tightening reduces total emissions - is robust across several modifications of the baseline model. We examine the implications of switching the emissions placement, controlling for weather indicators and energy prices, replacing FFR with another monetary policy instrument, changing the estimation periods, and using the quarterly baseline model with real GDP. We report the responses of emissions in Figure 3.3 and present the results for the macroeconomic variables in Figure H.1 of the Appendix. Table G.1 summarizes the trough effects and the monetary policy shock contribution to the forecast error variance of total CO_2 emissions.

The VAR alternative A1 places total CO_2 emissions first in the list of $X_{1,t}$ variables. This ordering rules out any impact effects of monetary policy shocks on emissions but allows the Fed

[10] Starting in Jan. 1973, we iterated VAR forward, setting to zero all disturbances except for the estimated monetary policy shocks. Following Coibion (2012), we truncated the first sixty months in reporting the results in Figure 3.2.

Figure 3.3: Effects of Monetary Policy Tightening on Total Emissions (%)
Alternative Specifications



Notes: Responses to a one-standard-deviation contractionary monetary policy shock. Darker shaded areas are the bootstrap one-standard-error confidence bands for the impulse responses represented by the *thick black lines*. Lighter shaded areas are the confidence intervals for the *thin red lines*. The estimation periods are indicated in the labels.

to react to contemporaneous movements in emissions. In this VAR specification, the through impact and FEV contribution of the monetary policy shock to total emissions are smaller relative to the baseline in the primary period. However, their magnitudes are more comparable in the extended period. More importantly, total emissions still decline in both periods.

EIA estimates CO_2 emissions series from fossil fuel consumption. The next two alternative models augment the baseline VAR with the variables pertinent to explaining energy demand. First, we expect weather variations and energy price changes to affect the demand for energy for heating and cooling and, consequently, CO_2 emissions generated by this energy consumption. The alternative A2 adds the U.S. average temperature and precipitation to the baseline VAR. Both series are from the U.S. National Oceanic and Atmospheric Administration. They are expressed as a change from a year ago due to high seasonality and placed after emissions in the VAR. Second, we expect the energy demand to be responsive to energy price changes. In the baseline VAR, energy prices were a part of the commodity price index. The VAR alternative A3 investigates the sensitivity of the results to including an energy price series explicitly. We use the cost of fossil fuel receipts at electric generating plants, inclusive of taxes, as a proxy for an aggregate price of fossil fuels.

Figure 3.3 shows that the response of total emissions to a contractionary monetary policy shock is negative and statistically significant for about two years in both periods for the A2 and A3 models. Although the contribution of monetary policy shocks to the forecast error variance of emissions in Table 1 declines relative to the baseline, it remains close to 10%.

Romer and Romer (2004) constructed a monetary policy shock from the minutes of the Federal Open Market Committee meetings and the Fed's internal forecasts. Their narrative shock has been widely used in the literature. Following Coibion (2012), we replace the FFR with the cumulative sum of Romer and Romer (R&R)'s series in our baseline VAR. We label this model specification as A4. The impact of a monetary policy tightening on total CO_2 emissions remains negative, as documented in Figure 3.3 and Table G.1. However, the responses are less precisely estimated, and the monetary policy shock's contribution to the FEV of emissions drops considerably.

Previous studies (e.g., Coibion 2012 and Ramey 2016) have documented the sensitivity of the macroeconomic effects of R&R shocks to different periods and estimation methods. For example, Ramey (2016) finds that a contractionary monetary policy shock based on the R&R's series has a stimulative effect on U.S. industrial production in the sample from January 1983 until December 2007. Figure H.1-(d) documents similarly puzzling positive output responses in our samples. From this perspective, the estimated effects of monetary policy shocks on macroeconomic variables in the baseline VAR with the FFR align more closely with the expected theoretical outcomes than those from the A4 model using the R&R measure.

Next, we investigate the sensitivity of our results to the periods of our analysis. Two additional samples are motivated by prior literature identifying monetary policy shocks. First, Coibion (2012) highlights a potential influence of the non-borrowed reserve targeting (1979-81) on VAR estimates. Starting our estimation in January 1984 ensures that the FFR was an appropriate policy instrument of the Fed during our study period. Second, Barakchian and Crowe (2013) show that recursive VAR models yield puzzling results in the sample from December 1988 to November 2007. In several leading specifications that they examine, a contractionary monetary policy shock increases both industrial production and prices. Hence, we re-estimate our baseline VAR using two additional periods: January 1984 to January 2005, and December 1988 to December 2005.

Figure H.1-(e) in the Appendix shows that the initial responses of industrial production, the unemployment rate, and CPI to a contractionary monetary policy shock go against the expected outcomes. However, the puzzling effects on the real activity measures are only short-lived, contrary to Barakchian and Crowe (2013). Industrial production declines and the unemployment rate increases, eventually. The peak policy effects on these variables are observed in the later periods. Prices also decline, although their IRF point estimates are not statistically significant.[11]

Despite some puzzling results for the macroeconomic variables, our baseline VAR model produces robust predictions for total emissions in the alternative samples. A contractionary monetary policy shock has a statistically significant negative impact on total CO_2 emissions in Figure 3.3. The impact is transitory, with the trough eighteen months after the shock. Another point to note is the smaller size of a typical monetary policy shock in the new samples. The

[11] Relative to Barakchian and Crowe (2013), we use a different set of variables. For example, we abstract from reserve measures but include the M1 aggregate and the unemployment rate. We have found that adding reserve measures led to more unstable monetary policy effects on the macroeconomic variables.

estimated standard deviation σ_m declines to 14.4 and 9.6 basis points. Nevertheless, the trough effects on emissions in the alternative periods, -0.18% and -0.10%, are comparable to those observed in our main sample.

Our final alternative, A6, focuses on quarterly data. We replace industrial production with real GDP and convert other series to quarterly by averaging the monthly values. Figure 3.3 and Table G.1 reveal that the IRF and FEV results related to the effects of a monetary policy tightening on total emissions in the quarterly models are comparable with the statistics in the monthly samples.

In summary, all alternative VAR models consistently demonstrate a negative influence of monetary policy shocks on total CO_2 emissions. A one-standard-deviation shock that increases the policy rate temporarily reduces total emissions, with the trough effects between -0.18% and -0.05% in the monthly specifications. These estimates center around -0.13% to -0.11%. The models disagree more on the quantitative relevance of monetary policy in explaining emissions fluctuations. However, the estimates of the monetary policy shock contribution to the FEV of total emissions remain modest.[12] This finding aligns with the conclusions of Attílio et al. (2023) and Khan et al. (2024), who document the limited role of U.S. monetary policy in different empirical models.

3.4.3 The Impact of Monetary Policy Shocks on Major Types of Polluters

To enhance our understanding of the environmental impact of monetary policy, we investigate how monetary policy shocks affect major types of polluters. To this end, we use the EIA's data on CO_2 emissions from the residential (homes and apartments), commercial (offices, stores, restaurants, and public gathering places), industrial (manufacturing, agriculture, mining, and construction), and transportation (movement of people and goods) sectors.

Table G.2 reports millions of metric tons of CO_2 emitted by each EIA's sector in 1996. We chose this year for illustration as it belongs to all of our data samples. Table G.2 also shows the composition of emissions by sources. Each sector directly contributes to air pollution by consuming coal, natural gas, or petroleum products. In addition, each sector pollutes indirectly

[12] Notably, the FEV statistics for emissions often surpass those for aggregate output, even though the trough effects of total emissions to monetary policy shocks are typically smaller.

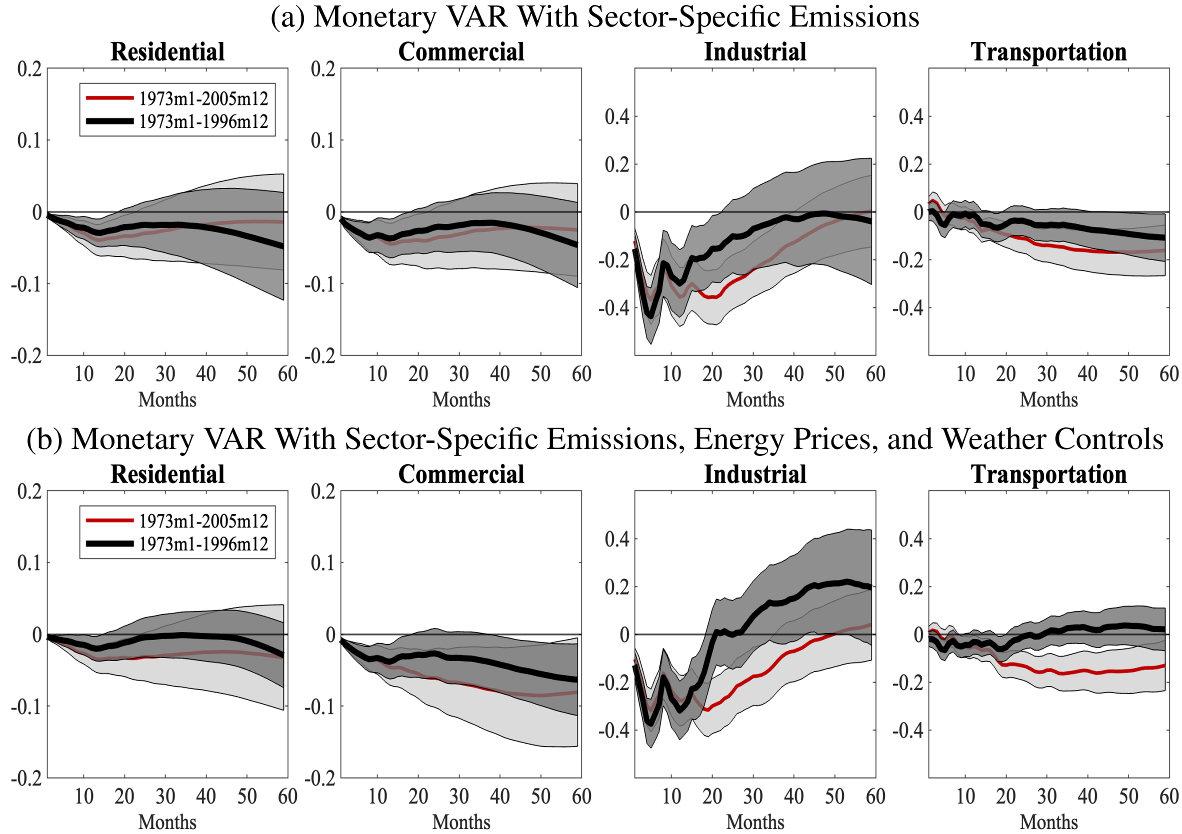
because of its use of electricity. Electricity is an intermediate good, and its generation and distribution are energy-intensive. EIA allocates emissions from the electricity sector to the four energy end-use sectors in proportion to their electricity consumption. For example, 25.85% of 1098.65 MMT of CO_2 emitted by the residential sector came from its use of natural gas, whereas 64.5% were assigned from electricity generation and transmission.

The EIA's sectors differ in their primary energy usage and rely on varying mixes of energy sources. The industrial and transportation sectors use fossil fuels as direct production inputs. Over 60% of industrial emissions stem from the combined use of coal, natural gas, and petroleum, while more than 95% of transportation emissions are linked to petroleum products. We expect emissions from these sectors to be closely tied to the level of aggregate economic activity and, therefore, relatively sensitive to the effects of monetary policy. By contrast, we expect lower sensitivity for residential and commercial emissions. Energy consumption is vital in maintaining physical comfort in homes and buildings (e.g., temperature, lighting, humidity) and fulfilling essential needs, such as refrigeration, laundry, and entertainment. A monetary contraction may reduce the energy demand through a fall in total income and changes in energy prices. However, the reduction in emissions could be offset by a decreased demand for clean air and environmental quality.

We re-estimate our baseline VAR by substituting total emissions with one of the sectoral emissions. To assess robustness, we include U.S. average temperature, precipitation, and one of the energy price measures, which is closely tied to a specific energy end-use sector. Specifically, we use the CPI for household energy, the producer price index (PPI) for electric power, the PPI for total energy, and the CPI for motor fuel.

Figure 3.4 and Table G.3 reveal heterogeneous effects of a monetary policy tightening on major polluters. The industrial sector exhibits the most significant reaction, with emissions declining immediately and reaching its trough five months after the shock. Their trough response ranges from -0.44% to -0.32%. Transportation emissions also decrease, exhibiting a more pronounced response in the extended period. By contrast, the residential and commercial sectors are minimally affected by monetary policy shocks. Although the IRF point estimates are negative and statistically significant, their magnitudes are small. The FEV statistics in Ta-

Figure 3.4: Effects of Monetary Policy Tightening on Emissions From Major Types of Polluters (%)



Notes: Responses to a one-standard-deviation contractionary monetary policy shock. Panel (a): monetary VAR with emissions from a specific energy end-use sector. Panel (b): VAR in panel (a) + average temperature and precipitation + the energy price specific to each sector. 1973m1–1996m12: *thick black lines*; 1973m1–2005m12: *thin red lines*. Darker and lighter shaded areas are the one-standard-error bootstrap confidence bands. See section 3.4.3 for details.

ble G.3 support the conclusions drawn from the IRF results, indicating that the Fed's actions historically had a pronounced impact on the industrial sector while exerting a weak influence on emissions from the residential and commercial sectors. Comparing the responses in panels (a) and (b), we conclude that adding weather controls and energy prices to the VAR models does not substantially alter our inferences about the effects of monetary policy shocks on sector-specific emissions.

The residential and commercial sectors jointly emit around 35% of all CO_2 emissions from energy consumption in the U.S. economy. Muted responses of emissions from these two sectors weaken the IRFs of total emissions. Table G.1 shows that, in many VAR specifications, the trough effects of a monetary policy shock on total emissions are often less than half the magnitude of its trough effect on industrial production. Total CO_2 emissions are often viewed as being directly tied to aggregate output. Our results indicate that a more nuanced approach to incorporating different polluting sectors is required for accurately assessing the environmental impacts of monetary policy.

3.5 Conclusions

Driven by the increasing involvement of central banks in addressing climate change, we examined the empirical effects of U.S. monetary policy on CO_2 emissions. Our analysis focused on conventional monetary policy shocks to the policy rate identified using the recursiveness assumption. The effect of monetary policy tightening on total emissions was consistently negative, though transitory and modest. However, the policy impact varied in strength across different polluting sectors.

Our findings have several implications for monetary policy. Theoretical models are critical inputs into policy design and evaluation, forecasting and scenario analysis. In a climate-changing world, monetary models must be adapted to integrate environmental factors. To ensure reliability, such models must be rigorously validated against empirical evidence, including environmental statistics. Our paper provides new empirical estimates. We find that a monetary policy tightening reduces total CO_2 emissions, in line with the interest rate transmission channel. Additionally, we find that emissions from energy end-use sectors respond differently to policy changes, reflecting variations in their energy needs. A common modelling approach that links emissions to aggregate output overlooks sectoral differences and may, therefore, overestimate the environmental impact of monetary policy. By refining theoretical models to include sector-specific polluters, researchers can better capture the complex interactions between monetary policy and climate outcomes.[13]

Another takeaway from our study concerns the role of central banks in reducing emissions. Monetary policy actions affect environmental outcomes. Theoretical studies (e.g., McKibbin et al. 2020) demonstrate complementarity between monetary and climate policies. When adjusted jointly, these two policies can lessen the adverse effects of a carbon tax on output and

[13] McKibbin et al. (2020) and Boneva and Ferruci (2022) also emphasize the need for disaggregated analysis.

inflation. Our empirical results confirm the ability of the Fed to influence CO_2 emissions. However, it is important not to overstate the potential of monetary policy in addressing climate change. The historical and forecast error variance decompositions indicate that monetary policy shocks have played a limited role in explaining emissions fluctuations. Even though central banks can adjust policies to complement environmental objectives, the primary responsibility for reducing emissions lies with fiscal measures and environmental regulation.

We focused on the impact of monetary policy shocks identified as surprise changes in the federal funds rate. Since the financial crisis of 2007-2008, the toolkit of central banks has expanded to include alternative policy instruments, such as quantitative tightening, credit easing and forward guidance. Future research can investigate the environmental impact of unconventional policy.

Appendix G

Tables

Table G.1: Effects of Monetary Policy Shocks on Total Emissions and Output

Model Name	Trough effect (%)				Maximal FEV contribution (%)			
	Total Emissions		Ind. Production		Total Emissions		Ind. Production	
	73-96	73-05	73-96	73-05	73-96	73-05	73-96	73-05
Monetary VAR			-0.19	-0.23			3.81	6.16
Baseline VAR	-0.12	-0.16	-0.22	-0.21	11.30	12.47	4.67	5.16
A1 Emissions First	-0.07	-0.14	-0.17	-0.18	3.54	7.96	2.30	3.50
A2 With Weather Controls	-0.11	-0.15	-0.22	-0.21	9.63	10.08	6.32	5.28
A3 With Energy Price	-0.11	-0.13	-0.24	-0.18	9.18	8.10	5.82	4.12
A4 With R&R	-0.05	-0.10	-0.11	-0.09	1.02	2.76	1.99	2.98
	84-05	88-05	84-05	88-05	84-05	88-05	84-05	88-05
A5 Alternative Periods	-0.18	-0.10	-0.35	-0.28	31.86	14.26	19.72	12.98
	Total Emissions		GDP		Total Emissions		GDP	
	73-96	73-05	73-96	73-05	73-96	73-05	73-96	73-05
A6 Quarterly with GDP	-0.20	-0.26	-0.30	-0.23	8.11	8.14	28.0	6.79

Notes: Columns 2–5 report the trough effects of emissions and output measures (IP or GDP) to a one-standard-deviation monetary policy shock. Columns 6–9 report the percentage contribution of the monetary policy shock to the forecast error variance of total CO_2 emissions and output. See Sections 3.4.1 and 3.4.2 for the model description.

Table G.2: Composition of CO_2 Emissions by Sector in 1996

Sector	Residential		Commercial		Industrial		Transportation	
E Source	MMT	(%)	MMT	(%)	MMT	(%)	MMT	(%)
Direct use of								
Coal	1.54	(0.14)	11.63	(1.32)	229.79	(12.70)	0.00	(0.00)
Natural Gas	284.00	(25.85)	171.08	(19.41)	507.71	(28.06)	39.07	(2.26)
Petroleum	104.48	(9.51)	57.12	(6.48)	395.17	(21.84)	1686.26	(97.55)
Sectoral share of								
Electric Power E	708.63	(64.50)	641.58	(72.79)	676.71	(37.40)	3.28	(0.19)
Total Emissions	1098.65	(100)	881.41	(100)	1809.39	(100)	1728.61	(100)

Notes: Authors' calculations from the annual Tables 11.2–11.5 in EIA (2023). MMT = millions of metric tons. E=emissions. Emissions from coal include coal coke net imports. Emissions from petroleum exclude biofuels. Columns with (%) report the percent contribution of each emissions source to total sector-specific emissions.

Table G.3: Effects of Monetary Policy Shocks on Sector-Specific Emissions

Sector	Trough effect (%)		Maximal FEV contribution (%)	
	73-96	73-05	73-96	73-05
(a) Monetary VAR with Sector-Specific Emissions				
Residential	-0.05	-0.04	3.07	3.29
Commercial	-0.05	-0.04	3.95	2.86
Industrial	-0.44	-0.37	12.82	16.92
Transportation	-0.11	-0.17	3.63	9.06
(b) Monetary VAR with Emissions, Energy Prices, and Weather Controls				
Residential	-0.03	-0.03	1.72	3.15
Commercial	-0.06	-0.08	5.59	5.33
Industrial	-0.37	-0.32	13.70	11.25
Transportation	-0.07	-0.16	2.04	9.24

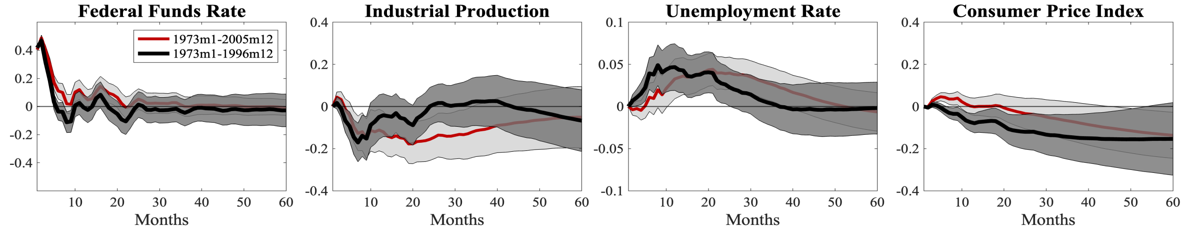
Notes: Columns 2-3 report the trough effects of emissions from the EIA's end-use sectors to a one-standard-deviation contractionary monetary policy shock. Columns 4-5 report the percentage contribution of the monetary policy shock to the forecast error variance of emissions.

Appendix H

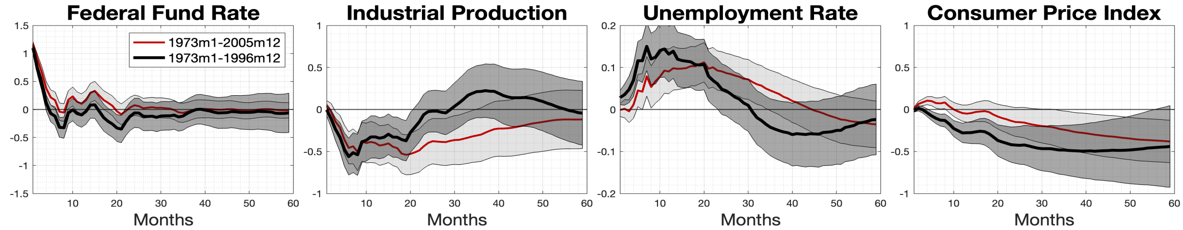
Figures

Figure H.1: Effects of Monetary Policy Tightening on the Macroeconomic Indicators (%)
Alternative Specifications

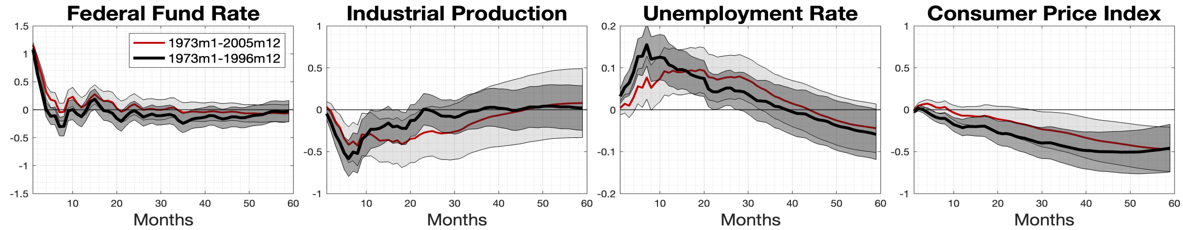
(a) A1 Emissions First



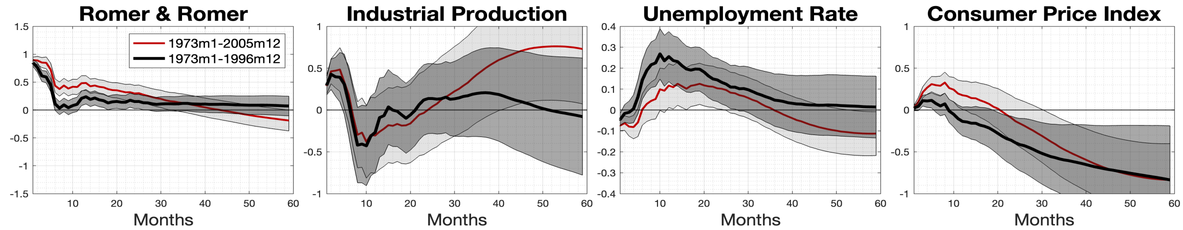
(b) A2 With Weather Controls



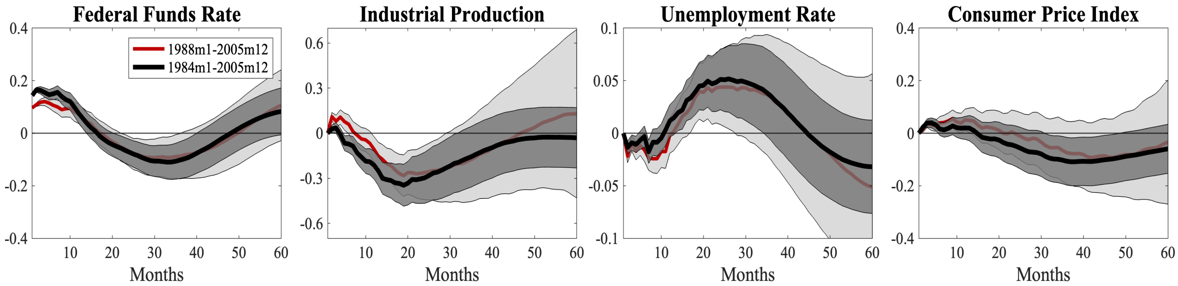
(c) A3 With Energy Price



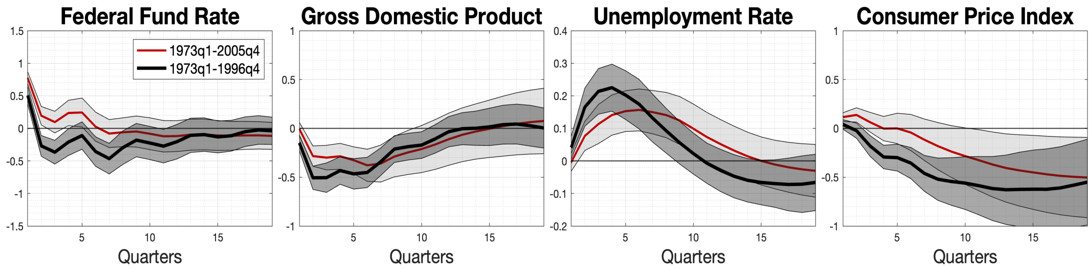
(d) A4 With R&R



(e) A5 Alternative Periods



(f) A6 Quarterly With GDP



Notes: The size of a monetary policy shock is normalized to increase the policy indicator (FFR or R&R) by 100 basis points in a monetary VAR augmented with emissions of a specific energy end-use sector. 1973m1–1996m12: thick black lines; 1973m1–2006m12: thin red lines. Darker and lighter shaded areas are the bootstrap one-standard-error confidence bands. See section 3.4.2 for the model description.

Appendix I

Data Sources

This appendix lists data sources, labels and types. The data transformations used in the paper are specified in Sections 3.1-3.3.

EIA = U.S. Energy Information Administration [https://www.eia.gov/totalenergy/data/monthly]; FRED = the database of the Federal Reserve Bank of St. Louis [https://fred.stlouisfed.org/]; NOAA = National Oceanic and Atmospheric Administration [https://www.ncdc.noaa.gov/cag/global/time-series]. Ramey (2016): [https://econweb.ucsd.edu/~vramey/research.html#mon]; sa = seasonally adjusted; nsa=not seasonally adjusted.

Macroeconomic variables IP: Industrial production total index (index 2017=100, sa); FRED [label INDPRO]. UR: Unemployment rate (percent, sa); FRED [label UNRATE]. CPI: Consumer Price Index for all urban consumers: all items in U.S. city average (index 1982-1984=100, sa); FRED [label CPIAUCSL]. Commodity price index (index); Ramey (2016) [label LPCOM]. FFR: Federal funds effective rate, averages of daily figures (percent, nsa); FRED [label FEDFUNDS]. M1 monetary aggregate (billions of dollars, sa); FRED [label M1SL]. RR: cumulative sum of the Romer&Romer's series; Ramey (2016) [label CUMRRSHOCK]. GDP: real gross domestic product (billions of chained 2012 dollars, sa annual rate, quarterly); FRED [label GDPC1].

Environmental variables Total CO_2 emissions: total energy CO_2 emissions from energy consumption (MMT of carbon dioxide, nsa); Table 11.1 in EIA (2023). Sector-specific emissions: Total energy *residential / commercial / industrial / transportation* sector CO_2 emissions (MMT of carbon dioxide, nsa); Tables 11.2-11.5 in EIA (2023). Average temperature: Contiguous U.S. average temperature (Fahrenheit, nsa); NOAA. Precipitation: Contiguous U.S. precipitation (inches, nsa); NOAA.

Energy prices Fossil fuel costs: Cost of fossil fuel receipts at electric generating plants (dollars per million Btu, nsa); Table 9.9 in EIA (2023) [Costs of coal, total petroleum, natural gas, and fossil fuel receipts, including taxes]. CPI Electricity: CPI for all urban consumers: Electricity in U.S. City Average (index 1982-1984=100, sa); FRED [label CUSR0000SEHF01]. CPI Motor fuel: CPI for all urban consumers: Motor Fuel in U.S. city average (index 1982-1984=100, sa); FRED [label CUSR0000SETB]. PPI Electric Power: PPI by Commodity: Fuels and Related Products and Power: Electric Power (index 1982=100, sa); FRED [label WPS054].

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