Hacettepe University Graduate School of Social Sciences

Department of Economics

ESSAYS ON TECHNOLOGICAL CHANGE AND ENVIRONMENTAL POLICY

Bilal ÇAYIR

Ph.D. Dissertation

Ankara, 2024

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YAYIMLAMA VE FİKRİ MÜLKİYET HAKLARI BEYANI

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Yükseköğretim Kurulu tarafından yayınlanan ***"Lisansüstü Tezlerin Elektronik Ortamda Toplanması, Düzenlenmesi ve Erişime Açılmasına İlişkin Yönerge"*** kapsamında tezim aşağıda belirtilen koşullar haricince YÖK Ulusal Tez Merkezi / H.Ü. Kütüphaneleri Açık Erişim Sisteminde erişime açılır.

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……/………/……

Bilal ÇAYIR

[1] *"Lisansüstü Tezlerin Elektronik Ortamda Toplanması, Düzenlenmesi ve Erişime Açılmasına İlişkin Yönerge"*

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(3) *Madde 7. 1. Ulusal çıkarları veya güvenliği ilgilendiren, emniyet, istihbarat, savunma ve güvenlik, sağlık vb. konulara ilişkin lisansüstü tezlerle ilgili gizlilik kararı, **tezin yapıldığı kurum** tarafından verilir *. Kurum ve kuruluşlarla yapılan işbirliği protokolü çerçevesinde hazırlanan lisansüstü tezlere ilişkin gizlilik kararı ise, **ilgili kurum ve kuruluşun önerisi** ile **enstitü** veya **fakültenin** uygun görüşü üzerine **üniversite yönetim kurulu** tarafından verilir. Gizlilik kararı verilen tezler Yükseköğretim Kuruluna bildirilir.*
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ETİK BEYAN

Bu çalışmadaki bütün bilgi ve belgeleri akademik kurallar çerçevesinde elde ettiğimi, görsel, işitsel ve yazılı tüm bilgi ve sonuçları bilimsel ahlak kurallarına uygun olarak sunduğumu, kullandığım verilerde herhangi bir tahrifat yapmadığımı, yararlandığım kaynaklara bilimsel normlara uygun olarak atıfta bulunduğumu, tezimin kaynak gösterilen durumlar dışında özgün olduğunu, **Doç. Dr. Onur YENİ** danışmanlığında tarafımdan üretildiğini ve Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Yazım Yönergesine göre yazıldığını beyan ederim.

[*İmza*]

Bilal ÇAYIR

ACKNOWLEDGEMENTS

Completing this dissertation has been a challenging yet immensely rewarding journey, and it would not have been possible without the guidance, support, and encouragement of several people.

First and foremost, I would like to express my deepest gratitude to my advisor, Assoc. Prof. Onur YENİ, for his exceptional mentorship, unwavering patience, and constant encouragement throughout this journey. His insightful guidance has not only shaped this dissertation but has also profoundly impacted my personal and academic growth. Thank you for believing in me, challenging me to reach new heights, and supporting me through every obstacle. I will always remember the lessons I have learned from him, both academically and beyond.

I am also sincerely thankful to the committee members, Prof. Dr. Selcen ÖZTÜRK, Assoc. Prof. M. Aykut ATTAR, Assoc. Prof. Tunç DURMAZ and Asst. Prof. İsmail ÇAKMAK for their helpful feedback, with special thanks to Assoc. Prof. M. Aykut ATTAR for his insightful contributions and suggestions.

To my wife, Elif, thank you for your endless love, patience, and unwavering belief in me. Your support has been my greatest source of strength and motivation. Finally, I extend my thanks to my family, friends and colleagues for their support during this journey.

ABSTRACT

ÇAYIR, Bilal. *Essays on Technological Change and Environmental Policy*, Ph.D Dissertation, Ankara, 2024.

In this thesis, we provide three essays that explore technological change and environmental policy based on the directed technical change model. We integrate theoretical and empirical analyses to examine how fossil energy cost, cross-industry technology spillovers and environmental policy shape innovation dynamics in clean and dirty technologies. The first chapter provides a detailed review of the directed technical change model, emphasizing its application to environmental economics. It highlights the importance of technology spillovers in influencing innovation dynamics, thus setting the theoretical foundation for the subsequent analyses. The second chapter develops a model of directed technical change that incorporates endogenous energy use, exogenous energy costs, and cross-industry spillovers. The model identifies conditions under which clean technologies can overcome the dominance of dirty technologies, offering insights into the role of substitutability and exogenous fossil energy costs in driving this transition. The third chapter investigates the factors that influence the distribution of innovations between clean and dirty energy technologies in 16 European countries. Our findings indicate that rising energy prices and research subsidies for clean technologies significantly support the development of clean energy innovation in European countries. Some of our findings suggest that tax policy contributes to dirty energy innovation. Given the challenges of transitioning directly to clean technologies, firms in fossil-based industries likely focus on downstream innovations to offset costs from environmental policies like energy taxes.

Keywords

Technological Change, Environmental Policy, Technology Spillovers, Energy, Innovation

ÖZET

ÇAYIR, Bilal. *Teknolojik Değişme ve Çevre Politikası Üzerine Makaleler*, Doktora Tezi, Ankara, 2024.

Bu tezde, yönlendirilmiş teknolojik değişme modeli temel alınarak teknolojik değişme ve çevre politikalarını inceleyen üç makale sunulmaktadır. Fosil enerji maliyetleri, endüstriler arası teknoloji yayılımları ve çevre politikasının temiz ve kirli teknolojilerdeki inovasyon dinamiklerini nasıl şekillendirdiğini teorik ve ampirik analizlerle ele almaktayız. Birinci bölüm, yönlendirilmiş teknolojik değişme modelinin ayrıntılı bir incelemesini sunarak bu modelin çevre ekonomisindeki uygulamasına odaklanmaktadır. Bu bölüm, teknoloji yayılımlarının inovasyon dinamiklerini etkilemedeki önemini vurgulayarak sonraki analizler için teorik bir temel oluşturmaktadır. İkinci bölüm, yönlendirilmiş teknolojik değişme modelini içsel enerji kullanımı, dışsal enerji maliyetleri ve endüstriler arası yayılımları içerecek şekilde geliştirmektedir. Bu model, temiz teknolojilerin kirli teknolojilere olan hakimiyetini nasıl aşabileceğine dair koşulları belirleyerek, bu geçişte ikame edilebilirlik ve dışsal fosil enerji maliyetlerinin rolüne ilişkin içsel bir çözüm sunmaktadır. Üçüncü bölüm, 16 Avrupa ülkesinde temiz ve kirli enerji teknolojileri arasındaki yeniliklerin dağılımını etkileyen faktörleri araştırmaktadır. Bulgularımız, artan enerji fiyatlarının ve temiz teknolojilere yönelik araştırma teşviklerinin Avrupa ülkelerinde temiz enerji inovasyonunu önemli ölçüde desteklediğini göstermektedir. Bazı bulgularımız, vergi politikalarının kirli enerji inovasyonuna katkıda bulunduğuna işaret etmektedir. Temiz teknolojilere doğrudan geçişin zorlukları göz önüne alındığında, fosil bazlı endüstrilerdeki firmalar muhtemelen enerji vergileri gibi çevre politikalarından kaynaklanan maliyetleri dengelemek için aşağı akış üretim işlemlerine yönelik inovasyonlara odaklanmaktadır.

Anahtar Sözcükler

Teknolojik Değişme, Çevre Politikası, Teknoloji Yayılımları, Enerji, İnovasyon

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ABBREVIATIONS

CES	Constant Elasticity of Substitution
EPO	European Patent Office
ETS	Emission Trading System
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IPF	Innovation Possibilities Frontier
JPO	Japan Patent Office
L.H.S	Left Hand Side
PSM	Pre-Sample Mean
R.H.S	Right Hand Side
TFP	Total Factor Productivity
USPTO	US Patent and Trademark Office
OECD	Organization for Economic Co-operation and Development
UNSD	United Nations Statistics Division

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INTRODUCTION

The effects of climate change are becoming increasingly severe, presenting huge challenges in preventing further global warming. Over recent decades, international initiatives have gained momentum, with significant milestones such as the 1992 Rio de Janeiro Summit and the subsequent Kyoto Protocol in 1997. These agreements signified the start of coordinated global efforts to curb emissions, evolving into comprehensive targets under the Paris Agreement of 2015. However, despite these efforts, projections by the Intergovernmental Panel on Climate Change (IPCC) indicate that surpassing critical warming thresholds of 1.5°C and 2°C is likely without more aggressive measures.

The dual challenge of mitigating greenhouse gas emissions while adapting to inevitable changes necessitates a deeper understanding of how technological progress can support these goals. In this regard, economic research increasingly highlights the pivotal role of innovation-driven transitions in energy systems.

Over the years, various policy proposals have been developed to combat climate change. Notable among these are the carbon tax, which places a price on greenhouse gas emissions, increased reliance on renewable and eco-friendly energy sources, and the emission trading system (ETS). Recent economic research has emphasized that technological development can play a crucial role in environmental policy and the fight against climate change. Often grounded in general equilibrium models, these studies focus on directed technical change in economies with multiple sectors. Directed technical change allows for a detailed analysis of how different factors influence the allocation of scientific research across sectors, especially in models where innovation has an endogenous dynamic. Such models are vital for understanding how innovation can drive the transition to a low-carbon economy. This approach is grounded in endogenous growth theory, with a focus on the concept of induced technical change dated back to Hicks (1932). The foundational works of Romer (1986) and Lucas (1988) highlight knowledge accumulation as a key driver of long-term economic growth. A central idea of endogenous growth theory is that production processes experience increasing returns to scale, in contrast to exogenous models like Solow's. In endogenous growth models, technological change is the result of efforts by individuals and firms to accumulate knowledge and maximize profits. This makes technological progress an endogenous outcome of economic activity, driven by innovation and investment in human capital (Romer, 1986; Lucas, 1988).

The concept of directed technical change in relation to climate change was pioneered by Acemoglu et al. (2012). They introduced a growth model incorporating environmental constraints and intertemporal endogenous directed technological change. The model features two sectors: dirty and clean. While the dirty sector generates negative environmental externalities through dirty machinery, the clean sector has no such negative impact. The final good is produced by combining inputs from both the dirty and clean sectors. The study aims to answer how technologies in these sectors will respond to environmental policies.

Their findings suggest that urgent measures like those proposed by Nordhaus and Stern (2006) are necessary to prevent environmental catastrophe. This is due to the initial productivity advantage and market size effect in the dirty sector. However, Acemoglu et al. (2012) argue that carbon taxes and research subsidies can optimally drive technological development and help avoid environmental disaster. Furthermore, once clean technologies are sufficiently advanced, research will naturally shift towards the clean sector, reducing the need for ongoing policy interventions. However, this conclusion is contingent upon sufficient substitutability between the dirty and clean sectors. Without this, long-term intervention becomes inevitable. A key contribution of their work is the idea that environmental disaster is more likely when the dirty sector relies on non-exhaustible resources. If exhaustible resources are used, rising extraction costs and decreasing resource availability could incentivize innovation in the clean sector, thereby mitigating the risk of environmental disaster without intervention.

The transition from fossil-based to clean energy systems is at the heart of the climate change discourse. While environmental policies such as carbon tax and research subsidy have been explored extensively, the role of cross-sector technological spillovers between clean and dirty technologies remains underexplored. Technology spillovers, particularly those based on knowledge, occur when knowledge is viewed as a public good and spread to individuals, firms, and sectors. This term, known as knowledge spillovers, is crucial in technological change. In the development of clean technologies, knowledge externalities from dirty sectors are often leveraged, allowing clean technologies to evolve without having to start entirely from scratch. Studies on energy technology spillovers typically analyze patent citation data, as the number of citations a patent receives reflects the extent of its technology diffusion. The more citations, the wider the spread of the technology. Research shows that spillovers between clean and dirty technologies accelerate the advancement of clean technologies, with clean technologies benefiting more significantly from these spillovers compared to their dirty counterparts (Dechezlepretre et al., 2013; Ocampo-Corrales et al., 2020).

Building on this emerging concept, the contributions of this dissertation to the existing literature are outlined as follows: First, this thesis advances the literature by emphasizing the role of cross-industry technology spillovers between clean and dirty technologies. Unlike many prior studies that largely overlook this dimension, the dissertation integrates spillovers into directed technical change models, providing a nuanced understanding of their impact on innovation dynamics. Second, building upon the foundational model by Acemoglu et al. (2012), the dissertation introduces a directed technical change model that accounts for endogenous energy use, exogenous energy costs, and spillovers between industries. Third, through applying panel count data techniques on patent data from 16 European countries, the dissertation empirically investigates how environmental policies, history of innovation, and energy costs affect innovation in clean and dirty technologies. This focus is a departure from much of the existing literature, which prioritizes clean innovations while mostly neglecting dirty technologies. Overall, our research incorporates a detailed examination of how technology spillovers, fossil energy costs and environmental policy influence the innovation landscape, offering fresh perspectives on their role in directing technical change.

The main objective of this thesis is to develop approaches highlighting how environmental policy tools and innovation spillovers between fossil-based and clean technologies can drive innovations toward clean technologies. To this end, the first chapter of this thesis provides a comprehensive review of the literature on the relationship between directed technical change and the environment, with a particular focus on the role of cross-sector technology spillovers between clean and dirty technologies. We identify a need for a thorough assessment of the literature on directed technical change models. This chapter begins by reviewing Acemoglu's (2002) foundational work on directed technical change, followed by the environmental and climate context introduced by Acemoglu et al. (2012). It then examines this literature's relatively underexplored role of cross-sector technology spillovers. The chapter’s findings show that research on directed technical change has primarily centered on the energy sector, with models focusing on factors such as energy cost and efficiency measures. Additionally, the limited theoretical and empirical evidence suggests that spillovers from dirty to clean technologies do occur and could play a role in advancing sustainable environmental goals.

In the second chapter, building on the insights from the first, we develop a directed technical change model featuring two industries: clean and dirty. Unlike previous studies, this model assumes endogenous energy use, exogenous energy costs, and cross-industry technology spillovers, focusing on the factors that drive innovations from fossil-based technologies toward renewable energy technologies. The chapter's key findings reveal that the shift to clean technologies is driven by the level of substitution rate, technology spillovers, and fossil energy costs. High substitution rates and strong spillovers promote clean innovation, while low substitution rates favor dirty technologies. High energy costs encourage clean innovation when conditions are favorable but otherwise focus on improving dirty technologies.

In the third chapter, we aim to empirically analyze the factors that influence the distribution of innovations between clean and dirty energy technologies in 16 European countries. To achieve this, we employ a Poisson regression model to assess the impact of environmental policy, history of innovation, and energy costs on the direction of innovation in both clean and dirty technologies. Given that we use patent counts as a measure of innovation, widely used in the literature, we apply panel count data techniques. While most existing studies focus primarily on clean innovations, this chapter contributes to the literature by exploring the determinants of both clean and dirty innovations, as well as the effects of various environmental policy instruments. Our findings indicate that rising energy prices and research subsidies for the clean sector significantly support the development of clean energy technologies in European countries.

The remainder of this dissertation is structured as follows: Chapter 1 reviews foundational and contemporary studies on directed technical change. Chapter 2 introduces a formal model to analyze the direction of technical change between clean and dirty technologies. Chapter 3 presents an empirical investigation into innovation trends, followed by a discussion of policy implications.

CHAPTER 1

TRANSITION TO CLEAN ECONOMY THROUGH INNOVATIONS AND TECHNOLOGY SPILLOVERS: A REVIEW OF DIRECTED TECHNICAL CHANGE MODELS

1.1. INTRODUCTION

High-skilled labor in the job market has consistently increased over many years. The skilled labor growth has resulted in a concentration of technological advancements within industries that heavily rely on such expertise. It is well-established that the distribution of technological change is not uniform across production factors and does not progress neutrally. In some countries, despite the growing number of skilled labor, there is a noticeable upward trend in their wage levels. This trend suggests a shift in technological change towards sectors demanding skilled labor with specific skills and abilities, commonly known as skill-biased technical change. This perspective is supported by Acemoglu's research, where he discusses how market forces in labor markets influence the direction of technological change within a comprehensive framework (Acemoglu 1998, 2002). As discussed in Section 2, the impact of price and market size determines the relative profitability of new technology across production factors. Furthermore, the balance between these effects is influenced by the elasticity of substitution and the extent of state dependence on the cost of various types of innovation, shaping what is termed the innovation possibilities frontier (IPF).

Following Acemoglu's pioneering studies, the directed technical change model is widely used in different areas of economic research, such as fiscal and monetary policies, international trade and investment, labor markets and environmental economics (Acemoglu 2012; Shangao et al. 2016; Fried 2018; Haas and Kempa 2018; Kim 2019; Afonso and Forte 2023; Hemous and Olsen 2021). However, how the direction of technical change responds to environmental policy has received more attention in recent years, particularly with the baseline paper titled "The Environment and Directed Technical Change" by Acemoglu, Aghion, Bursztyn and Hemous in 2012. The paper characterizes equilibrium conditions under a laissez-faire economy and optimal environmental policy to allocate innovation efforts between clean and dirty technologies to avoid environmental disaster by referring to the price, market and direct productivity effects. Following this paper, a growing body of literature continues to develop divergent and marginally modified versions of the environmental model of directed technical change.

In this paper, we aim to review the literature on the environment and directed technical change, encompassing both theoretical and empirical perspectives, with a particular focus on cross-sector technology spillovers. The role of cross-technology spillovers is pivotal in the shift towards clean energy and the global effort to combat climate change, impacting both fossil and clean energy production and consumption. Research on technology spillovers assumes significance within the directed technical change models due to its supportive role in advancing clean energy technologies and implementing environmental policies. However, it is noticeable that these spillovers are not adequately addressed in studies pertaining to the environment and directed technical change. Therefore, this review seeks to highlight the crucial interaction among cross-sector technology spillovers, environmental policies, and the direction of innovation.

The remainder of the paper is organized as follows: Section 1.2 presents the main aspects of the basic directed technical change model based on Acemoglu (1998, 2002). Section 1.3 explores the dynamics of the environmental model of directed technical change. Section 1.4 reviews the alternative models and extensions of the environmental model of directed technical change. Empirical evidence from related literature is discussed in section 1.5. Then, in section 1.6, we give special attention to cross-sector technology spillovers between clean and dirty technologies.

1.2. BASIC DIRECTED TECHNICAL CHANGE MODEL

Technological change does not diffuse uniformly across all factors of production. Some factors or industries may be more biased toward efforts in developing new technologies than others. As Acemoglu (1998, 2002) emphasized, the developments in the US labor market during the 1970s provided noteworthy insights. Data on the skilled labor market in the U.S. during these years indicate an increase in the quantity of skilled labor measured by the number of college graduates despite supply and demand dynamics in the labor market. Contrary to expectations, the wage level of skilled labor also increased during this period. This outcome supports the notion of skill-biased technological change, indicating a complementary relationship between the development of new technology and skilled labor. Acemoglu (1998, 2002) comprehensively explains why such a relationship exists. Accordingly, the increase in highly skilled workers has made it more profitable for innovators to develop high-tech solutions, enhancing their productivity. This highlights the interdependence between the growth of highly skilled workers and the profitability of developing innovative technologies.[1]

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[1] See “Why do new technologies complement skills? Directed technical change and wage inequality” by Acemoglu (1998) for more details about skill-biased technical change.

Acemoglu explains this relationship within the Directed Technical Change model framework, which allows the endogenization of the direction and bias of new technologies. For instance, one may assume an economy with two factors of production: skilled and unskilled labor, and thus, two types of technologies. Suppose the profitability of technologies based on skilled labor is higher than that of unskilled labor. In that case, profit-maximizing firms will be inclined to develop technologies based on skilled labor. In the paper titled “Why do new technologies complement skills? Directed technical change and wage inequality,” Acemoglu argues that when there is an increase in the supply of skilled labor, the market for skill-complementary technologies will expand, leading to the invention of more technologies. Therefore, he suggested that the market size effect is the determining factor in the direction of technological change.[2] Acemoglu’s observations in 1998 indicate that an endogenous increase in the ratio of skilled labor or a decrease in the cost of skills would result in wage inequality in favor of skilled labor, highlighting the influence of market forces on the direction of technological progress.

In his 2002 paper “Directed Technical Change”, Acemoglu systematically formalized this approach and investigated its effects on income inequality between rich and poor countries. This framework assumes that there are two inputs: labor, L, and Z for capital, skilled labor, or land. Technological progress is denoted by A. The production function, illustrating the production of the final good, is structured in a constant elasticity of substitution (CES) form and can be expressed as follows:

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[2] The market size effect refers to the expansion of the market for skill-complementary technologies due to an increase in the number of skilled workers.

$$\mathrm{Y} = \left(\gamma Y_L^{\frac{\varepsilon-1}{\varepsilon}} + (1-\gamma) Y_Z^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1.1}$$

In equation (1.1), Y_L and Y_Z denote the two inputs that are used in the production of the final good. One may consider that Y_L refers to unskilled labor-intensive input, and Y_Z is a skilled labor-intensive input. $\gamma \in (0,1)$ determines the share of two factors in final production, and $\varepsilon \in (0, \infty)$ is the elasticity of substitution between the two factors and implies that two factors are gross substitutes when $\varepsilon > 1$ and gross complements when $\varepsilon < 1$. The elasticity of substitution between the two inputs determines whether technological change is L-biased or Z-biased. The efficiency of labor-biased and Z-biased technologies is endogenously determined by the type and quality of machines produced by technology monopolists. The profitability of each type of technology also dictates the type of innovations that will be pursued. The production functions for inputs using these two types of technologies are as follows:

$$Y_L = \frac{1}{1-\beta}\left(\int_0^{N_L} x_L(j)^{1-\beta}\, dj\right) L^{\beta} \tag{1.2}$$

$$Y_Z = \frac{1}{1-\beta}\left(\int_0^{N_Z} x_Z(j)^{1-\beta}\, dj\right) Z^{\beta} \tag{1.3}$$

where $\beta \in (0,1)$ and total quantities of the two factors, L and Z, are supplied inelastically. x_L and x_Z denote the unskilled labor-complementary and skilled labor-complementary machines, respectively. The range of machines either used with unskilled or skilled labor is denoted by N_L or N_Z, respectively. Clearly, there are two different machine varieties used in the production of two different inputs and N_Z/N_L represents the relative productivity of skilled labor complementary factor.

The primary objective is to identify the determinants of the direction of technological change. The motivation for profit-maximizing firms to engage in more innovation is the desire to achieve greater profits. When examining the profit of technology monopolists, it is essential to consider the net present discounted value of profits rather than instantaneous profits. The net present discounted value of profits in labor and Z factors is expressed as follows:

$$V_L = \frac{\beta P_L^{1/\beta} L}{r} \quad \text{and} \quad V_Z = \frac{\beta P_Z^{1/\beta} Z}{r} \tag{1.4}$$

where P_L and P_Z are the product prices, and *r* is the time-varying interest rate. The larger V_Z compared to V_L, the more technologies based on the Z factor will be developed compared to those based on labor. The equation above reveals the factors determining the profitability of both technologies. Accordingly, V_Z and V_L are increasing in P_Z and P_L, implying a price effect and encouraging the development of technologies that use the input with a higher price. On the other hand, V_Z and V_L are increasing in Z and L, indicating that innovation favors the more abundant factor, expressed as the market size effect. Under the steady-state assumption and defining that $\sigma \equiv \varepsilon - (\varepsilon - 1)(1 - \beta)$, the paper expresses the profitability ratio of Z-complementary new machine production to L-complementary machine production:

$$\frac{V_Z}{V_L} = P^{1/\beta}\frac{Z}{L} = \left(\frac{1-\gamma}{\gamma}\right)^{\frac{\varepsilon}{\sigma}} \left(\frac{N_Z}{N_L}\right)^{-\frac{1}{\sigma}} \left(\frac{Z}{L}\right)^{\frac{\sigma-1}{\sigma}} \tag{1.5}$$

The price and market size effects determine the relative profitability of new technology in both production factors. When the elasticity of substitution between the two factors is greater than one, an increase in the relative factor supply Z/L will increase V_Z/V_L, allowing the market size effect to dominate the price effect. On the other hand, when the elasticity of substitution is less than one (complementary case), an increase in Z/L will lead to a decrease in V_Z/V_L, allowing the price effect to dominate. Consequently, the substitution ratio between the two factors determines which effect will dominate. If the price effect dominates, developing new technologies that enhance the efficiency of the scarce factor will be more profitable. Conversely, if the market size effect dominates, developing technologies that enhance the efficiency of the abundant factor will become more profitable.

In addition to the determining role of the elasticity of substitution, the degree of state dependence on the cost of different types of innovation (termed the IPF) can significantly shape the direction of technological change. The concept of the degree of state dependence essentially suggests that the future costs of innovations can be influenced by the current level of technology (or the current state of research and development). Taking into account the potential state dependence of the IPF, Acemoglu (2002) assumes that directing innovations towards the Z factor in the current period will result in a reduction in the relative costs of future Z-complementary innovations.

The results presented by Acemoglu (2002) provide crucial insights into the income gap between developed and less developed countries. In the developed countries, referred to as the North, directed technical change tends to make newly developed technologies more skill-biased than in less developed countries. This disparity contributes to a larger income gap between rich and poor nations. Since less developed countries generally have fewer skilled workers than advanced Northern countries, skill-biased technologies are not expected to have a significant role in less developed countries. Therefore, directed technical change is a factor that deepens income inequality.[3]

1.3. ENVIRONMENTAL MODEL OF DIRECTED TECHNICAL CHANGE

In 2012, Acemoglu et al. show the significance of price and market size effects in their Basic Directed Technical Change model, highlighting their impact on the response of diverse technologies to environmental policies in a two-sector model. Their study discusses intertemporal endogenous and directed technological change within the framework of a growth model that considers environmental constraints.

Acemoglu et al. (2012) focus on a comprehensive economic model comprising both dirty and clean sectors. While the dirty sector introduces a negative environmental externality through dirty machines, the clean sector is devoid of such adverse effects. The combination of inputs from these two sectors results in the production of the unique final good. Building on this foundation, the study explores how technologies directed in different sectors respond to environmental policies.

Analytical findings suggest that immediate definitive measures, compared to those proposed by Nordhaus and Stern, are imperative to avoid environmental catastrophe due to the advantages of the market size and initial productivity in the dirty sector (Nordhaus 2010; Stern 2009). However, Acemoglu et al. (2012) contend that using carbon taxes and research subsidies can serve as optimal environmental response tools, adequately steering technological development

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[3] For more detailed discussion and findings on the debates regarding directed technical change and income inequality, readers are referred to Antonelli and Scellato (2019), Chu et al. (2014) and Jerzmanowski and Tamura (2019).

and preventing environmental disasters. Furthermore, with the sufficient advancement of clean technologies, further intervention becomes unnecessary as research naturally shifts towards the clean sector. This proposition is based on the assumption of a sufficient substitution rate between the clean and dirty sectors; otherwise, permanent intervention becomes inevitable.

An important contribution of Acemoglu et al. (2012) lies in highlighting that the likelihood of an environmental disaster increases when the dirty sector utilizes non-exhaustible resources. In the case of exhaustible resources, extraction costs and diminishing stocks can incentivize innovation to transition to the clean sector, avoiding environmental disasters without intervention. However, this possibility diminishes when non-exhaustible resources are employed, as there are no associated costs.

The CES aggregate production function of a uniquely produced final good (Y_t) under competitive conditions is expressed as follows:

$$Y_t = \left(Y_{ct}^{(\varepsilon-1)/\varepsilon} + Y_{dt}^{(\varepsilon-1)/\varepsilon}\right)^{\varepsilon/(\varepsilon-1)} \tag{1.6}$$

where ε denotes the elasticity of substitution between clean and dirty intermediates. The final good is produced by two inputs from the clean (Y_{ct}) and dirty intermediate sectors. Intermediate production functions are as follows:

$$Y_{ct} = L_{ct}^{1-\alpha} \int_0^1 A_{cit}^{1-\alpha} x_{cit}^{\alpha}\, di \tag{1.7}$$

$$Y_{dt} = R_t^{\alpha_2} L_{dt}^{1-\alpha} \int_0^1 A_{dit}^{1-\alpha_1} x_{dit}^{\alpha_1}\, di \tag{1.8}$$

where $\alpha, \alpha_1, \alpha_2 \in (0,1)$, $\alpha_1 + \alpha_2 = \alpha$ and A_{jit} denotes the quality of *i*-type machine in sector denoted by $j \in (c, d)$ and R_t shows the consumption level of an exhaustible resource.[4] The innovation side of the economy is as follows:

$$A_{jt} = \left(1 + \gamma\eta_j s_{jt}\right)A_{jt-1} \tag{1.9}$$

In this framework, scientists face a choice each period to focus their research on either clean or dirty technology. They are then randomly assigned to a machine, with a chance of successful innovation determined by a probability parameter η_j in sector *j* (clean or dirty). Successful innovation improves machine quality by a factor of $1 + \gamma$. A scientist who successfully innovates becomes the entrepreneur for that period in producing the improved machine. If innovation fails, monopoly rights go to a randomly selected entrepreneur using the old technology. The IPF allows scientists to target a sector rather than a specific machine, ensuring allocation across machines in a sector. The IPF also normalizes the measure of scientists and denotes the scientist mass working on machines in each sector at a given time by s_{jt}. Finally, Acemoglu et al. (2012) define the environmental quality S_t as follows:

$$S_{t+1} = -\xi Y_{dt} + (1 + \delta)S_t \tag{1.10}$$

The equation (1.10) introduces the evolution of environmental quality over time. The right-hand side of the equation determines the change in environmental quality, subject to certain conditions. Specifically, when the right-hand side is

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[4] Acemoglu et al. (2012) define the evolution of the exhaustible resource as $Q_{t+1} = Q_t - R_t$. Q_t reflects the resource stock and $c(Q_t)$ is defined as per unit extraction cost.

within the interval $(0, \bar{S})$, environmental quality adjusts accordingly. If the right-hand side is negative, environmental quality remains at zero ($\bar{S}_{t+1} = 0$), and if it exceeds $\bar{S}$, environmental quality stabilizes at its maximum level. The parameter ξ signifies the environmental pollution rate due to the dirty input production, while δ represents the environmental regeneration rate.

The equation (1.10) captures the key aspects of environmental change, including the idea that greater degradation tends to lower the regeneration capacity. The upper bound $\bar{S}$ reflects the maximum environmental quality, acknowledging that pollution cannot be negative. This equation also discusses the concept of a point of no return, where if environmental quality reaches zero, it remains at zero indefinitely. This notion aligns with the concern among climate scientists that irreversible environmental disasters may occur.

1.3.1. Non-Exhaustible Resource

The factors determining the relative profitability of conducting research in the clean and dirty sectors are outlined as follows:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \times \left(\frac{P_{ct}}{P_{dt}}\right)^{1/(1-\alpha)} \times \frac{L_{ct}}{L_{dt}} \times \frac{A_{ct-1}}{A_{dt-1}} \qquad (1.11)$$

According to this equation, the factors determining innovation efforts in either the clean or dirty sectors are influenced by the price, market size, and direct productivity effects. As mentioned earlier, the price effect directs innovations towards the sector with higher prices, while the market size effect encourages innovations to occur in the sector with higher employment. On the other hand, the direct productivity effect indicates that innovations occur in the sector where the average productivity is relatively high.[5]

1.3.1.1. Substitution Case

When there is a substitution relationship between the two inputs, the assumption that the clean sector is relatively backward compared to the dirty sector implies that innovations must begin in the more advanced sector, the dirty sector.[6] In this case, while the average productivity of the sector producing dirty input continues to increase steadily, the productivity level of the clean sector remains constant. Additionally, when the substitution coefficient is greater than one, it leads to the unlimited growth of dirty input production. As a result, in the non-intervention scenario, equilibrium allocations drive the economy towards an environmental disaster. However, Acemoglu et al. (2012) argue that some degree of economic intervention may inhibit an environmental disaster. For instance, the government can allocate a proportional research subsidy through a lump-sum tax collected from households to encourage scientists to contribute to the clean sector. Accordingly, when there is a substitution relationship between inputs, temporary incentives applied for a certain period may be sufficient to redirect all research efforts to the clean sector. When the average efficiency ratio sufficiently increases in favor of the clean sector, directing research to the clean sector for scientists may become more profitable even without implementing research incentives. Consequently, having a sufficient level of substitution will ensure that temporary incentives lead to innovations towards clean technologies.

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5 The argument on innovation shifting towards more productive sectors reflects the notion of building on the shoulders of giants which implies a state dependence on the IPF.

6 That is, the Assumption 1 is $\frac{A_{c0}}{A_{d0}} < min\left\{(1+\gamma\eta_c)^{\frac{\varphi+1}{\varphi}}\left(\frac{\eta_c}{\eta_d}\right)^{\frac{1}{\varphi}}, (1+\gamma\eta_d)^{\frac{\varphi+1}{\varphi}}\left(\frac{\eta_c}{\eta_d}\right)^{\frac{1}{\varphi}}\right\}$ reflects that innovation starts with dirty technologies when there is no policy intervention.

1.3.1.2. Complementary Case

When there is a weak substitution relationship between clean and dirty inputs, in other words, a complementary relationship, Acemoglu et al. (2012) suggest that implementing impermanent intervention may not be enough to avoid an environmental disaster. In a complementary case, temporary intervention facilitates the redirection of research towards the clean sector. However, the production quantity of dirty input will continue to increase.[7]

1.3.1.3 Optimal Policy

The environmental form of the directed technical change model emphasizes the importance of research subsidy and carbon tax when shaping the optimal environmental policy. The laissez-faire equilibrium in the economy leads to three types of externalities. First, there is the environmental externality generated by dirty input producers. Second, there are knowledge externalities arising from research and development activities. Last, there is the standard static monopoly distortion in the price of machines subject to monopolistic competition. To eliminate externalities in the form of non-exhaustible resources used in the dirty input production, the socially optimal allocation is characterized, recommending lump-sum taxes and transfers. Therefore, Acemoglu et al. (2012) define the combination of (i) carbon tax on dirty input, (ii) research subsidy for clean innovations, and (iii) subsidy for the use of all machines as the first-best policy for socially optimal allocation. Consequently, market failures arising from inefficient use of machines due to monopolistic pricing are addressed with a subsidy for machines, environmental damages from dirty input production are mitigated with a carbon tax, and market failures by knowledge externalities on the IPF are

[7] For more details about complementary inputs and environmental policy, readers are referred to Appendix I in Acemoglu et al. (2012).

addressed with a research subsidy (directing innovation toward the clean sector to deal with future environmental externalities).

Acemoglu et al. (2012) describe a scenario where only carbon tax is used as the intervention tool for socially optimal allocation as a second-best policy. However, relying solely on a carbon tax to combat both current and future environmental externalities would necessitate higher tax rates, resulting in the distortion of current production and a significant reduction in consumption. At this point, an important question is whether the optimal environmental policy will be implemented permanently or temporarily. Accordingly, if there is sufficient substitution between clean and dirty inputs and the discount rate is low enough, temporarily applying research subsidy and carbon tax will be sufficient for the transition to clean innovation. However, the allocations required to correct monopoly distortions are beyond this scope. When the discount rate is sufficiently low, the positive long-term growth resulting from technological advancement in clean input (given the substitution relationship, there will be no increase in dirty input production) will be optimal. In this mechanism, research subsidies, properly determined at the right level, will work to surpass the productivity level of the clean sector over the dirty sector, making innovation in the clean sector more profitable. Subsequently, even without subsidies, innovation will continue in the clean sector.

1.3.2. Exhaustible Resource

Acemoglu et al. (2012) have also characterized the environmental model of directed technical change for the case where exhaustible resources are used in the dirty sector. In this specification, even without intervention, preventing an environmental disaster is possible because using exhaustible resources in the dirty sector leads to continuously increasing usage costs due to extraction costs and resource scarcity. However, it is initially assumed that there are no privately held property rights for exhaustible resources, and the usage cost is determined solely by the extraction cost. Later, it is assumed that property rights are vested in infinite-lived firms or consumers, and thus, the Hotelling Rule determines the price. Since exhaustible resources are used to produce dirty input, the stock of exhaustible resources now affects the price and market size. Accordingly, as the resource stock decreases, the efficiency of dirty input also decreases, and its price increases. In the final state, the ratio of expected profits in the two sectors becomes:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \kappa \frac{\eta_c c(Q_t)^{\alpha_2(\varepsilon-1)}}{\eta_d} \frac{(1+\gamma\eta_c s_{ct})^{\varphi-1}}{(1+\gamma\eta_d s_{dt})^{\varphi_1-1}} \frac{A_{ct-1}^{-\varphi}}{A_{dt-1}^{-\varphi_1}} \tag{1.12}$$

where κ denotes the time-invariant parameters, Q_t is the resource stock at time *t*, and the per unit extraction cost for the exhaustible resource is $c(Q_t)$ and is decreasing in Q_t. Accordingly, innovating in the clean sector will become more profitable with a substitution relationship between the two inputs as the resource stock depletes. In other words, decreasing resource stock will increase the relative cost of dirty input, narrow market size, and encourage innovation in the clean sector. A substitution elasticity greater than one will reduce the weight of dirty input in the final good, preserving environmental quality and enabling positive long-term growth without policy intervention. As a result, increasing resource prices and extraction costs naturally create an incentive towards clean technologies, demonstrating the possibility of economic growth that is less harmful to the environment compared to the baseline model.

1.3.2.1. Optimal Policy

In the case where non-exhaustible resources are used, the optimal regulation includes a subsidy that corrects monopoly distortions, a carbon tax on dirty input production, and research subsidy for the clean sector. Here, since the private extraction cost does not account for the value derived from the limited availability of exhaustible resources, the optimal allocation of resources also suggests the continuous implementation of a resource tax. On the other hand, the case where price-taking and profit-maximizing firms hold well-defined property rights over exhaustible resources has also been considered. In this case, the price of exhaustible resources is determined by the Hotelling rule. Accordingly, under the assumption that the cost of extraction is fixed and equal to $c > 0$, The pricing of exhaustible resources should be established in a manner where the marginal value of extracting one more unit today equals the discounted value of extracting an additional unit in the future.

The Hotelling rule implies that the resource price asymptotically increases at the same rate as the interest rate derived from the consumption Euler. Under these conditions, if the discount rate and the elasticity of substitution between the two sectors are sufficiently high, innovation occurs only in the clean sector. Under laissez-faire, the prevention of environmental disaster is possible. However, if the discount rate and elasticity of substitution are sufficiently low, avoiding environmental disaster without intervention is impossible. In other words, when the discount rate is low enough, the resource price increases more slowly than the average productivity of the dirty sector, and innovations eventually turn towards dirty technologies. When the discount rate is sufficiently high, the resource price increases rapidly enough to allow innovations to turn towards clean technologies within a limited period, ultimately avoiding disaster with temporary research subsidies. However, a prerequisite for this is a strong substitution relationship between the two sectors.

1.4. ALTERNATIVE MODELS AND EXTENSIONS

Following the pioneering study of Acemoglu et al. (2012), a growing body of literature continues to develop divergent and marginally modified models of the environmental model of directed technical change. Table 1 presents the reviewed literature regarding the extensions of the environmental models of directed technical change. First, Acemoglu et al. (2012) proposed some modeling alternatives to the model explained in the previous section. These modeling alternatives that are briefly explained below are specified as the direct impact of environmental degradation on productivity, alternative technologies, and substitution between productivity improvements and green technologies.

Table 1 Extensions of the Directed Technical Change Models

Year	Author(s)	Title	Modification
2012	Acemoglu D., Aghion P., Bursztyn L., Hemous D.	"The Environment and Directed Technical Change"	Direct impact of environmental degradation on productivity
2012	Acemoglu D., Aghion P., Bursztyn L., Hemous D.	"The Environment and Directed Technical Change"	Alternative technologies
2012	Acemoglu D., Aghion P., Bursztyn L., Hemous D.	"The Environment and Directed Technical Change"	Substitution between productivity improvements and green technologies.
2012	Hemous, D.	"Environmental Policy and Directed Technical Change in a Global Economy: The Dynamic Impact of Unilateral Environmental Policies."	Trade, unilateral policy
2014	Andre FJ., Smulders S.	"Fueling growth when oil peaks: Directed technological change and the limits to efficiency	Energy efficiency
2016	Acemoglu D., Akcigit U., Hanley D., Kerr W.	Transition to Clean Technology"	Energy Technology
2017	Lennox JA., Witajewski-Baltvilks J.	"Directed technical change with capital-embodied technologies: Implications for climate policy"	Capital embodiment, Obsolescence
2017	Van den Bijgaart I.	"The unilateral implementation of a sustainable growth path with directed technical change"	Trade, unilateral policy
2017	Witajewski-Baltvilksa J., Verdolinia E., Tavonia M.	"Induced technological change and energy efficiency improvements"	Energy efficiency

2018	Fried S.	“Climate Policy and Innovation: A Quantitative Macroeconomic Analysis”	Technology Spillovers
2018	Greaker M., Heggedal TR., Rosendahl KE.	“Environmental Policy and the Direction of Technical Change”	Innovation policy
2018	Haas C., Kempa K.	“Directed Technical Change and Energy Intensity Dynamics: Structural Change vs. Energy Efficiency”	Energy intensity, Energy efficiency
2019	Durmaz T., Schroyen F.	“Evaluating Carbon Capture and Storage in a Climate Model with Endogenous Technical Change”	Carbon capture and storage
2024	Casey G.	Energy Efficiency and Directed Technical Change: Implications for Climate Change Mitigation	Energy efficiency
2023	Kruse-Andersen PK.	“Directed technical change, environmental sustainability, and population growth”	Population growth
2023	Acemoglu D., Aghion P., Barrage L., Hemous D.	“Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution”	Energy transition

Direct Impact of Environmental Degradation on Productivity: This approach suggests that in the absence of any economic intervention, there will be an environmental disaster in a limited time, or consumption will converge to zero over time. In this approach, the decline in environmental quality negatively affects labor productivity in both sectors. In the absence of intervention, the productivity loss caused by environmental degradation due to the increasing average productivity of the dirty sector will lead to the convergence of total output and consumption to zero. Alternatively, the decrease in productivity may not be sufficient to counterbalance the rising productivity in the dirty sector, resulting in an environmental disaster within a limited time. The temporary research subsidies policy proposed by Acemoglu et al. (2012) in the basic model for the clean sector will prevent environmental disasters and convergence of consumption with lower short-term intervention costs in this case.

Alternative Technologies: In this modeling, Acemoglu et al. (2012) practically have the potential to reduce the environmental damage caused by dirty technologies through clean innovations. This approach suggests a framework where the average sectoral efficiencies of dirty and clean inputs correspond to a task fraction between clean and dirty technologies. Accordingly, clean innovations both increase the average efficiency of the clean sector and the quantity, reducing the pollution intensity of the aggregate production process. Therefore, this approach suggests that there could be a single type of Technical Change that reduces pollution in the existing production process.

Substitution Between Productivity Improvements and Green Technologies: Acemoglu et al. (2012) suggest eliminating the distinction between clean and dirty technologies and instead propose categorizing them as technologies that increase efficiency and reduce pollution. In this case, research can be directed towards improving the efficiency of dirty machines or reducing pollution levels. Without intervention, output may continue to grow indefinitely, leading to an environmental disaster. However, innovations that reduce pollution can guide technological development and help avoid disaster. In such a setting, intervention cannot be temporary, as in Acemoglu et al. (2012) baseline model, and must occur in the form of pollution reduction instead of productivity increase. This could potentially constrain long-term growth. Increasing pollution-reducing innovations on existing technologies here diminishes the relative importance of green innovation by overshadowing research on clean technologies. The conclusion is that there is a complementary relationship between clean technologies and pollution-reducing innovations rather than a substitution relationship.

Acemoglu et al. (2012) establish the foundation for models of directed technical change (DTC) by introducing a framework that explores the direct effects of environmental degradation on productivity, the availability of alternative technologies, and the substitution dynamics between dirty and clean technologies. This influential study served as a milestone for the following research, inspiring the development of diverse modeling approaches. However, these approaches are often studied in isolation, with limited attention to their interconnections. In this section, we critically review the various models in the literature, highlighting their relationships and offering a comprehensive perspective.

Acemoglu et al. (2012) suggest that temporary subsidies could be sufficient to prevent environmental disasters. However, this perspective overlooks the broader insights from open-economy models, such as those proposed by Hemous (2012) and Van den Bijgaart (2017). These models highlight the importance of technology spillovers and trade, revealing that temporary measures may fail to ensure long-term environmental sustainability. Hemous (2012) integrates the directed technical change framework into an open economy, examining whether a number of countries can achieve sustainable growth by implementing unilateral environmental policies. The model includes two countries (North and South) and two traded goods, one of which is defined as a polluting good produced using clean and dirty inputs, leading to global externalities. Additionally, Hemous (2012) introduces an extension that accounts for technology spillovers across countries. The model's findings indicate that carbon tax alone does not ensure sustainable growth or environmental quality preservation. However, temporary clean research subsidies and tariffs implemented in one country can lead to sustainable growth with high levels of environmental quality. These findings hold true even in cases where there are technology spillovers between countries. Van den Bijgaart (2017), employs a similar approach and analyzes the effects of unilateral policies on production and innovation using a two-country (local and foreign) model. The findings show that when foreign countries increase dirty goods production in response to local reductions, this also stimulates innovation in the dirty sector of those foreign countries. This indirect effect of unilateral policies on innovation can have significant implications for the type of unilateral policies implemented to achieve sustainable growth.

Andre and Smulders (2014) explore the relationship between energy use, productivity growth, and resource scarcity. They illustrate how the allocation of resources to the energy sector can drive technological change, offering valuable insights into this dynamic. The research deals with the influence of extraction costs and technological advancements on long-term economic dynamics and sustainability. The findings suggest that technological change responds to resource scarcity, with resource allocation to the energy sector adapting according to its production significance. Additionally, the paper reveals how energy scarcity shapes the bias of technological change and outlines its implications for overall innovation (Andre and Smulders 2014). This model parallels the work of Witajewski-Baltvilksa et al. (2017), which explores how productivity improvements in energy-intensive sectors can reduce energy demand. Unlike the baseline model of Acemoglu et al. (2012), this study incorporates energy-intensive and non-energy-intensive inputs into the production process instead of clean and dirty inputs. The theoretical findings of the model indicate that if there is a complementary relationship between the two types of inputs, innovations in the energy-intensive sector have a reducing effect on energy demand. The model explains this result with the market size effect, similar to the baseline model of Acemoglu et al. (2012). The level of these innovation efforts in the long term (in balanced growth path) depends on the growth rate of energy costs.

Both Andre and Smulders (2014) and Witajewski-Baltvilksa et al. (2017) emphasize the relationship between energy efficiency and technological change. However, Haas and Kempa (2018) offer an innovative contribution by distinguishing between the structural and efficiency effects of dynamics in energy intensity. Haas and Kempa (2018) marginally modify the environmental model of directed technical change by considering heterogeneous energy intensity dynamics in the presence of exhaustible resources. The paper decomposes aggregate energy intensity into structural effect and efficiency effect. While the structural effect defines structural adjustments in the sectors with low energy intensities, the efficiency effect defines the improvements in energy efficiency within sectors. The paper explains energy price growth and sectoral productivity as determinants of the relative importance of these two effects and drivers of the directed technical change. Accordingly, while the structural effect dominates the energy intensity dynamics if research is directed to the labor-intensive sector, the efficiency effect dominates when research is directed to the energy-intensive sector. The paper concludes that energy price shocks can redistribute innovation activities across sectors.

Durmaz and Schroyen (2019) examine the role of carbon capture and storage (CCS) technologies in resource allocation, emphasizing the critical need for a balance between clean and dirty technologies. The paper investigates whether carbon capture and storage and research and development efforts in this sector contribute to the socially efficient solution to the climate change problem. Durmaz and Schroyen (2019) address the Pareto-efficient policy allocation of resources across dirty, clean and carbon capture and storage sectors. The main findings highlight a critical level for the marginal cost of carbon capture and storage, at which marginal cost is above the critical level innovation first allocated in dirty and then clean energy. However, when the marginal cost of carbon capture and storage is below this critical level, innovations are allocated both in dirty energy and carbon capture and storage technology.

Fried (2018) modifies the Directed Technical Change framework, which assumes that innovation occurs in multiple types of energy by considering the assumption of technology spillovers between sectors, as the realization of innovation in only one energy type is inconsistent with real data. The final product is produced by the model using three inputs: fossil, green, and non-energy. Accordingly, limited innovation is allocated among fossil, green, and non-energy intermediate inputs. The study also externally accounts for the price of oil imports to model oil shocks. Fried (2018) employs a constant carbon tax implication to study the dynamic effects of climate policy with endogenous innovation. According to the findings, after 20 years, the tax causes the level of green innovation to be 50% higher than without the tax and fossil innovation to be 60% lower. In the model with the tax, the relative price of green energy to fossil energy is 7% lower after 20 years compared to the price in the without tax model, and it is 17% lower in the new balanced growth path.

Kruse-Andersen (2023) examines the impact of population growth on pollution, suggesting that more people could mean either more emissions or greater research capacity. Population growth can have two potentially opposing effects on pollution emissions. Accordingly, more people may imply more production and thus more emissions, or more people may imply an increase in research capacity, which depending on the direction of research, can reduce the emission intensity of production. Kruse-Andersen (2023) questions how to achieve a specific climate target in the presence of these two effects. Under the assumption of simultaneous research in both dirty and clean technologies, both analytical and numerical results have shown that population growth remains a burden on the environment, even if all innovation efforts are directed towards clean technologies. Kruse-Andersen (2023) provides a more detailed analysis of the impact of population dynamics on environmental sustainability compared to the works of Acemoglu et al. (2012) and Greaker et al. (2018) on innovation direction. However, further quantitative analysis may be needed to better predict the long-term effects of population growth on sustainability.

Acemoglu et al. (2023) assess the short- and long-term effects of the shale gas revolution, highlighting the potential of fossil fuels to slow innovation. This study addresses the indirect effects of fossil fuel dependence on clean energy innovation, emphasizing the need for a combined approach of carbon taxes and clean incentives. However, this suggestion may overlook forces such as trade and technology diffusion, which other literature discusses.

The literature on environmentally directed technical change (DTC) offers various modeling approaches for achieving sustainable growth and environmental sustainability goals. However, the findings from these studies need to be integrated into a more consistent and actionable framework for policy design. The reviewed models address key issues such as energy efficiency, carbon capture, technology spillover, and population dynamics. However, these studies are often analyzed in isolation. For instance, Andre and Smulders (2014)'s work on energy scarcity and efficiency could enhance a broader energy policy framework when considered alongside Haas and Kempa (2018)'s research on how energy price shocks affect innovation. Similarly, Acemoglu et al. (2023)'s paper on the indirect effects of the shale gas revolution could be integrated with Fried (2018)'s exploration of the connection between carbon taxes and innovation spillovers. Despite these insights, the findings underscore the complexity of policy design. For example, while temporary subsidies (Acemoglu et al., 2012) may be effective in the short term, they could fail to be sustainable in the long term if international cooperation and technology diffusion are not taken into account (Hemous, 2012; Van den Bijgaart, 2017). The effectiveness of carbon capture technologies is constrained by economic feasibility and cost-effectiveness (Durmaz and Schroyen, 2019), pointing to the need for a combined approach to carbon pricing and technological incentives. Socioeconomic factors like population growth also play a crucial role in both directing innovation and ensuring sustainable resource management (Kruse-Andersen, 2023).

Overall, this section highlights that achieving environmental sustainability requires an integrated approach to technological innovation and energy policies. Future research can develop more comprehensive policy recommendations by linking models more effectively and combining different approaches.

The models reviewed in this literature survey address topics such as directing innovation, energy efficiency, carbon capture technologies, and capital dynamics within the framework of environmentally directed technical change. However, several key limitations are apparent. Specifically, the mechanisms driving the speed and effectiveness of technology spillovers, as well as the long-term economic and environmental impacts of fossil energy costs (e.g., environmental and social costs) have not been thoroughly examined. Future studies should focus on bridging these gaps by developing strategies to accelerate technology spillovers and creating policy frameworks that endogenize exogenous costs. Such approaches could offer more comprehensive and effective solutions for achieving environmental sustainability.

1.5. EMPIRICAL LITERATURE

After analyzing the foundation in 1998 and 2002 within the framework of directed technical change, along with environmental policies in 2012, the dynamics of environmental policy and climate change mitigation continue to be examined through theoretical and empirical applications. In this context, Acemoglu et al. (2012) initially analyzed the environmental model of directed technical change with a basic application. Subsequently, these analyses have continued with different sector preferences and specifications. This section discusses the findings of the numeric and econometric literature on directed technical change and the environment.

Acemoglu et al. (2012) presented the findings of a quantitative study for the theoretical model in the context of a non-exhaustible resource setup. In the analysis, they tested the effects of different discount rate values and the elasticity of substitution on optimal environmental policy and the transition to clean technology. The analysis considered a period of 5 years, and it was assumed that the carbon tax was zero before the implementation of the optimal policy. Based on the substitutability assumption between clean and dirty energy types, the elasticity of substitution was tested for two different values, 3 and 10. These two values, were chosen to emphasize the significant role of the elasticity of substitution. Similarly, two different values were also anticipated for the discount rate, determined as 0.001 per annum, suggested by Stern, and 0.015 per annum, suggested by Nordhaus. Accordingly, when the elasticity of substitution is 10 and 3, and the discount rate is 0.001, an optimal policy emerges that requires all innovation efforts to be urgently directed towards clean technologies. With the elasticity of substitution 3 and a discount rate of 0.015, the transition to clean technologies takes place approximately within 50 years. When the elasticity of substitution is 10, it was observed that research subsidies are implemented at a lower level and in a shorter period. With the elasticity of substitution 10, the implementation of a carbon tax in a small amount and for a short period is considered sufficient for the transition to clean technology. However, when the elasticity of substitution is 3, and the discount rate is 0.015, the transition to clean technology and production is delayed, necessitating the application of a carbon tax at a higher level and for a longer period (over 185 years). On the other hand, when the elasticity of substitution is 10, the temperature increase initially occurs at a small level, then decreases, reaching pre-industrial levels after 90 years. With the elasticity of substitution 3 and a discount rate of 0.015, the temperature increases over 300 years, almost reaching catastrophic levels. The findings of Acemoglu et al. (2012) essentially demonstrated that if the substitution relationship between dirty and clean technologies is sufficiently high, the discount rates of Stern and Nordhaus have a limited impact on the optimal environmental policy. Besides, using only a carbon tax as a policy intervention requires a higher tax level. Lanzi and Wing (2011) empirically examine the impact of energy prices on innovation in the fossil fuel and renewable energy sectors within a two-sector framework, offering a contrast to the theoretical model of Acemoglu et al. (2012). By using real data from OECD countries, their study fills an empirical gap in the literature, measuring the elasticity value and determining how changes in energy prices influence innovation levels between the two sectors. This framework establishes and estimates the relationship between relative energy prices and relative innovation levels between the two sectors. The findings, based on data from 23 OECD countries during the period 1978-2006, indicate that changes in relative energy prices lead to changes in relative innovation levels between fossil and renewable technologies. Additionally, the elasticity of substitution between fossil and renewable sectors is determined to be 1.64. The results suggest an increase in innovation in renewable technologies, while in fossil technologies, innovation initially rises but starts decreasing after reaching a threshold level of relative prices.

Unlike the previous studies, Fried (2018) compares the effects of both endogenous and exogenous innovations on reducing carbon emissions and optimizes the carbon tax level based on these dynamics. Moreover, by considering interactions such as technology spillovers between the green and fossil energy sectors, the paper addresses a gap in the literature by analyzing how these interactions influence the carbon tax. The paper analyzes energy price increases triggered by historical oil shocks, identifying oil shocks as a proxy for climate policy-induced energy price increases, with the early 1970s oil shocks considered historical examples. The analysis sets the elasticity of substitution at 1.5 between green energy, fossil energy, and oil imports. Fried (2018) follows a two-stage approach. First, innovations are treated endogenously, while in the second stage, they are included in the exogenous model. A fixed carbon tax is included between 2015 and 2019. The level of the carbon tax is determined to reduce carbon emissions by 30% relative to the balanced growth value within 20 years (2030-2034). The level of the tax depends on whether innovations are determined as endogenous or exogenous. In the endogenous innovation model, machines, researchers, and workers are part of a dynamic process influenced by the carbon tax. In the exogenous innovation model, the number of researchers remains constant at the baseline balanced growth value while machines and workers respond to the tax. The findings indicate that the carbon tax has a significant impact on reducing emissions in the endogenous model, and the level of the tax required to achieve a 30% reduction in emissions within 20 years would decrease by 19.2%. Fried (2018) also contributes to the relevant literature by accounting for technology spillovers between the green and fossil sectors. The paper assumes that the spillover rate can be between 0.3 and 0.9. The results show that strong spillover rates decrease the changes in relative technologies, thus reducing the impact of endogenous innovations on the size of the carbon tax. However, even at the highest spillover rate of 0.9, endogenous innovations are found to reduce the size of the carbon tax by over 15%.

Haas and Kempa (2018) focus on the effects of energy prices and technological changes on energy intensity, emphasizing sectoral structural changes and within-sector energy efficiency improvements. This study analyzes cross-country energy intensity dynamics by addressing the differences between energy-intensive and labor-intensive sectors. Haas and Kempa (2018) aggregate 32 sectors in 26 Organization for Economic Co-operation and Development (OECD) countries into energy-intensive and labor-intensive sectors, covering the period between 1995 and 2007. The model is calibrated based on 1995 data, and energy intensity and determinant changes are simulated until 2007. Haas and Kempa (2018) calculate the average energy intensity, categorizing sectors with intensity above the average as energy-intensive and those below as labor-intensive. The elasticity of substitution between the two sectors is set at 2. The findings indicate that the larger the increase in energy prices, the more pronounced the decrease in energy intensity. The overall decrease in energy intensity is more significant in countries where technical change is directed towards labor-intensive sectors. In 11 out of the 26 countries, innovation efforts are oriented towards energy-intensive sectors, and therefore, the dynamics of energy intensity are dominated by the efficiency effect.

Hou, Roseta-Palma, and Ramalho (2020) take a different approach from Haas and Kempa by analyzing the factor bias of technological change across countries. Their study shows that technological change typically shifts towards energy use, increasing energy consumption rather than labor. This highlights how technological change affects production factors, focusing more on the broader impact than on direct sectoral dynamics aimed at reducing energy intensity. They conduct an analysis of directed technical change in production activities for 16 developed and developing countries between 1991 and 2014. In the study, a stochastic frontier model was estimated using three inputs: capital, labor, and energy within the production function. The results obtained by calculating the factor bias index show that technological change is mostly directed towards energy. Countries exhibit different bias orders regarding technological change, but overall, technological change tends to be directed towards energy rather than labor.

Hou and Song (2022) focus on optimizing the energy structure, particularly within the context of China. Their study examines the transition from fossil fuels to electricity and from thermal energy to clean energy through the lens of technological change. It explores how technological advancements impact the transformation of the energy structure. The study also highlights that technological change could potentially reverse the desired energy transition, underscoring the need for policies like carbon taxes to counterbalance these effects. Hou and Song (2022) explore the role of directed technical change in improving the energy structure in China. The study suggests that optimizing the energy structure would support the decarbonization process. In this analysis, using a translog production function, three different inputs are considered: thermal power, clean energy, and traditional fossil energy. The study investigates the path of improving the energy structure, specifically substituting fossil energy with electricity and substituting thermal power with clean energy, and then examines whether directed technical change optimizes the energy structure in China. Findings suggest a substitution relationship between thermal power and clean energy during the internal transition process. In the external transition process, technical change is directed towards fossil energy instead of thermal power and clean energy, indicating a substitution relationship among these three inputs. This implies that the effect of technical change operates contrary to the transition of the energy structure from fossil energy to electricity. Therefore, the study suggests that the Chinese government should implement measures such as carbon taxes to eliminate the impact of directed technical change and optimize the energy structure.

The main difference between these three studies lies in their focus and analytical approach to reducing energy intensity: Haas and Kempa concentrate on sectoral structure and efficiency improvements, Hou and Roseta-Palma analyze technological changes in production factors, while Hou and Song focus on policies aimed at transforming the energy structure.

Other approaches explore how directed technological change can contribute to environmental sustainability from various perspectives beyond the energy sector. As a novel approach, Yang et al. (2020) contribute to the directed technical change literature with a distinct application. Their study explores the impact of a directed technical change associated with big data on environmental quality. The findings indicate that as the relative benefits of R&D in clean technology increase, the utilization of big data further enhances environmental quality. Moreover, while the application of big data may diminish incentives for R&D in clean technology to avert environmental disasters, its influence on environmental taxes varies depending on the advancement of clean technology levels. Zhou et al. (2020) investigate the impact of industrial structural rationalization, upgrading, and eco-industrialization processes on energy and environmentally focused technological progress. During the process of industrial structural change, inter-sectoral technical efficiency improvements cause the flow of production factors from low-efficiency sectors to high-efficiency sectors, leading to changes in the economy's composition. To achieve this, a spatial autoregression model is constructed using panel data covering the years 2000-2016 for the 30 provinces of China. The empirical results demonstrate that directed technical change is based on multidimensional industrial structural changes. Particularly at the national level, industrial structural rationalization can incentivize all forms of directed technical change.

Recent research on environmental policies and climate change has been enriched through both theoretical and empirical analyses within the framework of directed technical change models. These studies cover various topics, including the transition to clean technologies, the interplay between energy prices and technological change, sectoral differences, the dynamics of energy intensity, and the environmental impacts of innovations. Starting with Acemoglu et al.'s (2012) foundational model, studies like those by Fried (2018) and Lanzi and Wing (2011) have examined the roles of carbon taxes and innovations. Research by Haas and Kempa (2018) and Hou et al. (2020) has focused on changes in energy intensity and optimizing energy structures, while Yang et al. (2020) have highlighted the environmental impacts of big data usage. Overall, this body of literature provides valuable insights for policymakers by assessing the multifaceted effects of directed technical change on energy transition and sustainability.

To conclude, the environmental model of directed technical change literature, generally links the model to environmental policies based on energy type, price, and efficiency measures. However, we notice that the relevant literature has not adequately explored technology spillovers between clean and dirty technologies or their effects on relative productivity levels and the costs of environmental policies. Therefore, the next section takes an in-depth examination of the relationship between technology spillovers and directed technical change.

1.6. CROSS-INDUSTRY TECHNOLOGY SPILLOVERS

Directed technical change models effectively cover topics like the direction of innovations, energy efficiency, carbon capture technologies, and capital dynamics. However, some key areas remain underexplored, particularly the effects of technology spillovers on sustainability.

Technology spillovers can play a significant role in the transition to clean energy and the fight against climate change in fossil and clean energy production and consumption. Looking at technology spillovers on a knowledge basis, knowledge characterized by the public good property can spread to other individuals, firms, and sectors to some extent, known as knowledge spillovers. Earlier studies addressed technology spillovers and their implications for economic growth (Arrow 1972; Caballero and Jaffe 1993; Jaffe 1986; Romer 1986; Romer 1990). Then, some of the papers investigate the theoretical and empirical foundations of technology spillovers, exploring various aspects such as trade, international investment, competition and productivity growth within the framework of endogenous technological change (Acemoglu 2002; Acemoglu and Akcigit 2012; Aghion and Howitt 1990; Keller 2004; Keller and Yeaple 2009). A large body of literature examines intra-industry and inter-industry technology spillovers from various perspectives and analyzes the dynamics determining them. However, given that this review focuses on directed technical change from an environmental perspective, we limit our coverage in this section to technology spillovers emerging between clean and dirty technologies.

Often, when inventing and developing clean technologies, the knowledge externalities emerging from dirty sectors and technologies are utilized to bring about clean technologies instead of starting from scratch. For instance, as highlighted by Donald (2023), during the development of the first Tesla prototype, engineers redesigned the internal combustion engine by filling it with batteries rather than starting from scratch. As Fried (2018) cited from Perlin (2000), another example of spillovers between clean and dirty technologies is the mass commercialization of solar cells, driven by oil companies demanding energy to power lights on their offshore rigs. On the other hand, clean technologies also potentially provide a form that can facilitate the spread of innovations to different technologies. Dechezlepretre et al. (2013) have demonstrated that innovations emerging in clean energy exhibit a much higher spillover effect and generality compared to dirty energy.

Technology spillovers are often overlooked in research related to environmental policies for transitioning to a low-carbon economy. However, technology spillovers that may arise in clean and dirty energy technologies can significantly combat climate change. Considering spillovers between clean and dirty energy technologies within the directed technical change framework mostly does not draw attention in the existing literature. A rare example of this framework by Fried (2018) considers within and cross-sector innovation spillovers in green and fossil energy types. Fried (2018) differs from Acemoglu et al. (2012) by suggesting that innovations can occur not only within one type of technology or industry but in both sectors involving clean and dirty production. This is made possible through cross-sector technology spillovers. In a setup where the spillover rate ranges between 0.3 and 0.9, Fried (2018) shows that with a strong spillover rate, the differences in relative technology levels between clean and dirty sectors are expected to decrease over time.

As another example, Hemous (2012) offers an extension that considers the possibility of cross-country technology spillovers in a model economy where unilateral environmental policies are implemented in two countries, North and South. The theoretical and numerical findings indicate that in the presence of knowledge spillovers or international innovative firms, a transition to clean innovation in the South can be achieved with policies in the North, thereby preventing a disaster without the South needing to specialize in the non-polluting sector.

Studies examining the spillover of different types of energy technologies are often analyzed through data related to patents (citations) developed on these technologies rather than relying on numerical analyses. Because the more citations a patent receives, the more the technology is diffused. From this perspective, Dechezlepretre et al. (2013) employ patent citation data to show the relative intensity of knowledge spillovers in clean and dirty technologies considering energy production, automobiles, fuel and lighting. The paper strongly implies the relative advantage of clean patents in all four technologies and explains this superiority by the two properties of clean technologies, namely, generalizability and being a new area for innovation compared to dirty technologies. Similarly, in the analysis conducted by Ocampo-Corrales et al. (2020) based on patent data for European regions, it has been found that clean energy technologies have a greater scientific foundation compared to other technologies. Additionally, the study highlights that they significantly benefit from scientific and technological knowledge flows from distant places. The research emphasizes that this case is specific to clean technologies and distinguishes them from other cutting-edge technologies and technologies related to energy generation from traditional energy sectors.

In the analysis conducted by Jee and Srivastav (2022) using patent citation data, it is suggested that the majority of clean technologies do not receive direct knowledge flow from dirty technologies but are indirectly connected. It has been proposed that, although to a lesser extent, areas such as geothermal energy, clean metals, and carbon capture and storage are more susceptible to technological spillovers than dirty technologies. Fernandez et al. (2022) conducted a regression analysis to examine the determining factors of patented knowledge diffusion between renewable energy technologies and other energy patents (such as fossil and nuclear patents) carried out by firms. Firstly, the findings indicate that patents making more references to the literature and previous patents achieve greater diffusion. On the other hand, joint patents with other firms or universities have a negligible impact on renewable energy technology. Another notable finding of the study is that the collaboration between firms and universities in patents related to other forms of energy hinders the diffusion of innovations.

The overall literature suggests that technology spillovers between clean and dirty technologies support the progress of clean technologies and that clean technologies benefit more from spillovers compared to dirty ones.

1.7. CHAPTER SUMMARY

In this paper, we review the growing literature on the environment and directed technical change, placing particular emphasis on cross-sector technology spillovers. The foundational theory of directed technical change asserts that technological advancements are not neutral and are likely to be directed toward specific production factors due to the effects of price and market size. The environmental implications of this theory provide practical insights into addressing challenges such as climate change.

Acemoglu et al. (2012) extend the earlier directed technical change framework by incorporating environmental policy and innovations, presenting several noteworthy implications. These include (i) the possibility of achieving sustainable growth through the implementation of temporary policies (a combination of a carbon tax and research subsidy) with a sufficient substitution rate between clean and dirty technologies, (ii) the facilitation of a shift to clean innovation when using exhaustible resources in dirty input production, and (iii) in contrast to models with exogenous technology, a more optimistic scenario is portrayed, but with a call for immediate and decisive action.

In this review, we ask two pivotal questions concerning the environmental model of directed technical change. First, does empirical literature align with the theoretical conclusions of the model? Second, how do cross-sector technology spillovers, which are not considered in the baseline environmental model of directed technical change, impact the direction of innovations during the transition to a low-carbon economy? The overall sense from the empirical literature suggests that directed innovations in clean technologies respond to environmental policy and generally link the directed technical change model to environmental policy based on energy type, energy price, and energy efficiency measures. Relevant literature on technology spillovers emphasizes the crucial role of technology spillovers in advancing clean energy and combating climate change. It discusses instances where knowledge from dirty sectors contributes to clean technology development and vice versa. Overall, technology spillovers between clean and dirty technologies support the progress of clean technologies and those clean technologies benefit more from spillovers compared to dirty ones. However, we observe that the impact of technology spillovers on the productivity levels of clean and dirty technologies, and their sensitivity to changes in fossil energy costs, have not been sufficiently addressed in the existing literature on directed technical change.

There are several points that need to be considered by future research. For instance, there is a need for further quantitative and empirical analyses to develop an understanding of the environmental effects that may arise from integrating cross-sector and cross-country technology spillovers with directed technical change. Furthermore, since there is no consensus on whether there is a substitution or complementary relationship between clean and dirty technologies, obtaining more empirical evidence on this matter could be beneficial.

CHAPTER 2

GREENING THE ECONOMY WITH FOSSIL ENERGY COSTS AND INNOVATION SPILLOVERS: INSIGHTS FROM A DIRECTED TECHNICAL CHANGE MODEL

2.1. INTRODUCTION

The costs associated with fossil energy usage hold an essential role in economic activities, simultaneously emerging as one of the paramount issues in recent times due to their pivotal connection with climate change. The dependence on fossil energy resources deepens the devastating effects of climate change, and thus, preventing global warming has become quite a challenging issue. Despite numerous joint actions and efforts, the share of renewable energy in the total final energy consumption remains at significantly low levels (19.1% in 2020) (UNSD, 2023). The dimensions of climate change and the predictions about the near future have started to be perceived as catastrophic beyond a serious warning.

Different policy proposals have been developed for many years to prevent climate change. In particular, the environmental policy and climate change literature widely discusses policy tools such as taxing greenhouse gas emissions under the carbon tax, switching to renewable and environmentally friendly energy sources, and the ETS. In recent years, economic research has drawn attention to that, arguing technological change can contribute to the fight against climate change in terms of environmental policy. These studies predominantly employ general equilibrium models, grounded in the framework of directed technological change within economies that include multiple intermediate inputs. This approach is based on endogenous growth theory, particularly the concept of induced technical change. In the seminal papers of Romer (1986) and Lucas (1988), knowledge accumulation is identified as a key driver of economic growth, with increasing returns to scale in production processes serving as a core assumption of endogenous growth theory. Unlike Solow models with exogenous technological change, this framework defines technological change as endogenous, driven by agents' efforts to accumulate knowledge and maximize profits (Romer, 1986; Lucas, 1988). Additionally, the concept of induced technical change suggests that technological progress responds to economic conditions and market signals. Based on this foundation, directed technological change allows us to examine which factors will allocate scientific research between industries producing intermediate inputs with different characteristics in the modelling where innovation has an endogenous dynamic. Therefore, such models help us understand the role of innovation in the transition to a low-carbon economy.

Modelling directed technology toward climate change dating back to pioneering study of Acemoglu et al. (2012) titled “The Environment and Directed Technical Change”. Based on the seminal papers on directed technical change in 1998 and 2002, Acemoglu et al. (2012) presented the environmental model of directed technological change. The model considers endogenous innovation and examines how innovations can be distributed among intermediate industries with different characteristics (Acemoglu, 1998; Acemoglu, 2002, Acemoglu et al., 2012). The paper focuses on a general equilibrium model with intermediate inputs: dirty and clean. While dirty input production causes a negative environmental externality by using dirty machines, clean input production has no negative effect. The unique final good is produced by combining these two inputs. Acemoglu et al. (2012) suggest that using carbon tax and research subsidies can be optimal environmental response tools to drive technological development and avoid environmental disasters. Moreover, when clean technologies are sufficiently developed, there will be no need for further intervention as research will be directed toward this intermediate industry. The study seeks to answer how innovations directed at different inputs will respond to environmental policies. Findings show that urgent definitive measures such as Nordhaus (2002) and Stern (2009) are necessary to avoid environmental catastrophe because of the advantage of the market size effect and initial productivity in the dirty technologies (Nordhaus, 2010; Stern, 2009).

An extension of the environmental model of directed technical change by Haas and Kempa (2018) explores heterogeneous energy intensity dynamics. They consider energy-intensive and labor-intensive intermediate inputs instead of dirty and clean ones (Haas and Kempa, 2018). Acemoglu et al. (2012) model the energy price as a function of the resource stock since they analyze how the depletion of an exhaustible resource might induce a redirection of technical change towards a clean input production due to continuously increasing prices. Haas and Kempa (2016) use an exogenous price for energy and endogenous energy use, as their focus is the analysis of energy intensity dynamics in alternative (historical) scenarios with different energy price growth rates. Then, they analytically decompose energy intensity into a sector and an efficiency effect. The relative importance of these effects is determined by energy price growth and relative sector productivity, which drive the direction of research.

Considering both endogenous innovation and following the seminal paper of Acemoglu et al. (2012), various modelling approaches have been employed in the literature. Previously, Gerlagh (2008) demonstrates that induced technological change resulted in a shift from knowledge accumulation in energy production to energy savings. Acemoglu et al. (2016) revisit the approach used in their earlier research, applying it to firm-level data in the US energy sector.

While they emphasize the theoretical foundation of combining carbon taxes with research subsidies, their findings suggest that the optimal policy relies more heavily on research subsidies. Fried (2018) constructed a general equilibrium model incorporating endogenous innovation in fossil, green, and non-energy inputs. By considering cross-sector technology spillovers and historical oil shock data, the author illustrates that a carbon tax stimulates innovation in green technologies. Durmaz and Schroyen (2020) expand the environmental model of directed technical change by introducing a third intermediate sector, Carbon Capture and Storage. The study addresses the Pareto-efficient policy allocation of resources and suggests that, based on the estimates of the marginal cost of carbon capture and storage, the renewable energy regime dominates the fossil energy regime. Another extension of the environmental model of directed technical change, developed by Pesenti (2022), introduces a third intermediate good responsible for adaptation. The author investigates the existence of innovation in all three input technologies, but the model does not yield an interior balanced growth path where innovation occurs in all three technologies.

In this paper, we aim to examine how (relative) past productivity and fossil energy costs interact with allocating research across dirty and clean intermediate industries in the presence of cross-industry technological spillovers. Moreover, we question whether fossil energy costs could shift innovation efforts by limiting the relative past productivity. Our theoretical approach is in the spirit of Acemoglu et al. (2012) and Haas and Kempa (2016), but we contribute to the directed technical change literature differently. Building on Acemoglu et al. (2012), the model features a production function with two inputs: a clean input, which relies on renewable resources and causes no environmental pollution, and a dirty input, which uses fossil fuels and generates pollution. However, following Haas and Kempa (2016), this study uses exogenous energy price and endogenous energy use since we focus on the effect of relative productivity levels and technology spillovers on the direction of technical change in energy technologies. Our model features clean and dirty input production, with fossil energy use in the dirty intermediate good production.

The common feature of the models presented by Acemoglu et al. (2012) and Haas and Kempa (2018) is the oversight of technological spillovers between intermediate industries, assuming that technological spillovers are equal to zero. However, as highlighted by Fried (2018), empirical findings, especially those derived from the US, indicate that clean and dirty innovations have co-occurred positively since 1970. Indeed, Fried's (2018) simulated model demonstrates that a stronger cross-sector spillover rate reduces the productivity gap between clean and dirty technologies. Therefore, following Fried (2018), this study considers the potential existence of technological spillovers among intermediate industries producing clean and dirty inputs. Through technological spillovers, innovation emerging in one input technology can enhance the productivity level of another.

The rest of the paper is organized as follows: Section 2.2 defines the model economy. In this section, we define the environment, preferences, technologies, market structures, decision problems and market clearing conditions. Section 2.3 characterizes the decentralized equilibrium and presents the main results of the model. Section 2.4 concludes.

2.2. MODEL ECONOMY

This section builds a general equilibrium model with endogenous technological change. The following subsections introduce the model environment, production technologies and define the market structures. Then we write the decision problems and market clearing conditions.

2.2.1. Environment

We consider an infinite-horizon discrete time economy denoted by $t \in \{0,1,\ldots\}$.

2.2.1.1. Demographic Structure

The model economy is inhabited by a continuum of households, including workers, scientists, final good producer, intermediate input producers and machine producers. There is a fixed mass of workers $(L > 0)$ employed in the intermediate input production and a fixed mass of scientists $(S > 0)$ hired by machine producers. Technological change emerges through the productivity-enhancing innovations created by scientists who decide in which intermediate industry they will conduct research.[8]

2.2.1.2. Endowments

Workers

Workers supply labor to the intermediate input industries. Intermediate industries employ workers to operate their clean and dirty input production. Workers in this context are assumed to be homogeneous and mobile across industries, ensuring competitive wages.

Scientists

Scientists are responsible for innovation, focusing on enhancing the productivity of industry-specific machines. The allocation of scientists between the clean and

[8] We use “industry” term instead of formerly used “sector”. Intermediate input produced using machines powered by clean energy is produced in the clean industry, while one relying on fossil energy is produced in the dirty industry.

dirty industries is endogenous and influenced by factors such as relative wages, productivity levels, and spillover effects. The total mass of scientists can move freely between industries.

Energy

The model includes two types of energy resources, each associated with a specific intermediate input industry:

Fossil Energy

Fossil energy resources are used explicitly in the production of the dirty intermediate input. This resource is treated a costly input, with their utilization contributing to negative environmental externality. The cost of fossil energy is exogenous and plays a role in determining the direction of innovation and the relative productivity of industries.

Renewable Energy

Renewable resources, such as solar and wind, are used in the production of the clean intermediate input. These resources are freely available and do not incur any explicit cost. Unlike fossil energy, renewable resources are characterized by their environmental neutrality, making them a critical component of the clean industry's production process.

2.2.2. Preferences

A representative household maximizes utility by consuming the final good; the utility function is:

$$U(C_t) = \frac{C_t^{1-\sigma}}{(1-\sigma)} \tag{2.1}$$

where C_t is the household's consumption at time t, and $1/\sigma$ denotes the inter-temporal elasticity of substitution. The budget constraint is:

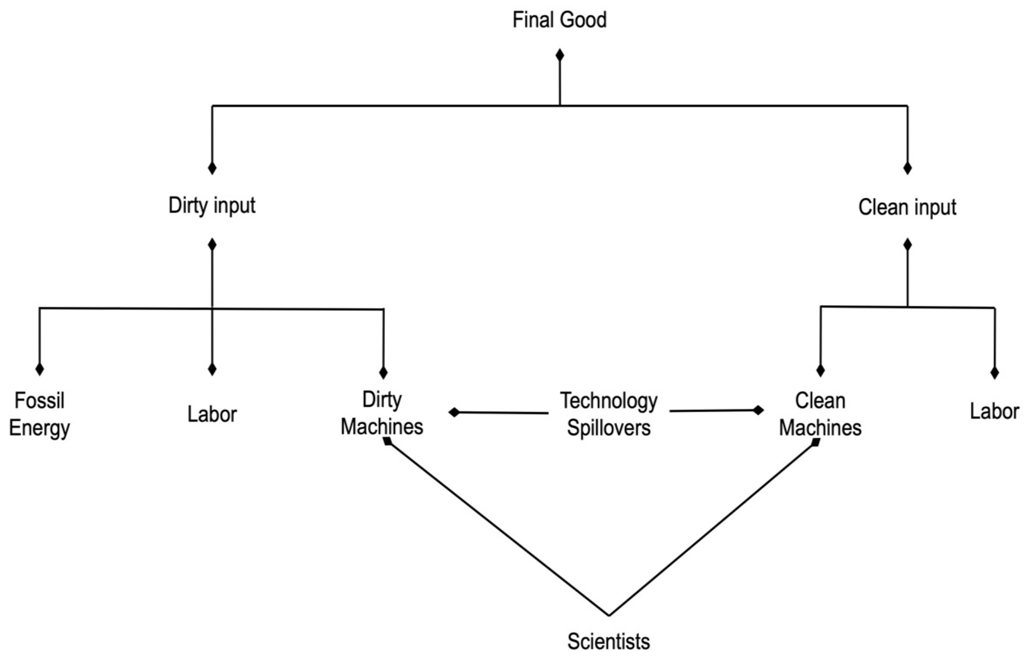
$$C_t = w_t^L L_{dt} + w_t^L L_{ct} + w_t^S S_{dt} + w_t^S S_{ct} + \int_0^1 (\pi_{dit} + \pi_{cit}) di \qquad (2.2)$$

where w_t^L denotes the wages of workers, and, w_t^S denotes the wages of scientists in dirty and clean intermediate input industries, while $(\pi_{dit} + \pi_{cit})$ represents the total profits of machine producers in both intermediate input industries. The representative household does not save, so it consumes all its income and earns from the wages of workers and scientists and the profits of machine producers.

2.2.3. Technologies

Our model is a modified version of the environmental model of directed technical change proposed by Acemoglu et al. (2012). But we incorporate numerous features from Acemoglu et al. (2012), Haas and Kempa (2018), and Fried (2018) during the modelling process. However, the most distinctive characteristics that make this paper unique involve investigating how productivity-enhancing research will be distributed across intermediate industries when considering endogenously determined energy usage, an exogenous fossil energy cost, and the possibility of technology spillovers between the two intermediate input technologies. Figure 1 displays the nested tree structure for the production side of the economy.

Figure 1 Nested Production Structure



2.2.3.1. Final Good Production

The final good Y, is produced competitively using dirty, Y_d and clean, Y_c, intermediate inputs. The production of dirty input, derived from fossil energy resources, leads to negative externalities. In contrast, clean input sourced from renewable resources is characterized by the absence of adverse environmental effects. According to the CES production function:

$$Y_t = \left(Y_{ct}^{\varepsilon-1/\varepsilon} + Y_{dt}^{\varepsilon-1/\varepsilon}\right)^{\varepsilon/\varepsilon-1} \qquad (2.3)$$

where ε is the elasticity of substitution between dirty and clean inputs. Accordingly, $\varepsilon > 1$ when the two inputs are (gross) substitutes, $\varepsilon < 1$ means two inputs are (gross) complements and $\varepsilon = 1$ refers the Cobb-Douglas case. Throughout the paper, we assume that the two inputs are (gross) substitutes ($\varepsilon > 1$).

2.2.3.2. Intermediate Input Production

The two intermediate industries under consideration are the dirty, which utilizes fossil energy resources and produces environmentally harmful input with high emissions, and the clean, which represents the industry producing inputs using renewable energy sources with negligible emissions.

The two intermediate inputs, Y_c and Y_d which are indexed by $j \in (c, d)$ are produced competitively and purchased by a final good producer at market prices. Each intermediate production function includes labor, L_{jt}, and a continuum of industry-specific machines, x_{jit}, where i indicates industry-specific machine type. The intermediate production functions are as follows:

$$Y_{ct} = L_{ct}^{1-\alpha} \int_0^1 A_{cit}^{1-\alpha}\, x_{cit}^{\alpha} di \tag{2.4}$$

$$Y_{dt} = E_{dt}^{\alpha_2} L_{dt}^{1-\alpha} \int_0^1 A_{dit}^{1-\alpha_1}\, x_{dit}^{\alpha_1} di \tag{2.5}$$

where $\alpha = \alpha_1 + \alpha_2$, and $\alpha, \alpha_1, \alpha_2 \in (0,1)$, A_{jit} is the quality of machine of type i at time t, and x_{jit} is the quantity of this machine. A profit-maximizing intermediate input producer chooses labor and machines by taking prices as given. In this production technology, dirty input uses fossil energy resource, E_{dt}. However, we assume that clean input does not include a clean energy resource in production explicitly since renewable resources such as solar and wind are freely available for human use.[9]

2.2.3.3. Machines

Each intermediate industry has a uniform group of machine producers, each manufacturing specific machines at a constant cost of ψ_c and ψ_d unit of the final good in clean and dirty industries, respectively. In other words, supplying one unit of clean type of machine costs ψ_c units of the final good and dirty type of machines costs ψ_d units of the final good. These machines are subsequently sold to producers of intermediate goods.

In every period, machine producers enlist the services of scientists to enhance the productivity of machines within their industry, reflected as A_{jit} growth through innovation. This endogenous innovation leads to progressive technology enhancement, primarily focusing on the technology infused within the machines employed for intermediate input production. We assume that machine producers within an industry act symmetrically.

[9] An example is photovoltaic solar panels, which directly convert sunlight into electricity. Recent research on solar energy, has introduced new solutions for achieving high temperatures above 1000°C using solar power. It is emphasized that semi-transparent materials (e.g., quartz) effectively capture infrared (IR) radiation by absorbing solar radiation. Consequently, higher temperatures can be achieved inside the material than on its surface (Thermal trapping effect). This type of technology is considered to make decarbonization possible in industrial processes requiring high temperatures, such as cement production and metallurgical extraction (Casati et al., 2024).

2.2.3.4. Innovation

In our model, innovation arises from the efforts of scientists working on industry-specific machines. Successful innovations lead to improvements in machine quality and productivity enhancements. Consequently, endogenous innovation drives a productivity-enhancing process of creative accumulation. We define the average productivity in intermediate industry *j*;

$$A_{jt} = \int_0^1 A_{jit}\, di \tag{2.6}$$

The technological progression for machine producers for machine type i within every industry *j* evolves according to the following law of motion:

$$A_{jit} = A_{jt-1}\left(1 + \lambda S_{jit}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right) \tag{2.7}$$

The parameter λ signifies the success of scientists in generating innovation and remains consistently positive. Here, S_{jit} is the mass of scientists working on machines in industry j at time t. We assume that innovation effort is active in all industries implying that $S_{cit} > 0$ and $S_{dit} > 0$ for all i and all t. Then, η characterizes the transformation of research yields as the scientist count rises. A value of η between 0 and 1 implies diminishing returns for scientific research within a single period, reflecting the concept termed the “stepping on toes effect” in endogenous innovation literature (Greaker et al., 2018). This effect highlights that having more scientists in the same industry increases the likelihood of replicating a discovery, with innovation being productive only when it unveils something novel. If η equals one, constant returns to research are present, and if it surpasses one, increasing returns occur. In this analysis, we will assume diminishing returns to research, hence η lies within the range of 0 and 1. A_{jt-1} and A_{t-1} represent the average quality of machines in industry *j* and the overall productivity level at time $t-1$ respectively.

The parameter ϕ quantifies the degree of innovation spillovers between intermediate industries. The range of ϕ spans from zero to one, where $\phi = 0$ signifies the absence of spillovers. The ratio $\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}$ is termed the total factor productivity (TFP) catch-up ratio, characterizing the influence of cross-industry spillovers on an industry's productivity. This ratio reflects the intuitive notion that intermediate industries that lag behind others tend to gain more from spillovers. In other words, the higher the ratio, the less productive an industry has been historically compared to the average, implying greater potential for benefiting from spillovers.

2.2.4. Market Structures

This economy is characterized by several forms of trade. First, households consume/buy the final good sold by the final good producer and this final good is the numeraire of this economy. Second, intermediate input producers sell clean and dirty inputs Y_{jt} at the price P_{jt} in a competitive market and the final good producer is the buyer here. Third, machine producers sell industry-specific machines, x_{jit}, at the price P_{jit} in a monopolistically competitive market and intermediate input producers are the buyers now. Last, workers and scientists sell their labor at the wages w_t^L and w_t^S in competitive markets, respectively. Intermediate input producers and machine producers are the buyers in the worker and scientist markets, respectively.

The market for the final good is perfectly competitive. The final good producer purchases intermediate clean ($\boldsymbol{Y_c}$) and dirty ($\boldsymbol{Y_d}$) inputs at market prices. The two intermediate inputs, $\boldsymbol{Y_c}$ and $\boldsymbol{Y_d}$ are also produced competitively in clean and dirty industries, respectively.

Clean and dirty machines are produced by industry-specific machine producers and sold to the intermediate input producers. Machine producers operate under a monopolistically competitive market and hold the power to set prices, resulting in profits from machine sales, following Acemoglu et al. (2012). The technology of industry-specific machines at any given time depends on the past knowledge level within the industry and the innovation efforts of employed scientists. As described in Fried (2018), innovations in industry-specific machines grant the machine producer an exclusive one-period patent. After this patent expires, other machine producers can access and incorporate the technological advancements that were previously protected.

The job market for scientists is competitive, requiring market wage payment, w_t^S. The market for workers is also competitive. Scientists and workers freely move across clean and dirty industries.

2.2.5. Decision Problems

This section introduces the decision problems of the agents in the economy. These are the problems of the household, the representative final good producer, intermediate input producer, industry-specific machine producer, and scientists.

2.2.5.1. Final Good Producer’s Problem

The cost minimization problem of the representative final good producer is:

$$\min_{Y_{ct},Y_{dt}} \quad P_{ct}Y_{ct} + P_{dt}Y_{dt} \tag{2.8}$$

subject to the final good production technology in (2.3). Solving for the competitively produced final good producer's maximization problem and using (A.2.2) and (A.2.3), the relative production and price of the two inputs are as follows:

$$\frac{Y_{ct}}{Y_{dt}} = \left(\frac{P_{dt}}{P_{ct}}\right)^{\varepsilon} \quad , \quad \frac{P_{ct}}{P_{dt}} = \left(\frac{Y_{ct}}{Y_{dt}}\right)^{-\frac{1}{\varepsilon}}. \tag{2.9}$$

This equation shows that there is an inverse relationship between the relative prices and relative supplies. Defining that $P_{ct}Y_{ct} + P_{dt}Y_{dt} = P_tY_t$, where P_t is the price index, we normalize the final good as numeraire for all *t* and the price index is as follows:

$$(P_{ct}^{1-\varepsilon} + P_{dt}^{1-\varepsilon})^{\frac{1}{1-\varepsilon}} = 1 \tag{2.10}$$

2.2.5.2. Intermediate Input Producers' Problem

Intermediate input producers maximize their profits by deciding the quantity of labor, industry-specific machines, and fossil energy demand (in dirty industry). Since clean input production does not use fossil energy resources in the production process, we have to solve the maximization problems in each industry separately.

Clean Industry

The maximization problem of a representative input producer in clean input production can be written as follows:

$$\max_{L_{ct},x_{cit}} \Pi_{Y_c} = P_{ct}L_{ct}^{1-\alpha}\int_0^1 A_{cit}^{1-\alpha}\, x_{cit}^{\alpha} di - w_t^L L_{ct} - \int_0^1 P_{cit}\, x_{cit} di. \tag{2.11}$$

Using the first order conditions with respect to the quantity of labor demand, labor demand in the clean industry can be expressed as: (see (A.2.5) and (A.2.6)).

$$L_{ct} = \left[\frac{(1-\alpha)P_{ct}}{w_t^L}\int_0^1 A_{cit}^{1-\alpha}\, x_{cit}^{\alpha} di\right]^{\frac{1}{\alpha}}. \tag{2.12}$$

Then solving for machine demand in clean industry according to (A.2.7) yields:

$$x_{cit} = \left(\frac{\alpha P_{ct}}{P_{cit}}\right)^{\frac{1}{1-\alpha}} L_{ct}A_{cit}. \tag{2.13}$$

Dirty Industry

The maximization problem of a representative input producer in dirty industry can be written as follows:

$$\max_{L_{dt},x_{dit},E_t} \Pi_{Y_d} = P_{dt}E_t^{\alpha_2}L_{dt}^{1-\alpha}\int_0^1 A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1}\, di - w_t^L L_{dt} - \int_0^1 P_{dit}\, x_{dit} di - c_{Et}E_{dt}. \tag{2.14}$$

The user cost of fossil energy is given by c_{Et}. Using the first order condition with respect to the quantity of machines in dirty industry (A.2.11), the machine demand in dirty industry can be written as:

$$x_{dit} = \left(\frac{\alpha_1 P_{dt} E_{dt}^{\alpha_2} L_{dt}^{1-\alpha}}{P_{dit}}\right)^{\frac{1}{1-\alpha_1}} A_{dit}. \tag{2.15}$$

Then first order conditions for quantity of labor demand (A.2.9) and (A.2.12) gives the labor demand:

$$L_{dt} = \left(\frac{w_t^L}{(1-\alpha) P_{dt} E_{dt}^{\alpha_2} A_{dit}^{1-\alpha_1} x_{dit}^{\alpha_1}}\right)^{-\frac{1}{\alpha}}. \tag{2.16}$$

From the first order condition (A.2.13), the fossil energy demand can be written as:

$$E_{dt} = \left(\frac{c_{Et}}{\alpha_2 P_{dt} L_{dt}^{1-\alpha} A_{dit}^{1-\alpha_1} x_{dit}^{\alpha_1}}\right)^{\frac{1}{\alpha_2 - 1}}. \tag{2.17}$$

2.2.5.3. Machine Producers’ Problem

The machine market operates under monopolistic competition, granting producers some market power to determine both the quantity and price of the machines they offer for sale. Now, we solve the maximization problem of a representative machine producer problem for both intermediate inputs.

Clean Industry

The monopolist producer of machine i in industry c chooses first x_{cit} and then S_{cit} to maximize profits $\Pi_{cit} = P_{cit}x_{cit} - \psi_c x_{cit}$, subject to inverse demand curve and then the evolution of technology, respectively.

The maximization problem of a representative machine producer in clean industry can be written as:

$$\max_{x_{cit}} P_{ct} L_{ct}^{1-\alpha} \alpha A_{cit}^{1-\alpha} x_{cit}^{\alpha} - \psi_c x_{cit} \tag{2.18}$$

subject to the demand for machines in clean industry. The first order condition for clean machine quantity implies that profit maximizing machine price P_{cit} is a constant mark up over marginal cost, thus $P_{cit} = \frac{\psi_c}{\alpha}$. Then assuming that $\psi_c = \alpha^2$ as in Acemoglu et al. (2012), which leads to $P_{cit} = \alpha$, then the equilibrium machine demand in clean industry in (2.13) will be:

$$x_{cit} = P_{ct}^{\frac{1}{1-\alpha}} L_{ct} A_{cit} \tag{2.19}$$

Using the definition of demand for machines x_{cit}, equilibrium price for machines P_{cit} and technological change A_{cit}, the maximization problem of the machines producer problem in clean industry subject to the choice of the number of scientists can be expressed as:

$$\max_{S_{cit}} \left(\Pi_{cit} = \alpha(1-\alpha) P_{ct}^{\frac{1}{1-\alpha}} L_{ct} A_{ct-1} \left(1 + \lambda S_{cit}^{\eta} \left(\frac{A_{t-1}}{A_{ct-1}} \right)^{\phi} \right) - w_t^S S_{cit} \right) \tag{2.20}$$

The first order conditions of the maximization problem relative to choice of the number of scientists is given in (A.2.14). Finally, we remove the machine index in the last equation of (A.2.14) yields:

$$w_t^S = \frac{\alpha(1-\alpha)\eta\lambda(A_{ct-1})^{1-\phi}(A_{t-1})^{\phi}x_{ct}}{S_{ct}^{1-\eta}A_{ct}} \tag{2.21}$$

Dirty Industry

The monopolist producer of machine i in industry *d* chooses first x_{dit} and then S_{dit} to maximize profits $\Pi_{dit} = P_{dit}x_{dit} - \psi_d x_{dit}$, subject to inverse demand curve and then the evolution of technology. The maximization problem of a representative machine producer in dirty industry can be written as:

$$\max_{x_{dit}} P_{dt}L_{dt}^{1-\alpha}E_{dt}^{\alpha_2}\alpha_1 A_{dit}^{1-\alpha_1}\, x_{dit}^{\alpha_1} - \psi_d x_{dit} \tag{2.22}$$

subject to the demand for machines in dirty industry. The first order condition for dirty machine quantity implies that profit maximizing machine price P_{dit} is a constant mark up over marginal cost, thus $P_{dit} = \frac{\psi_d}{\alpha_1}$. Assuming that $\psi_d = \alpha_1^2$ as in Acemoglu et al. (2012), which leads to $P_{dit} = \alpha_1$, then the equilibrium machine demand in dirty industry in (2.15) will be:

$$x_{dit} = \left(P_{dt}E_{dt}^{\alpha_2}L_{dt}^{1-\alpha}\right)^{\frac{1}{1-\alpha_1}}A_{dit} \tag{2.23}$$

Using the definition of demand for machines x_{dit}, equilibrium price for machines P_{dit} and technological change A_{dit}, the maximization problem of the machines producer problem in dirty industry subject to the choice of the number of scientists can be expressed as:

$$\max_{S_{dit}}\left(\Pi_{dit}=\alpha_1(1-\alpha_1)\left(P_{dt}E_{dt}^{\alpha_2}L_{dt}^{1-\alpha}\right)^{\frac{1}{1-\alpha_1}}A_{dt-1}\left(1+\lambda S_{dit}^{\eta}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi}\right)-w_t^S S_{dit}\right) \quad (2.24)$$

The first order conditions of the maximization problem relative to choice of the number of scientists is given in (A.2.15). Finally, we remove the machine index in the last equation of (A.2.15) yields:

$$w_t^S=\frac{\alpha_1(1-\alpha_1)\eta\lambda(A_{dt-1})^{1-\phi}(A_{t-1})^{\phi}x_{dt}}{S_{dt}^{1-\eta}A_{dt}} \quad (2.25)$$

2.2.5.4. Scientist's Problem

Scientists are typically faced with an optimization problem in a market where free mobility is possible, choosing the industry that offers them the highest wage. In this scenario, the industry offering the highest wage will continuously attract innovations to itself. However, as observed in Acemoglu et al. (2012), this case is valid when there is no innovation spillover ($\phi=0$). In this paper, assuming innovation spillovers between intermediate industries, we consider that innovation can occur in both forms of input, resulting in scientists naturally receiving equal wages in both industries. However, this case is closely related to the extent of innovation spillovers. In cases where the spillover is sufficiently high, the past productivity advantage will weaken, allowing innovations to emerge in both industries. In the absence of a sufficient level of innovation spillover, the past productivity effect will guide innovations in favor of the advanced industry in terms of industrial productivity.

2.2.6. Market Clearing Conditions

In this section, we define the market clearing conditions for the model economy. First, market clearing for the unique final good is:

$$Y_t = C_t + \left(\psi_c \int_0^1 x_{cit} di + \psi_d \int_0^1 x_{dit}\, di \right) + c_{Et} E_{dt}. \tag{2.26}$$

Second, market clearing for labor requires:

$$L_{dt} + L_{ct} \leq L \tag{2.27}$$

where the L.H.S. denotes the total demand of workers and the R.H.S. denotes the fixed exogenous supply of workers.

Last, market clearing for scientists requires:

$$S_{dt} + S_{ct} \leq S \tag{2.28}$$

where the L.H.S. is the total demand of scientists and the R.H.S. is the fixed exogenous supply of scientists.

2.3. EQUILIBRIUM

This section derives the equilibrium conditions for all the variables. In this economy, there is no policy intervention, so that will characterize the laissez-faire equilibrium.

We define the equilibrium as a sequence of wages w_t^L, w_t^S, prices for intermediate inputs (P_{jt}) and machines (P_{jit}), intermediate output (Y_{jt}), demands for machines (x_{jit}), labor (L_{jt}), scientists (S_{jt}), the exogenous energy price (c_{Et}), and fossil energy demand (E_{dt}) such that in each period:

- S_{jit}, P_{jit} and x_{jit} maximizes profits of i-type machine producer in industry $j \in (c, d)$.
- Y_{jt} maximizes profits of final good producers.
- L_{dt}, E_{dt} maximizes profits of the dirty input producers and L_{ct} maximizes profits of clean input producers.
- Prices for intermediate inputs (P_{jt}), prices of machines (P_{jit}), and wages ($\mathrm{w}_\mathrm{t}^L, \mathrm{w}_\mathrm{t}^\mathrm{S}$) clear the markets for intermediate inputs, machines and the two types of labor respectively.

2.3.1. Equilibrium Allocations

In this section, we present the equilibrium allocation of fossil energy demand, labor and scientist by considering the solved maximization problems. To make this possible, we rewrite the equations regarding intermediate production functions and fossil energy demand.

Substituting equilibrium demand (2.19) in the clean input production (2.4) yields that:

$$Y_{ct} = L_{ct} A_{ct} P_{ct}^{\frac{\alpha}{1-\alpha}} \tag{2.29}$$

Substituting equilibrium demand (2.23) in the dirty input production (2.5) yields that:

$$Y_{dt} = E_{dt}^{\frac{\alpha_2}{1-\alpha_1}} L_{dt}^{\frac{1-\alpha}{1-\alpha_1}} A_{dit} P_{dt}^{\frac{\alpha_1}{1-\alpha_1}} \tag{2.30}$$

Then, solving for equilibrium energy input demand by substituting machine demand (2.23) in (2.17) yields:

$$E_{dt} = \left(\frac{\alpha_2 A_{dt}}{c_{Et}}\right)^{\frac{1-\alpha_1}{1-\alpha}} L_{dt} P_{dt}^{\frac{1}{1-\alpha}} \tag{2.31}$$

Then, plugging (2.31) into (2.30) gives the equilibrium dirty input production as follows:

$$Y_{dt} = \left(\frac{\alpha_2 A_{dt}}{c_{Et}}\right)^{\frac{\alpha_2}{1-\alpha}} P_{dt}^{\frac{\alpha}{1-\alpha}} L_{dt} A_{dt} \tag{2.32}$$

The equation suggests an inverse relationship between the production of dirty inputs and the cost of fossil energy. In other words, rising fossil energy costs could discourage the production of these inputs. However, the equation also indicates that when industrial productivity reaches a sufficiently high level, the impact of fossil energy costs may become negligible for producers of intermediate inputs.

We also substitute the energy input demand (2.31) in machine demand in the dirty industry (2.23) to get a simpler form:

$$x_{dit} = \left(\frac{\alpha_2^{\alpha_2} P_{dt}}{c_{Et}^{\alpha^2}}\right)^{\frac{1}{1-\alpha}} A_{dit} L_{dt} \tag{2.33}$$

Now turning to the wage for labor, substituting equilibrium machine demand in clean industry into the (A.2.6) yields:

$$w_t^L = (1-\alpha) P_{ct}^{\frac{1}{1-\alpha}} A_{ct} \tag{2.34}$$

Substituting equilibrium machine demand in dirty industry (2.23) into the (A.2.9) yields:

$$w_t^L = (1-\alpha) P_{dt}^{\frac{1}{1-\alpha_1}} E_{dt}^{\frac{\alpha_2}{1-\alpha_1}} L_{dt}^{-\frac{\alpha_2}{1-\alpha_1}} A_{dt} \tag{2.35}$$

Labor market is perfectly competitive and we assume that there is a free movement between the two industries. Thus, clean and dirty industries have identical wages in equilibrium. Then, setting the labor wages ratio and combining with (2.31) gives the relative prices and productivities as follows:

$$\frac{P_{ct}}{P_{dt}} = \frac{\alpha_2^{\alpha_2}}{c_E^{\alpha_2}} \frac{A_{dt}^{1-\alpha_1}}{A_{ct}^{1-\alpha}} \tag{2.36}$$

Setting the relative supply of dirty input (2.32), and clean input (2.29) gives the ratio:

$$\frac{Y_{ct}}{Y_{dt}} = \left(\frac{c_E}{\alpha_2 A_{dt}}\right)^{\frac{\alpha_2}{1-\alpha}} \frac{L_{ct}}{L_{dt}} \frac{A_{ct}}{A_{dt}} \left(\frac{P_{ct}}{P_{dt}}\right)^{\frac{\alpha}{1-\alpha}} \tag{2.37}$$

Substituting equation (2.9) and (2.36) in the above equation and defining that $\varphi \equiv (1-\alpha)(1-\varepsilon)$, $\varphi_1 \equiv (1-\alpha_1)(1-\varepsilon)$, the relative labor allocation can be expressed as:

$$\frac{L_{ct}}{L_{dt}} = \left(\frac{c_E^{\alpha_2}}{\alpha_2^{\alpha_2}}\right)^{(\varepsilon-1)} \frac{A_{ct}^{-\varphi}}{A_{dt}^{-\varphi_1}} \tag{2.38}$$

Now, turning to the innovation side and the choice of scientist, we can rewrite (2.21) and (2.25) using $x_{jit} = Y_{jt}P_{jt}$ as follows:

$$w_t^S = \frac{\alpha(1-\alpha)\eta\lambda(A_{ct-1})^{1-\phi}(A_{t-1})^{\phi}Y_{ct}P_{ct}}{S_{ct}^{1-\eta}A_{ct}} \tag{2.39}$$

$$w_t^S = \frac{\alpha_1(1-\alpha_1)\eta\lambda(A_{dt-1})^{1-\phi}(A_{t-1})^{\phi}Y_{dt}P_{dt}}{S_{dt}^{1-\eta}A_{dt}} \tag{2.40}$$

Equations (2.39) and (2.40) show that the production of clean $(Y_{ct}P_{ct})$ and dirty $(Y_{dt}P_{dt})$ inputs is directly proportional to the wages of scientists working in these industries. Since the market for scientists is perfectly competitive, the wage of a scientist in any industry is expected to equal the marginal return to innovation in that industry. This implies that input production in an industry is directly linked to the marginal return of innovation within that industry.

Then, we substitute x_{cit} and x_{dit} in (2.39) and (2.40) respectively:

$$w_t^S = \frac{\alpha(1-\alpha)\eta\lambda(A_{ct-1})^{1-\phi}(A_{t-1})^{\phi}P_{ct}^{\frac{1}{1-\alpha}}L_{ct}A_{ct}}{S_{ct}^{1-\eta}A_{ct}} \tag{2.41}$$

$$w_t^S = \frac{\alpha_1(1-\alpha_1)\eta\lambda(A_{dt-1})^{1-\phi}(A_{t-1})^{\phi}\left(P_{dt}E_{dt}^{\alpha_2}L_{dt}^{1-\alpha}\right)^{\frac{1}{1-\alpha_1}}A_{dt}}{S_{dt}^{1-\eta}A_{dt}} \tag{2.42}$$

The relative wage for scientists is as follows:

$$1 = \frac{\alpha(1-\alpha)(A_{ct-1})^{1-\phi}P_{ct}^{\frac{1}{1-\alpha}}L_{ct}S_{ct}^{-(1-\eta)}}{\alpha_1(1-\alpha_1)(A_{dt-1})^{1-\phi}P_{dt}^{\frac{1}{1-\alpha_1}}L_{dt}^{\frac{1-\alpha}{1-\alpha_1}}S_{dt}^{-(1-\eta)}E_{dt}^{\frac{\alpha_2}{1-\alpha_1}}} \tag{2.43}$$

The wage for scientists must be identical in equilibrium since the market for scientists is perfectly competitive. Then, the relative allocation of scientists must be:

$$\frac{S_{ct}}{S_{dt}} = \left[\frac{\alpha(1-\alpha)}{\alpha_1(1-\alpha_1)}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{1-\phi}\left(\frac{P_{ct}^{\frac{1}{1-\alpha}}}{P_{dt}^{\frac{1}{1-\alpha_1}}}\right)\left(\frac{L_{ct}}{E_{dt}^{\frac{\alpha_2}{1-\alpha_1}}L_{dt}^{\frac{1-\alpha}{1-\alpha_1}}}\right)\right]^{\frac{1}{1-\eta}} \tag{2.44}$$

Exploiting equilibrium fossil energy demand E_{dt} (2.31) in (2.44) yields that:

$$\frac{S_{ct}}{S_{dt}} = \left[\frac{\alpha(1-\alpha)}{\alpha_1(1-\alpha_1)}\left(\frac{c_{Et}}{\alpha_2 A_{dt}}\right)^{\frac{\alpha_2}{1-\alpha}}\left(\frac{P_{ct}}{P_{dt}}\right)^{\frac{1}{1-\alpha}}\frac{L_{ct}}{L_{dt}}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{1-\phi}\right]^{\frac{1}{1-\eta}} \tag{2.45}$$

Equation (2.45) allows to examine the factors that determine the relative allocation of research in equilibrium.

1. Past Productivity Effect: Defined by the ratio of past productivities to the power of $1-\phi$.
2. Price Effect: Represented as $\left(\frac{\mathrm{P_{ct}}}{\mathrm{P_{dt}}}\right)^{\frac{1}{1-\alpha}}$, it steers innovation towards industries with higher prices.
3. Market Size Effect: This is captured by the labor ratio and leads scientists to industries with greater employment and, correspondingly, more machinery.

The past productivity effect can be further divided into two components:

- A "Direct Productivity Effect" as described by the ratio of past productivities $\left(\frac{\mathrm{A_{ct-1}}}{\mathrm{A_{dt-1}}}\right)$. This draws scientists to more advanced industries, illustrating the path dependence in research and cross-period spillovers within the same industry.

- "Spillover Effect" expressed as $\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{-\phi}$. This effect encourages scientists to move towards the less developed industry, with its intensity increasing as the spillover parameter ϕ becomes larger. This reflects the idea that less advanced industries benefit more from spillovers coming from other industries. Due to the range of ϕ lying between zero and one, the value of ϕ is invariably positive. Consequently, the direct productivity effect usually dominates, although its impact decreases as the spillover parameter ϕ increases. This illustrates how cross-industry technology spillovers can reduce the influence of past productivity in scientific research.

Now, combining (2.36) and (2.38) with (2.45) and defining $\omega = \frac{\alpha(1-\alpha)}{\alpha_1(1-\alpha_1)}\left(\frac{1}{\alpha_2^{\alpha_2}}\right)^{\varepsilon-1}$ yields:

$$\frac{S_{ct}}{S_{dt}} = \left[\omega(c_E^{\alpha 2})^{(\varepsilon-1)}\,\frac{A_{ct}^{-\varphi-1}}{A_{dt}^{-\varphi_1-1}}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{1-\phi}\right]^{\frac{1}{1-\eta}} \tag{2.46}$$

Since productivity growths are constant in balanced growth path, the relative productivity level will be fixed in time. Thus, we define that $\frac{A_{ct}^{-\varphi-1}}{A_{dt}^{-\varphi_1-1}} = \left(\frac{A_{ct-1}}{A_{dt-1}}\right)$. Therefore, the equation (2.46) evolves as follows:

$$\left(\frac{S_{ct}}{S_{dt}}\right) = \omega^{\frac{1}{1-\eta}}\,(c_{Et}^{\alpha 2})^{\frac{\varepsilon-1}{1-\eta}}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\frac{2-\phi}{1-\eta}} \tag{2.47}$$

The relative allocation of scientists is determined by cross-industry spillovers, time-invariant parameters, fossil energy prices, the level of past productivities, and returns to scientific research. Now, a strong spillover rate and weak return to scientific research limits the past productivity effect. Then increasing exogenous fossil energy cost (increasing in S_{ct}) motivates technical change toward clean energy if $\varepsilon > 1$. However, if $\varepsilon < 1$, then increasing exogenous fossil energy cost motivates technical change toward dirty energy (increasing in S_{dt}).

Following (2.47), we can discuss the factors determining the relative number of scientists working in the clean industry.

Substitution Rate

The substitution rate (ε) between the clean and dirty industries is a key factor influencing scientists' choices about where to focus their innovation efforts. Its impact can be analyzed as follows:

Substitution Case ($\varepsilon > 1$)

A high substitution rate between the two industries allows clean technologies to quickly gain market share as their productivity improves, making the clean sector more appealing to scientists (market size effect). With greater substitutability, clean and dirty technologies can replace each other more easily. Consequently, rising fossil energy costs further enhance the competitive edge of clean technologies, accelerating the shift of scientists toward the clean industry (transition dynamics). Although not explicitly discussed here, high substitution rate is likely to increase the effectiveness of policies like carbon taxes and research subsidies, ensuring faster returns on investments in clean technologies.

Complementary Case ($\varepsilon < 1$):

When the clean and dirty technologies are complementary (a lower substitution rate), the productivity advantage of dirty industries becomes persistent, leading scientists to continue focusing on this industry. This makes the shift to clean technologies more challenging. If clean and dirty technologies are complementary, scientists may find it less attractive to move to the clean industry, as clean technologies depend on the productivity of dirty ones. A low substitution rate hinders the market's natural transition to clean technologies, necessitating long-term and ongoing policy interventions.

Technology Spillovers

Technology spillovers enable knowledge transfer between clean and dirty technologies, shaping the focus of scientists. Strong spillovers can either narrow or widen the productivity gap between these industries. When spillovers are robust, clean technologies can advance faster by drawing on insights from dirty technologies, attracting more scientists to the clean industry. This process helps reduce the initial disadvantage (assumed by Acemoglu et al., 2012) of clean technologies and levels the playing field between the two industries. Combined with a high substitution rate, strong spillovers further accelerate the shift of scientists toward clean technologies. Moreover, they can lessen the need for prolonged and intensive policy interventions.

The Role of Fossil Energy Cost

Fossil energy costs are a significant exogenous factor here that influences how scientists allocate their efforts between clean and dirty industries. An increase in fossil energy costs makes clean technologies more appealing. However, the extent of this effect depends on the substitution rate and spillover effects. With a high substitution rate ($\varepsilon > 1$) and a strong spillover rate, increasing fossil energy costs can quickly drive scientists toward the clean industry. On the other hand, when fossil energy costs are low, innovation in dirty technologies becomes more profitable, leading scientists to be less inclined to focus on clean technologies.

With a low substitution rate ($\varepsilon < 1$), the impact of increasing fossil energy costs on clean and dirty technologies becomes more complex and limited. A low substitution rate means that clean and dirty technologies are complementary, rather than directly interchangeable, so they are used together rather than one replacing the other. In this context, higher fossil energy costs may encourage innovation that improves the efficiency of dirty technologies, such as efforts to reduce energy intensity or develop new carbon capture and storage (CCS) technologies. Since dirty technologies cannot easily be replaced by clean ones, the economy may remain reliant on them even as fossil energy costs increase. As a result, increasing fossil energy costs could prompt scientists to focus on developing cost-reducing, efficiency-enhancing, and low-emission innovations within the dirty industry, increasing investment in technologies that optimize fossil energy use.

2.4. CHAPTER SUMMARY

In this paper, we establish a model economy to examine how industrial relative productivity levels and fossil energy costs in the presence of positive technology spillovers influence the allocation of innovations across dirty and clean intermediate industries. Using a directed technical change model, this chapter explores the factors determining the distribution of endogenous innovations shaped by the research efforts of scientists between industries producing dirty and clean inputs under laissez-faire conditions.

Our theoretical findings suggest that the substitution rate between clean and dirty technologies, along with technology spillovers and fossil energy costs, are crucial in shaping scientist allocation and guiding innovation efforts. When the substitution rate is high ($\varepsilon > 1$), clean technologies can more easily replace dirty ones, making the clean industry more attractive and driving faster transitions. In contrast, a low substitution rate ($\varepsilon < 1$) means clean and dirty technologies complement each other, maintaining the productivity advantage of dirty technologies and keeping scientists focused on dirty innovation. Technology spillovers further influence this balance by transferring knowledge between the industries; strong spillovers help close the productivity gap, particularly when the substitution rate is high, accelerating the shift to clean technologies. Exogenous fossil energy costs also play a significant role: higher costs tend to encourage clean innovation when substitution and spillovers are strong, while low substitution rates direct efforts toward improving efficiency and reducing the emissions of dirty technologies. These forces collectively underline the market-driven processes that govern the transition to clean technologies.

CHAPTER 3

ENERGY COSTS, ENVIRONMENTAL POLICY AND DIRECTED TECHNICAL CHANGE: EVIDENCE FROM EUROPE

3.1. INTRODUCTION

There is growing evidence that environmental policies can effectively direct innovation toward clean technologies, enhancing environmental standards. By reducing reliance on fossil fuels and encouraging the adoption of renewable energy sources, these policies contribute to lowering carbon emissions. However, achieving a sharp transformation in energy use appears challenging due to both economic and social constraints. While innovation is increasingly viewed as a key driver of this shift, it has not yet fully assumed its role as a central focus in the fight against climate change.

Innovation or technological development more broadly, is heavily influenced by historical habits and existing structures, making it inherently path-dependent. This makes the transition from a fossil fuel-based economy to a clean energy economy more complex than it may seem. The directed technical change literature provides important policy insights to help overcome the productivity advantage of dirty technologies and accelerate the shift to clean technologies. Drawing on seminal works by Acemoglu et al. (2012) and Acemoglu et al. (2016), the literature generally advocates for a combination of policy instruments, such as carbon taxes and research subsidies for clean technologies. It is particularly emphasized that solely implementing a carbon tax would excessively distort initial production, whereas research subsidies can significantly facilitate the transition to clean technologies. Moreover, delays in implementing these policies would result in higher economic and environmental costs, given the productivity advantage of fossil-based energy systems.

Policy instruments like carbon taxes or trading, renewable energy incentives, and research subsidies play a critical role in fostering the development and diffusion of clean technologies. These instruments have attracted significant attention in both theoretical and practical domains in related literature. However, much of the existing research focuses on specific countries or regions, where the impact of such policies can differ considerably. This geographic limitation complicates the generalizability of findings, making it challenging to assess the broader effectiveness of policy recommendations in countries and regions with varying economic, political, and social structures.

This chapter aims to contribute to directed technical change literature by empirically investigating how energy costs and environmental policies drive technological innovation towards clean or dirty innovations. We examine the potential roles of energy costs, stringent environmental policies, and research subsidies. This study examines not only tax-based policies but also the impact of energy prices, a primary determinant of energy consumption, on the direction of innovation. The analysis is based on annual data from 16 European countries, covering 2000-2020 period. The study utilizes various datasets, including patent counts for clean and fossil energy technologies, energy prices, and policy measures such as carbon taxes and emissions trading systems. By exploring the dynamics between these factors, we aim to understand the motivations behind clean and dirty innovations on the direction of technological change.

The remaining sections of the paper are organized as follows: Section 3.2. presents the existing literature. Section 3.3. introduces data, methodology and results. We discussed our findings and policy recommendations in Section 3.4. The main results and limitations are evaluated in the conclusion.

3.2. LITERATURE REVIEW

Directed technical change has emerged as a central concept for addressing environmental and climate change challenges. The influential research by Acemoglu et al. (2012) has significantly contributed to this field, showing how technological change can be intentionally guided to achieve economic growth and environmental sustainability. This body of work emphasizes the potential of technological advancements to promote economic development and lessen environmental harm simultaneously.

Despite their recognized importance, comprehensive empirical evidence at the regional or country level remains limited, particularly within diverse entities like the European Union. Existing studies often focus on individual nations, hindering the generalizability of findings and the formulation of broadly applicable policy recommendations. Lanzi and Wing (2010) find that in a panel of 23 OECD countries, an increase in relative energy prices shifts innovation toward clean energy technologies. Similarly, Ley et al. (2016) observe a positive relationship between industry-specific energy prices and clean innovations within an OECD panel. Kruse and Wetzel (2016) note that this positive relationship between energy prices and clean innovations among OECD countries becomes more pronounced, especially after the Kyoto Protocol agreement in 1997. Amin et al. (2021) suggest that in a panel of 46 countries, net fossil energy-importing nations are more inclined to invest in renewable energy technologies when oil prices rise. In the context of China, Liu et al. (2020) find that while energy prices support clean energy innovations in central and western China, they do not have the same effect in the eastern region. Lin and Chen (2018) indicate that in China, electricity prices positively influence long-term innovation in renewable energy technologies. Sector-specific findings by Aghion et al. (2016) reveal that tax-inclusive energy prices in the automotive industry support clean innovations while suppressing dirty ones.

Policy instruments like carbon taxes, renewable energy incentives, and emissions trading systems (ETS) are also essential for promoting clean technologies and reducing dependence on fossil fuels. Acemoglu et al. (2012) suggest that if clean and dirty technologies are sufficiently substitutable, temporary tax and subsidy policies can redirect innovation toward clean technologies, leading to sustainable growth. Calel and Dechezleprêtre (2016) find that among firms regulated by the EU ETS, low-carbon innovation increases by up to 10% without displacing innovation in other technologies. Oppelt (2024), using the synthetic control method in a study on Sweden, finds that carbon taxes significantly and strongly support clean innovations. In a similar study on China, Wang et al. (2020) divide the country into six regions and find that the China's Carbon ETS has regionally varying effects on clean innovations. Cheng and Yu (2024) suggest that the China's Carbon ETS promotes clean innovations. Naqvi and Stockhammer (2018), drawing on a post-Keynesian macroeconomic model, argue that continuous resource tax growth is necessary to direct technological change toward a cleaner economy. However, they recommend combining this policy with a planned government spending program to boost demand and encourage investment.

Furthermore, alongside policy tools like taxes and carbon trading systems, public and private research subsidies for clean technologies is a crucial component of environmental policy. Empirical evidence highlights the relationship between R&D budgets and clean innovation. Johnstone et al. (2010) demonstrate that public policies play a significant role in supporting clean technologies, particularly emphasizing the need for subsidies in high-cost energy technologies like solar. Dong et al. (2019) show that in China’s automotive industry, clean R&D subsidies are more effective in improving environmental quality over the long term. Gugler et al. (2024) find that in European countries, clean innovations respond more effectively to clean R&D subsidies than to environmental taxes and regulations.

Finally, we observe the relative importance of the past knowledge effect as a factor determining the direction of technological change or innovation. Acemoglu (2002, 2007) discusses the concept of the IPF, noting that path dependency may occur, meaning that innovations are built on existing technologies. This idea, often referred to as "Building on the shoulders of giants" implies that progress in a particular technology makes future advancements in that technology more effective. Aghion et al. (2016) provide evidence from the automotive industry, showing that the sector exhibits path dependency, driven by spillovers and firms' own histories of innovation.

The existing literature provides both theoretical and empirical evidence that energy costs and environmental policies direct innovations toward clean technologies. However, the literature reveals two key gaps. First, there is a need for a comprehensive analysis that considers energy costs and environmental policy instruments alongside their past knowledge stocks. Second, while current research often focuses on whether energy costs and environmental policies direct innovations toward clean technologies, there is a notable lack of findings regarding their impact on innovations in dirty technologies.

3.3 COUNT DATA ANALYSIS

3.3.1. Data

The study utilizes annual data for 16 European countries from 2000 to 2020. The analysis includes some European countries due to substantial data gaps in countries outside the selected 16. The period starting in 2000 was chosen because the dataset for clean energy and fossil energy patents begins in that year. Table 2 provides definitions of the variables used and the dataset's sources.

Table 2 Definition and Sources of Selected Variables

Name	Definition	Source
CLEANPAT	IEA: extracted from the OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats. (patent counts)	IEA
DIRTYPAT	IEA: extracted from the OECD STI Micro-data Lab: Intellectual Property Database, http://oe.cd/ipstats. (patent counts)	IEA
ENRP	real index (base 2010) of economy-wide energy prices	Liddle, B. (2022)
ENRTAX	Energy Taxes: Percentage of GDP	EUROSTAT
CLEANSUB	IEA Energy Technology RD&D Budgets: USD (2023 prices and exchange rates)	IEA
DIRTYSUB	IEA Energy Technology RD&D Budgets: USD (2023 prices and exchange rates)	IEA
EFSUB	IEA Energy Technology RD&D Budgets: USD (2023 prices and exchange rates)	IEA
GDP	GDP per capita (constant 2015 US$)	World Bank national accounts data.
TERTIARY	Gross enrollment ratio	World Bank Databank
CTIMP	1: carbon tax implemented / 0: carbon tax is not implemented	Dolphin, G., Xiahou, Q. (2022).
ETSIMP	1: ETS implemented / 0: ETS is not implemented	Dolphin, G., Xiahou, Q. (2022).

The data on clean and dirty energy patents are sourced from the International Energy Agency, which extracts them from the OECD's Intellectual Property Database. These data are based on patent counts, covering the number of published applications for patents of invention. Table 3 provides a detailed breakdown of clean and dirty energy patents by technology. According to International Energy Agency (IEA) (2024) data, the top technologies generating the most patents in the global clean energy sector in recent years are: Storage (excluding e-mobility), industry energy efficiency or substitution, building energy efficiency, solar, and e-Mobility. In contrast, the dirty energy sector shows the most patent activity in downstream processing technologies, followed by upstream technologies and transmission distribution.

Table 3 Clean and Dirty Energy Patents by Technology

Patents by Sector		**Patents by Technology**
Clean Energy Patents		Agriculture energy efficiency Air - rail – marine Bioenergy Building energy efficiency Carbon capture and storage Energy efficiency Grid, Hydrogen and fuel cells Industry energy efficiency or substitution Nuclear Other renewables Renewable energy integration in buildings Renewables Solar Storage (not e-mobility) Vehicle fuel efficiency Wind e-Mobility
Dirty Energy Patents	Upstream	Coal and solid fuels exploration and mining Conventional oil and gas exploration and extraction Unconventional oil and gas exploration and extraction
	Processing Downstream	Coal-to-gas Coal-to-liquids and gas-to-liquids Gas conditioning Hydrogen fuel production Oil refining Solid fuel conditioning
	Transmission distribution	Compressed gaseous fuel shipping Gas fuel pipelines Gaseous fuel distribution Liquid fuel distribution (gas stations)

		Liquid fuel pipelines Liquid fuel tanker shipping Rail tanker liquid fuels transport Road tanker gaseous fuels transport Road tanker liquid fuels transport Solid fuel shipping Stationary tank storage for gases Stationary tank storage for liquids Underground gaseous fuel storage Underground liquid fuels storage

IEA (2024), Energy Technology Patents Data Explorer, IEA, Paris

Data on energy prices are sourced from the real index of economy-wide energy prices developed by Liddle (2022) and extended via the CPI-all items series from OECDStat. The energy tax data, expressed as a percentage of (Gross Domestic Product) GDP, are collected from the EUROSTAT database. This tax encompasses a broad definition based on fossil energy sources, including components such as energy products for transport purposes (unleaded petrol, leaded petrol, diesel, other energy products like LPG, natural gas, kerosene, or fuel oil), energy products for stationary purposes (light fuel oil, heavy fuel oil, natural gas, coal, coke, biofuels, electricity consumption and production, district heat consumption and production, other energy products for stationary use), and greenhouse gases (carbon content of fuels, emissions of greenhouse gases).

Our analysis also considers various factors while testing the motivations behind clean and dirty innovations. We account for government spending on energy technology, including central or federal government budgets and state-owned companies' budgets on sectors such as clean energy, fossil fuels, and efficiency. Energy efficiency encompasses techniques, processes, equipment, and systems designed to deliver increased services with the same energy input or maintain service levels with reduced energy consumption. In the industrial sector, the focus is on developing energy-efficient processes, techniques, and equipment. R&D efforts concentrate on design, insulation materials, energy management systems, lighting, heating, cooling, and ventilation technologies for buildings. In transportation, the emphasis is on designing energy-efficient vehicles, utilizing new materials, enhancing powertrains, developing electric vehicle infrastructure, and exploring alternative fuels. Other areas of energy efficiency R&D include waste heat recovery, community-level solutions, agricultural and forestry applications, heat pumps, and measurement systems.

We also consider the countries' patent stocks as a proxy for countries' past knowledge or history of innovation. This allows us to observe the effect of past knowledge on current innovation efforts. Following Aghion et al. (2016), we calculate the clean and dirty patent stocks using the perpetual inventory method.

$$PATstock_{jit} = PAT_{jit} + (1 - \delta)PAT_{jit-1}$$

where $j \in (Clean, Dirty)$, $PATstock_{jit}$ is the patent stock and PAT_{jit} is a nonnegative patent count for country *i* = 1, ..., *N*, at time *t* = 1, ..., *T.* We consider the depreciation of R&D capital, δ, as 20% commonly assumed in the literature. Kruse and Wetzel (2016) emphasize that a country's overall patent activities can influence clean and dirty patent technologies. Moreover, we control GDP per capita and tertiary school enrollment. Figure 2 displays descriptive statistics for all variables.

Figure 2: Descriptive Statistics

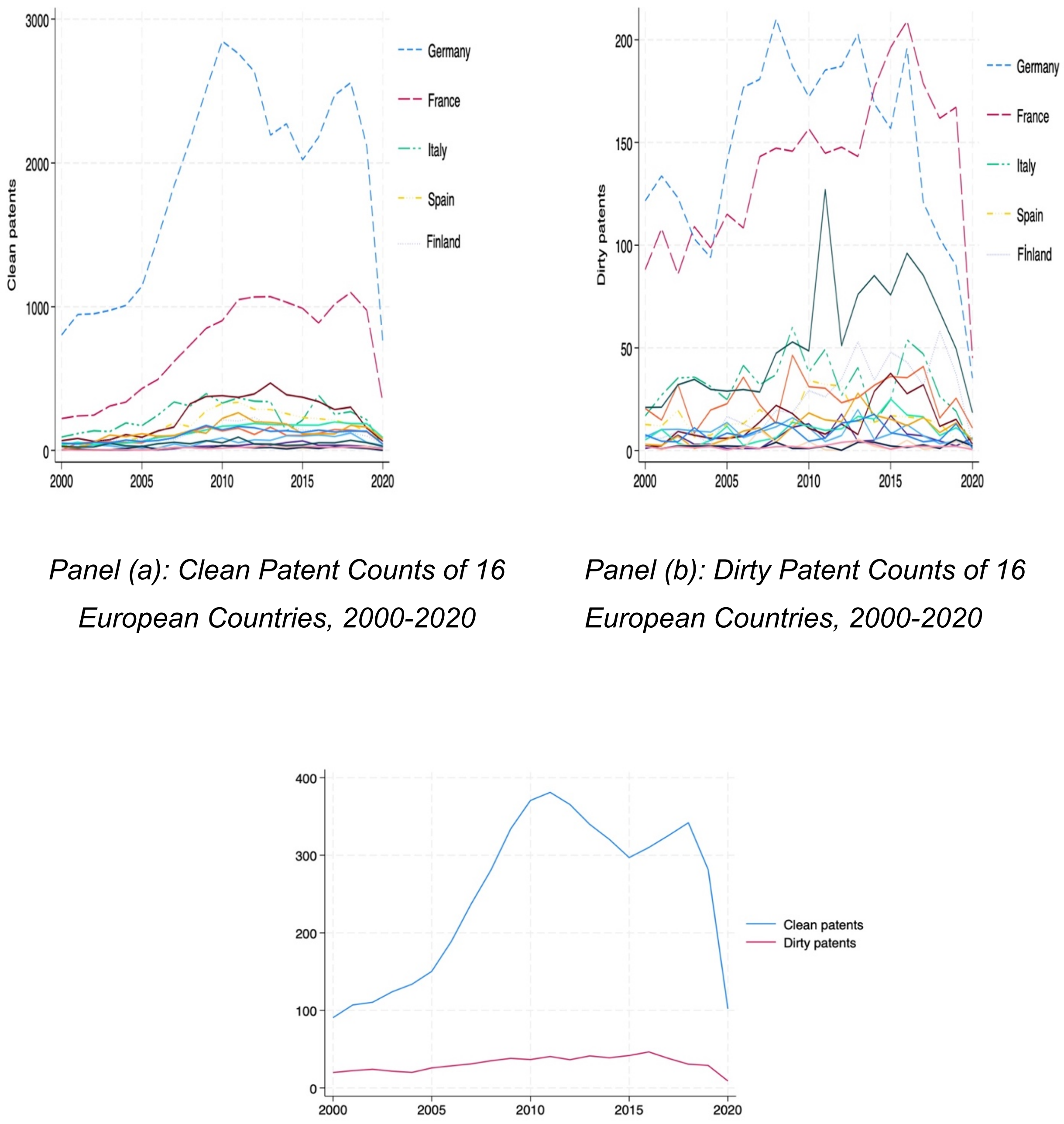
Variables	Mean	Std. Deviation	Min	Max
Clean Patents	247.320	487.021	0.29	2846
Dirty Patents	31.218	47.453	0.14	210.02
Energy Price	4.541	0.126	4.186	4.796
Energy Tax	0.540	0.261	0.301	1.078
Clean Subsidy	66.638	75.321	0	362.297
Dirty Subsidy	31.807	60.697	0	345.889
Efficiency Subsidy	68.646	73.928	0	403.114
Triadic Patents	848.446	1393.504	1.366	7641.34
GDP	10.471	0.577	8.901	11.375
Tertiary Enrollment	4.198	0.198	3.393	4.569
Own Stock Clean Patents	6.299	1.840	1.098	10.561
Own Stock Dirty Patents	4.583	1.631	0	8.035

Figure 3 illustrates the number of patents for clean and dirty technologies in 16 European countries from 2000 to 2020. Panel (a) shows that Germany leads in clean patent applications, followed by France. However, as we approach 2020, patent applications in Germany decline, converging with those in France. Thus, Germany and France are the leading European countries in clean patent applications.

Panel (b) reveals that Germany and France also dominate in patent applications for dirty technologies, exhibiting parallel trends. Panel (c), which depicts the average patent applications for both clean and dirty technologies across the 16 European countries, indicates that during the 2000-2020 period, the trend in patenting clean technologies consistently surpassed that of dirty technologies.

This suggests that the number of patent applications for clean technologies in Europe was significantly higher than those for dirty technologies.

Figure 3 Number of Patent Applications in 16 European Countries



Panel (a): Clean Patent Counts of 16 European Countries, 2000-2020

Panel (b): Dirty Patent Counts of 16 European Countries, 2000-2020

Panel (c): Average Patent Counts, 2000-2020

Since around 2013, the decline in energy prices in Europe has played a key role in the reduction of clean energy patents. As fossil fuel prices became cheaper, investments in alternative technologies, such as renewable energy and energy efficiency, became less attractive, which likely contributed to the decrease in clean energy patents. Additionally, from around 2017, the falling share of energy taxes in GDP may have led to a decline in patents related to fossil fuel technologies, particularly in downstream processes. This suggests that as fossil fuels became more affordable, investments in high-carbon energy technologies weakened, resulting in a drop in patent activity in this sector.

Figure 4 presents the economy-wide energy prices for 16 European countries from 2000 to 2020, indexed to the year 2010. Energy prices generally trended upward until around 2010, after which they exhibited a fluctuating pattern until 2020.

Figure 4 Energy Price (Index: 2010=100), 2000-2020

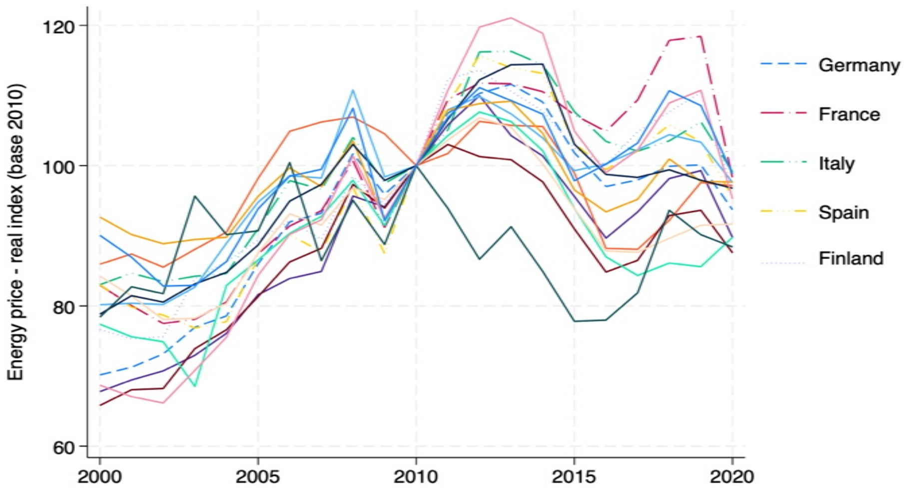


Figure 5 illustrates the energy taxes as a share of GDP for 16 European countries from 2000 to 2020. It shows that Italy has implemented the highest energy taxes in recent years. In contrast, Germany and France, which rank highly in patenting dirty technologies, have more moderate energy tax rates.

Figure 5 Energy Taxes: Percentage of GDP, 2000-2020

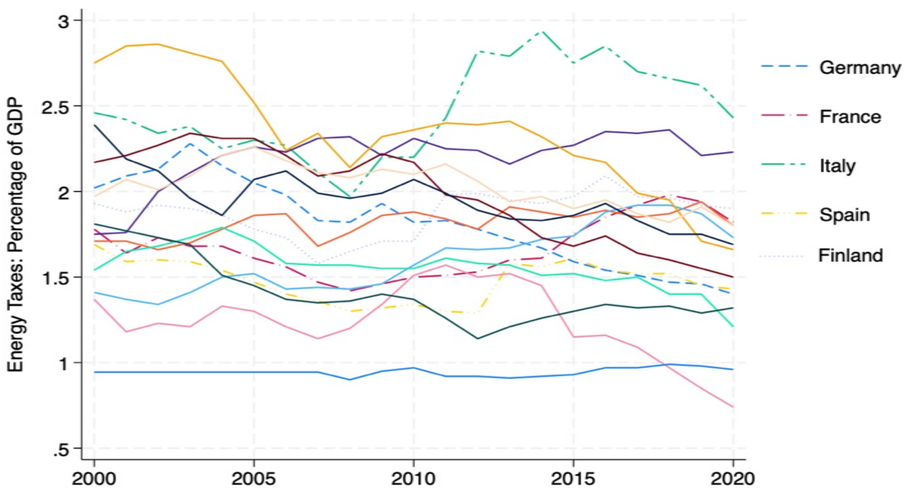
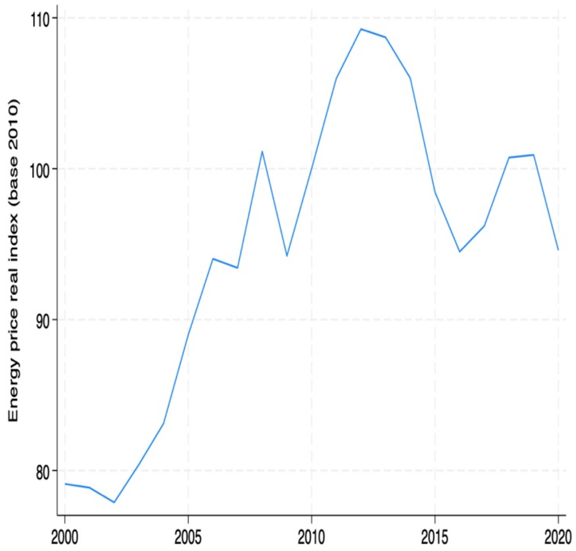


Figure 6 visualizes the average energy prices, energy taxes, and energy technology R&D budgets for 16 European countries from 2000 to 2020. In Panel (a), the economy-wide energy prices in the examined countries show a steady increase until around 2013, when they entered a declining trend. Panel (b) depicts the share of energy taxes in GDP, showing a decline until approximately 2009, followed by an increase (though not to previous levels), and then a sharp decline between 2016 and 2020. Panel (c) presents the R&D budgets allocated for energy technologies. It is observed that, from around 2003 onwards, the funding for clean and energy-efficient technologies surpasses that for dirty technologies. Except the last couple of years, the budgets for clean and energy-efficient technologies have been at similar levels.

Figure 6 Average Energy Price, Energy Taxes and IEA Energy Technology RD&D Budgets in 16 European Countries



Panel (a) Economy-wide energy prices

Panel (b): Energy Taxes

Panel (c): Energy Technology RD&D Budgets

3.3.2. Methodology

Using standard Ordinary Least Squares (OLS) regression to estimate count variables, such as patent counts, is challenging due to certain assumptions. Count variables often violate key OLS assumptions, such as conditional normality and homoscedasticity (constant variance). Count data techniques are recommended as an alternative since these variables typically exhibit non-normal conditional distributions and fail to meet the constant variance assumption. The Poisson distribution, which better accommodates integer values and is more appropriate for count data, is often seen as a better fit for such analyses compared to the normal distribution (Coxe et al. 2009).

As our study aims to explain the determinants of clean and dirty innovations using patent counts, we utilize count data methods. To achieve this, we implement a Poisson regression model for our panel data, and the model in exponential form is as follows:

$$PAT_{jit} = exp(x'_{it}\theta + \omega_i) + \varepsilon_{jit} \tag{3.1}$$

where PAT_{jit} is a nonnegative patent counts of energy type *j* (clean and dirty) for country *i* = 1, ..., *N*, at time *t* = 1, ..., *T*. Then, x'_{it} represents the vector of independent variables, ω_i is the country-specific fixed effect and ε_{jit} is the error term.

In our analysis, we focus on two dependent variables: clean energy patents (CLEANPAT) and dirty energy patents (DIRTYPAT). Thus, we test two separate models based on energy costs, environmental policies, and patent stocks to reveal the determinants of clean and dirty innovations.

We use economy-wide energy price (ENRP), energy tax (ENRTAX) and clean (Own stock clean) and dirty (Own stock dirty) patent stocks as explanatory variables. Furthermore, we employ R&D subsidies for clean (CLEANR&D), dirty (DIRTYR&D) and energy efficiency (EFR&D) separately as explanatory variables to observe the effect of research subsidies on the direction of technical change. While Aghion et al. (2016) also incorporated R&D subsidies for energy technologies into their analysis, their approach differed from ours in that they utilized the aggregate value of these subsidies, without distinguishing between the specific types of energy technologies. As a novel approach, we use decomposed data for R&D subsidies in energy technologies as clean, dirty and energy efficiency subsidies. In our model, we control for GDP per capita level and tertiary education enrollment ratio. Finally, we incorporate two dummy variables as environmental policy measures, indicating the implementation of a carbon tax (CTIMP) and emission trading system (ETSIMP).

However, traditional fixed effect count data models assume strict exogeneity in all regressors, making it impossible to observe the impact of past observations on current outcomes. Blundell et al. (2002) proposed the pre-sample mean (PSM) estimator as a solution, using pre-sample information of the dependent count data variable within a linear feedback model. Following Blundell et al. (2002)'s approach we define the country-specific fixed effect as:

$$\omega_i = \xi ln\overline{PAT}_{ji} \tag{3.2}$$

where $\overline{PAT}_{ji} = (1/TP)\sum_{n=1}^{TP} PAT_{jin}$ represents the PSM of our dependent variables, i.e. clean and dirty patent counts, in year *n*. *TP* is the number of observation and ξ is the related parameter to be estimated. This estimator provides reliable results, particularly in the presence of linear feedback and unobserved heterogeneity. According to Monte Carlo simulation findings from Blundell et al. (2002), the PSM estimator has shown significantly better performance than the quasi-differenced Generalized Method of Moments (GMM) estimator.

Partially following the methodology of Aghion et al. (2016), we employ three distinct regression models: energy price-energy tax, energy price only, and energy tax only. This approach allows us to discern the individual and combined effects of energy prices and taxes on both clean and dirty innovation. To ensure the robustness of our results, we conduct sensitivity analyses by evaluating the regression across three different model specifications, each incorporating various combinations of control variables and environmental policy indicators. This comprehensive approach enables a more nuanced understanding of their impact on clean and dirty innovation.

3.3.3. Regression Results

Table 4 reports our regression results for the dependent variable clean patents in column (1) – (3) and we repeat the same procedure for the dependent variable dirty patents in column (4) – (6).

A common result in columns (1) - (3) is that the coefficient of the economy-wide energy price is positive and statistically significant for clean energy patents. The elasticities between 1.773 and 1.980 indicate that a 10% increase in energy price is associated with about 17%-20% more clean energy patents, respectively, under different specifications. Aghion et al. (2016), in their analysis of the automotive industry across 80 countries, found that a 10% increase in fuel prices led to a 10% increase in clean energy patents. Similarly, Kruse and Wetzel (2016) concluded that an increase in energy prices positively affects solar energy patents. However, there is no significant effect of energy tax on clean patents.

Another common result in the first three columns is that countries with a history of clean innovation (own stock clean) proxied by lagged patent stocks exhibit a strong tendency to persist in developing clean technologies, characterized by a notable elasticity between 0.212 and 0.222.

As a novel approach, we use decomposed data for the R&D subsidies includes spending from central or federal government budgets, as well as budgets of state-owned companies on energy technologies, into clean, dirty and efficiency subsidies. Our findings in Table 4, strongly show that clean subsidies have a positive and significant effect on clean patents. The estimated coefficients between 0.242 and 0.263 indicate that a 10% increase in clean subsidies is associated with about 2.4%-2.6% increase in clean patents. In contrast to the effect of clean subsidies, dirty and energy efficiency subsidies are not statistically significant for clean patents.

Table 4 Regression with Energy Price and Energy Tax

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.212***	0.220***	0.222***			
	(0.0416)	(0.0767)	(0.0701)			
Own Stock Dirty				0.308***	0.410***	0.406***
				(0.105)	(0.111)	(0.100)
Energy price	1.980***	1.755***	1.773***	0.618	0.439	0.318
	(0.222)	(0.235)	(0.281)	(0.696)	(0.660)	(0.696)
Energy tax	-0.201	0.000926	-0.0175	0.230	0.382	0.249
	(0.156)	(0.161)	(0.186)	(0.257)	(0.246)	(0.254)
Clean R&D	0.242***	0.263***	0.263***	-0.154***	-0.167***	-0.107
	(0.0643)	(0.0751)	(0.0795)	(0.0393)	(0.0494)	(0.0737)
Dirty R&D	0.0219	0.00769	0.00806	0.0237	-0.0472	-0.0429
	(0.0521)	(0.0689)	(0.0689)	(0.0759)	(0.0724)	(0.0669)
Efficiency R&D	-0.00897	0.0187	0.0204	-0.00990	-0.0472	0.0375
	(0.0492)	(0.0566)	(0.0592)	(0.0531)	(0.0724)	(0.0724)
GDP		1.487**	1.475**		0.156	0.0502
		(0.742)	(0.734)		(0.588)	(0.508)
Tertiary		-0.572	-0.591		-1.428***	-1.901***
		(0.502)	(0.524)		(0.430)	(0.491)
CTIMP (Dummy)			0.0221			0.390**
			(0.0798)			(0.171)
ETSIMP (Dummy)			0.0221			0.109
			(0.0798)			(0.121)
Constant	-5.473***	-18.08**	-17.93**	-1.323	3.080	7.218
	(0.860)	(8.450)	(8.683)	(2.457)	(5.820)	(6.251)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

Columns (4) and (6) report the estimation results using the same procedure in the first three columns, but this time, we use the dirty patents variable as the dependent variable. First, our findings for economy-wide energy price and tax do not produce a statistically significant impact on dirty patents. Interestingly, implementing a tax policy (CTIMP) positively affects dirty innovation efforts.

Another common result in columns (4) - (6) is that countries with a history of dirty innovation (own stock dirty) exhibit a strong tendency to persist in developing clean technologies, characterized by a notable elasticity between 0.308 and 0.410.

Columns (1) - (3) in Table 5 show the results regarding the dependent variable clean patents using only energy price variable instead of energy tax. We find very similar coefficients for the countries' history of innovation in clean technologies, energy prices, and clean R&D subsidies compared with our earlier estimates on clean patent activities.

Table 5 Regression with Energy Price instead of Energy tax

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.218*** (0.0424)	0.220*** (0.0766)	0.222*** (0.0710)			
Own Stock Dirty				0.307*** (0.0994)	0.416*** (0.0930)	0.420*** (0.0947)
Energy price	1.862*** (0.214)	1.756*** (0.205)	1.760*** (0.248)	0.644 (0.659)	0.570 (0.561)	0.424 (0.682)
Clean R&D	0.224*** (0.0654)	0.263*** (0.0763)	0.262*** (0.0815)	-0.170*** (0.0396)	-0.167*** (0.0442)	-0.108 (0.0680)
Dirty R&D	0.0434 (0.0453)	0.00763 (0.0644)	0.00884 (0.0664)	-0.00429 (0.0492)	-0.0692 (0.0521)	-0.0543 (0.0520)
Efficiency R&D	0.00243 (0.0487)	0.0187 (0.0568)	0.0212 (0.0606)	-0.0301 (0.0453)	-0.0358 (0.0738)	0.0287 (0.0675)
GDP		1.485** (0.740)	1.505** (0.766)		-0.617 (0.966)	-0.401 (0.805)
Tertiary		-0.571 (0.514)	-0.596 (0.531)		-1.130** (0.439)	-1.780*** (0.503)
CTIMP (Dummy)			0.0174 (0.0583)			0.451*** (0.143)
ETSIMP (Dummy)			-0.0123 (0.0619)			0.0785 (0.114)
Constant	-5.433*** (0.859)	-18.06** (8.404)	-18.21** (8.878)	-0.874 (1.968)	10.26 (8.753)	11.52 (8.586)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

We also repeat the procedure for the dependent variable dirty patents in Table 5. We find similar effects for lagged dirty patent stock and carbon tax implementation (CTIMP) dummy compared with our earlier estimates on dirty patent activities.

Columns (1) - (3) in Table 6 show the results regarding the dependent variable clean patents using only energy tax variable instead of energy price. Accordingly, there is no significant effect of energy tax on clean innovation. We find similar signs for lagged clean patent stock and clean R&D subsidies compared with our earlier estimates on clean patent activities. In this specification, we observe that implementing an emission trading system (ETSIMP) in Europe significantly contributes to clean energy patenting.

We also repeat the procedure for the dependent variable dirty patents in Table 6. In model (6), carbon tax policy positively influences dirty patent activity in Europe. While this finding is rare in the literature, some studies suggest that stringent environmental policies can support the development of fossil-based energy technologies alongside clean energy technologies. Lanzi et al. (2012) note that as fossil fuel prices rise in 11 OECD countries, patenting activity in clean technologies increases, and patenting in fossil technologies also continues to grow, though at a slower pace. We find similar effects for lagged dirty patent stock compared with our earlier estimates on dirty patent activities.

Table 6 Regression with Energy Tax instead of Energy Price

	Clean Patents			Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.401*** (0.0318)	0.420*** (0.0573)	0.366*** (0.0768)			
Own Stock Dirty				0.370*** (0.0679)	0.451*** (0.0683)	0.420*** (0.0782)
Energy tax	-0.00803 (0.178)	0.246 (0.210)	0.282 (0.268)	0.243 (0.245)	0.423 (0.263)	0.287 (0.269)
Clean R&D	0.377*** (0.0816)	0.368*** (0.0877)	0.323*** (0.0952)	-0.183*** (0.0697)	-0.191** (0.0818)	-0.113 (0.0848)
Dirty R&D	0.0433 (0.0664)	-.0025478 (0.077)	-0.000643 (0.0750)	0.0338 (0.0825)	-0.0438 (0.0773)	-0.0410 (0.0674)
Efficiency R&D	-0.0242 (0.0625)	0.0235 (0.0654)	0.0309 (0.0806)	-0.0447 (0.0443)	-0.0282 (0.0583)	0.0230 (0.0698)
GDP		1.856* (1.085)	1.787 (1.150)		0.323 (0.510)	0.148 (0.561)
Tertiary		-1.216*** (0.389)	-1.253*** (0.412)		-1.525*** (0.338)	-1.987*** (0.485)
CTIMP (Dummy)			0.0278 (0.101)			0.387** (0.178)
ETSIMP (Dummy)			0.186*** (0.0418)			0.151 (0.112)
Constant	1.218** (0.492)	-13.38 (11.53)	-12.29 (12.22)	0.931 (0.869)	3.304 (5.414)	7.719 (5.661)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

To address potential overdispersion, we also tested the models using negative binomial regression, the results of which are presented in Appendix 4. Our findings generally align with those from the Poisson regression. Finally, we also check the cross effects of past clean and dirty innovation stocks with our Poisson regression model and the results are reported in Table 7.

Table 7 Cross Effects of Past Clean and Dirty Innovations

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.155*** (0.020)	0.142 (0.114)	0.318** (0.160)	-0.145** (0.070)	-0.104 (0.067)	-0.191*** (0.065)
Own Stock Dirty	0.072*** (0.0229)	0.097 (0.145)	0.104 (0.207)	0.676*** (0.081)	0.640*** (0.080)	0.681*** (0.081)
Energy price	1.985*** (0.0594)	1.871*** (0.225)		-0.624** (0.278)	-0.603** (0.297)	
Energy tax	-0.193*** (0.024)		0.00327 (0.195)	0.203** (0.093)		0.197** (0.092)
Clean R&D	0.252*** (0.017)	0.239*** (0.067)	0.393*** (0.096)	-0.106 (0.072)	-0.102 (0.074)	-0.111 (0.073)
Dirty R&D	0.020*** (0.006)	0.040 (0.044)	0.041 (0.067)	0.067** (0.031)	0.077** (0.030)	0.064** (0.031)
Efficiency R&D	-0.015 (0.011)	-0.007 (0.041)	-0.033 (0.046)	-0.078* (0.047)	-0.087* (0.046)	-0.098** (0.045)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

Columns (1) and (3) of Table 7 indicate that countries with a history of innovation in clean energy technologies are significantly more likely to continue innovating in clean technologies in the future, with elasticities ranging from 0.155 to 0.318.

In contrast, Columns (4) through (6) show that countries with a history of innovation in dirty energy technologies are much more likely to persist in innovating in dirty technologies, with elasticities of 0.640 and 0.681. These findings suggest that the impact of past dirty innovation on future dirty innovation is substantially greater than that of past clean innovation on future clean innovation. Moreover, a history of clean innovation is negatively associated with future dirty innovation, with elasticities of -0.104 and -0.191, implying that countries with a history of clean innovation are less likely to innovate in dirty technologies moving forward.

As highlighted in the Data section and depicted in Figure 3, a notable observation is the sharp decline in the number of clean patents recorded in 2020. This decline is likely influenced by the disruptions caused by the COVID-19 pandemic. To account for the potential impact of the pandemic on our analysis, we re-estimated all models after excluding the year 2020 from the dataset. The revised results remained largely consistent with the original findings, confirming the reliability of our conclusions. As a piece of evidence, we report the results of the analysis for Table 7, using the dataset excluding the year 2020, in Appendix 4.

3.4. DISCUSSION

This study contributes to the literature on directed technical change and environment in the energy sector. The empirical results reveal several key insights into the dynamics of clean and dirty innovation activities across 16 European countries from 2000 to 2020.

First, the positive and statistically significant effect of energy prices on clean patenting highlights the critical role of energy costs as a driver of innovation in clean energy technologies. This finding aligns with the expectations of the directed technical change model, which suggests that higher energy costs can incentivize the development of cleaner alternatives. This finding also aligns with the time series, panel data analysis, and firm-level results obtained by authors such as Lanzi and Wing (2010), Aghion et al. (2016), Ley et al. (2016), and Lin and Chen (2018).

Aghion et al. (2016) suggest that rising energy costs suppress dirty patent activities, slowing down innovation in fossil technologies within the automotive industry. However, our findings do not show such a clear slowdown in the context of 16 European countries. In fact, some of our findings suggest that energy tax positively influences dirty innovation. Our dirty innovation indicator largely reflects patent counts from the downstream processing sector, along with contributions from upstream and transmission distribution technologies. This pattern may reflect a path dependency, where sectors specializing in dirty technologies focus on making existing fossil-based systems (specifically in downstream processing and transmission distribution) more efficient rather than transitioning sharply toward clean technologies. Policies like environmental or energy tax can increase the operational costs of firms working with fossil energy technologies, such as coal, oil, and gas. To manage these costs, companies may turn to developing more energy-efficient technologies. As Lanzi et al. (2012) argue, rising fossil energy prices or carbon taxes can drive innovation toward both clean and dirty technologies through an efficiency effect. Wang et al. (2021) suggest that advancements in coal-to-gas conversion under downstream processing improve air quality, aligning with environmental policy goals.

Our indicator of dirty innovation mainly reflects activities within the downstream processing of fossil fuels, such as coal-to-gas transitions. This indicates a preference for using intermediates like gas during the shift from fossil fuels to clean energy. Given the challenges of transitioning directly to clean technologies, it seems reasonable for firms in fossil-based industries to focus on downstream innovations to avoid the additional costs imposed by environmental policies like energy taxes. However, this approach could delay fully adopting fully renewable clean energy. Aghion et al. (2019) argue that if intermediates like gas are used to transition from fossil fuels to clean technologies, it should only be implemented within a limited timeframe.

Brown et al. (2022) take a different view, suggesting that environmental taxes can support R&D in sectors where new inventions are hard to generate but knowledge transfer is relatively easy. Firms specializing in dirty technologies may invest in R&D to acquire technical expertise through technology transfer. Furthermore, the current tax rates in Europe might not be optimal. As Yang et al. (2019) noted in their study of China, the tax system does not fully support innovation in clean energy technologies.

Our findings also highlight the importance of R&D subsidies in promoting clean energy innovations. The significant positive effect of clean R&D subsidies on clean patents supports the notion that targeted financial support can effectively direct technological advancements towards cleaner energy technologies. This result is consistent with previous studies, such as Acemoglu et al. (2012), Acemoglu et al. (2016), Johnstone et al. (2010), Dong et al. (2019) and Gugler et al. (2024), which emphasize the role of subsidies in guiding the direction of innovation. While clean R&D subsidies positively impact clean patent activities, dirty subsidies have a positive and significant effect on dirty patent activities, indicating that the specificity of subsidies is crucial in achieving desired outcomes. We also find weak evidence regarding the impact of energy efficiency subsidies on dirty patent activities.

Moreover, we also validate the positive contribution of history of innovation in both future clean and dirty patent activities. The coefficients of the lagged stock variables indicate that previous innovations in clean (dirty) energy contribute to technological developments in clean (dirty) innovation in the future. Aghion et al. (2016) also report a similar effect and magnitude on the auto industry for the path dependency hypothesis. This section of the analysis suggests another important finding. European countries with a history of clean innovation are likely to generate less dirty innovation in the future.

In conclusion, this study offers strong empirical evidence on the key forces influencing technological innovation in Europe's energy sector. The results highlight the critical roles of energy costs, targeted R&D subsidies, and history of innovation in guiding the direction of technological change. However, the inconsistent impact of environmental policy measures and the varying effects of economic and educational factors indicate that a more refined policy approach may be necessary to promote clean energy innovations effectively. Future research, especially studies encompassing a more comprehensive array of countries and exploring cross-sectoral spillovers, would enhance our understanding of these complex dynamics.

3.5. CHAPTER SUMMARY

This study presents empirical findings on how energy costs, environmental policy, and history of innovation influence the direction of technological change. By using panel count data techniques, we analyze the impacts of energy price, energy tax, R&D subsidies and countries' history of innovation on clean and dirty innovation propensity. We also control the effect of GDP per capita and tertiary school enrollment ratio on innovation activities.

Our regression results align with several key findings in the directed technical change literature. First, we show that higher energy price is associated with a higher innovation effort in clean energy technologies but its effect on dirty innovation is ambiguous. Second, our findings highlight the essential role of research subsidies in the direction of technical change, as Acemoglu et al. (2012) emphasized, particularly given the higher elasticity of clean R&D subsidies compared to dirty ones. Last, we confirm the path dependency hypothesis, suggesting that countries with a higher propensity for innovation in clean (dirty) technologies are more likely to innovate in clean (dirty) technologies in the future.

Several limitations should be acknowledged to contextualize the findings and guide future research. First, one significant limitation is the potential for cross-sector technology spillovers, which the study does not fully address. Technological advancements in one sector can influence and drive innovations in other sectors. However, the current analysis does not capture these cross-sector interactions. Second, the study focuses on 16 European countries without comparing the results with those of other regions or countries. This limitation restricts the generalizability of the findings. Different regions may have varying levels of policy stringency, innovation capacities, and economic structures. A comparative analysis with non-European countries or other regions could provide a more comprehensive understanding of how contextual factors shape these dynamics.

CONCLUSION

One of the key areas where technological change have the greatest impact is energy sector. Technological improvements have made it possible to use both renewable and non-renewable energy sources more efficiently and effectively. In this context, technological change is essential for either replacing unsustainable production methods based on fossil fuels with sustainable, renewable energy alternatives or improving the efficiency of current fossil fuel use.

While engineering continues to drive technological progress, a key question for economists remains: How feasible is a full transition to clean technologies for economies still heavily reliant on fossil fuels, given the path dependency of these technologies? One of the most comprehensive answers to this question comes from Acemoglu et al. (2012). Their research shows that without government intervention through environmental policies, dirty technologies will retain a relative productivity advantage over clean technologies, making the fight against climate change unsuccessful. They propose that the optimal policy involves applying carbon taxes and research subsidies for clean technologies together for a certain period. Under the condition that the substitution rate between clean and dirty technology sectors is sufficiently high, this approach can permanently improve the productivity of clean technologies and support efforts to combat climate change.

In this thesis, we explore the pivotal role of technological change in addressing the global challenge of transitioning from fossil-based to renewable energy systems. Our analysis highlights the importance of fossil energy costs, cross-industry technology spillovers and environmental policy in directing innovation efforts towards clean energy technologies.

One of the central insights of this research is the critical role of substitution rates, spillovers, and energy costs in determining the direction of technological change. The theoretical model developed in this dissertation incorporates these factors, demonstrating their influence on the allocation of innovation efforts across clean and dirty sectors. Specifically, it shows that strong technology spillovers and high substitution rates can mitigate the productivity advantage of dirty technologies, thereby accelerating the transition to clean technologies. Empirical findings further validate and extend these theoretical insights. Using patent data from 16 European countries, the analysis confirms that rising energy prices and targeted research subsidies significantly enhance clean technology innovation. However, the results also underline the persistence of path dependency in technological innovation: countries with a strong historical focus on dirty or clean technologies tend to continue along these trajectories. The theoretical result discussed in Chapter 2, where a low substitution rate between clean and dirty technologies leads to higher fossil energy costs driving dirty innovation, is partially observed in Chapter 3 for European countries. Our empirical findings suggest that, in certain specifications, energy taxes (especially as indicated by the carbon tax dummy) stimulate dirty innovation. We attribute this notable outcome to the fact that, within our sample, the dirty innovation indicator is primarily based on energy patents related to downstream processing technologies.

The directed technical change model and empirical analysis in the last two chapters of this dissertation raise several important questions for future research beyond the scope of the questions addressed. First, the model developed in the second chapter could be further enhanced by incorporating an environmental constraint, which would provide a more comprehensive and holistic analysis. Second, in the third chapter's country-level panel data analysis, the lack of access to country-level patent citation data restricts our ability to fully capture the effects of technology spillovers, which are typically proxied by patent citations in the literature. By organizing patent citations by country using existing databases, a comprehensive citation dataset can be created. This would provide a valuable resource for conducting more detailed analyses of technological trends, innovation patterns, and cross-country technology spillovers.

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APPENDIX 1 ORIGINALITY REPORT

	HACETTEPE ÜNİVERSİTESİ SOSYAL BİLİMLER ENSTİTÜSÜ	Doküman Kodu *Form No.*	FRM-DR-21
		Yayım Tarihi *Date of Pub.*	04.01.2023
	FRM-DR-21 Doktora Tezi Orijinallik Raporu *PhD Thesis Dissertation Originality Report*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 09/12/2024

Tez Başlığı: Essays on Technological Change and Environmental Policy

Yukarıda başlığı verilen tezimin a) Kapak sayfası, b) Giriş, c) Ana bölümler ve d) Sonuç kısımlarından oluşan toplam 112 sayfalık kısmına ilişkin, 09/12/2024 tarihinde tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda işaretlenmiş filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 19 'dur.

Uygulanan filtrelemeler**:

1. ☒ Kabul/Onay ve Bildirim sayfaları hariç
2. ☒ Kaynakça hariç
3. ☐ Alıntılar hariç
4. ☒ Alıntılar dâhil
5. ☒ 5 kelimeden daha az örtüşme içeren metin kısımları hariç

Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orijinallik Raporu Alınması ve Kullanılması Uygulama Esasları'nı inceledim ve bu Uygulama Esasları'nda belirtilen azami benzerlik oranlarına göre tezimin herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumlarda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

Bilal Çayır

Öğrenci Bilgileri				
	Ad-Soyad	Bilal ÇAYIR		
	Öğrenci No	N19146933		
	Enstitü Anabilim Dalı	İktisat		
	Programı	İktisat Doktora (İng)		
	Statüsü	**Doktora** ☒	**Lisans Derecesi ile (Bütünleşik) Dr** ☐	

DANIŞMAN ONAYI

UYGUNDUR.
Doç. Dr. Onur YENİ

*Tez **Almanca** veya **Fransızca** yazılıyor ise bu kısımda tez başlığı **Tez Yazım Dilinde** yazılmalıdır.
**Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orjinallik Raporu Alınması ve Kullanılması Uygulama Esasları İkinci bölüm madde (4)/3'te de belirtildiği üzere: Kaynakça hariç, Alıntılar hariç/dahil, 5 kelimeden daha az örtüşme içeren metin kısımları hariç (Limit match size to 5 words) filtreleme yapılmalıdır.

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GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

Date: 16/10/2024

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Bilal Çayır

Student Information				
	Name-Surname	Bilal ÇAYIR		
	Student Number	N19146933		
	Department	Economics		
	Programme	Doctor of Philosophy in Economics		
	Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

SUPERVISOR'S APPROVAL

APPROVED
Assoc. Prof. Dr. Onur YENİ

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		Yayım Tarihi *Date of Pub.*	22.11.2023
	FRM-DR-12 Doktora Tezi Etik Kurul Muafiyeti Formu *Ethics Board Form for PhD Thesis*	Revizyon No *Rev. No.*	02
		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞINA

Tarih: 09/12/2024

Tez Başlığı*: Essays on Technological Change and Environmental Policy

Yukarıda başlığı verilen tez çalışmam:
1. İnsan ve hayvan üzerinde deney niteliği taşımamaktadır.
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Gereğini saygılarımla arz ederim.

Bilal Çayır

Öğrenci Bilgileri				
	Ad-Soyad	Bilal Çayır		
	Öğrenci No	N19146933		
	Enstitü Anabilim Dalı	İktisat		
	Programı	İktisat (İng)		
	Statüsü	**Doktora** ☒	**Lisans Derecesi ile (Bütünleşik) Dr** ☐	

DANIŞMAN ONAYI

UYGUNDUR.
Doç. Dr. Onur YENİ

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		Revizyon Tarihi *Rev.Date*	25.01.2024

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

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Bilal Çayır

Student Information				
	Name-Surname	Bilal Çayır		
	Student Number	N19146933		
	Department	Economics		
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	Status	**PhD** ☒	**Combined MA/MSc-PhD** ☐	

SUPERVISOR'S APPROVAL

APPROVED

Assoc. Prof. Onur YENİ

APPENDIX 3 DECISION PROBLEMS

Final Good Producer Problem

$$\mathcal{L} = P_{ct}Y_{ct} - P_{dt}Y_{dt} + \lambda\left[Y_t - \left(Y_{ct}^{\varepsilon-1/\varepsilon} + Y_{dt}^{\varepsilon-1/\varepsilon}\right)^{\varepsilon/\varepsilon-1}\right] \qquad (A.2.1)$$

where λ is the Lagrange multiplier.

FOCs imply that:

$$P_{ct} = \lambda \mathrm{Y}_{\mathrm{ct}}^{-\frac{1}{\varepsilon}}\left(Y_{ct}^{\varepsilon-1/\varepsilon} + Y_{dt}^{\varepsilon-1/\varepsilon}\right)^{\frac{1}{\varepsilon-1}} \qquad (A.2.2)$$

$$P_{dt} = \lambda Y_{dt}^{-\frac{1}{\varepsilon}}\left(Y_{ct}^{\varepsilon-1/\varepsilon} + Y_{dt}^{\varepsilon-1/\varepsilon}\right)^{\frac{1}{\varepsilon-1}} \qquad (A.2.3)$$

$$Y_t = \left(Y_{ct}^{\varepsilon-1/\varepsilon} + Y_{dt}^{\varepsilon-1/\varepsilon}\right)^{\varepsilon/\varepsilon-1} \qquad (A.2.4)$$

Intermediate Input Producers' Problem

Clean Input

Solving for Labor and wage in clean industry yields:

FOCs:

$$L_{ct}: (1-\alpha)P_{ct}L_{ct}^{-\alpha}A_{cit}^{1-\alpha}x_{cit}^{\alpha} - w_t^L = 0 \qquad (A.2.5)$$

$$w_t^L = (1-\alpha)P_{ct}L_{ct}^{-\alpha}A_{cit}^{1-\alpha}x_{cit}^{\alpha} \qquad (A.2.6)$$

Solving for machine demand in clean industry:

$$x_{cit}: P_{ct}L_{ct}^{1-\alpha}\alpha A_{cit}^{1-\alpha}x_{cit}^{\alpha-1} - P_{cit} = 0 \qquad (A.2.7)$$

Dirty Input

Solving for machine demand, labor and energy demand in dirty industry:

FOCs:

$$x_{dit}: P_{dt}E_{dt}^{\alpha_2}L_{dt}^{1-\alpha}A_{dit}^{1-\alpha_1}\alpha_1 x_{dit}^{\alpha_1-1} - P_{dit} = 0 \qquad (A.2.8)$$

$$L_{dt}: (1-\alpha)P_{dt}E_{dt}^{\alpha_2}L_{dt}^{-\alpha}A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1} - w_t^L = 0 \qquad (A.2.9)$$

$$E_{dt}: \alpha_2 P_{dt}E_t^{\alpha_2-1}L_{dt}^{1-\alpha}A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1} - c_E = 0 \qquad (A.2.10)$$

Solving for (A.2.8) yields,

$$P_{dt}E_{dt}^{\alpha_2}L_{dt}^{1-\alpha}A_{dit}^{1-\alpha_1}\alpha_1 x_{dit}^{\alpha_1-1} = P_{dit} \qquad (A.2.11)$$

Solving for (A.2.9) yields,

$$(1-\alpha)P_{dt}E_{dt}^{\alpha_2}L_{dt}^{-\alpha}A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1} = w_t^L \qquad (A.2.12)$$

Finally, solving for (A.2.10) yields that,

$$\alpha_2 P_{dt}E_{dt}^{\alpha_2-1}L_{dt}^{1-\alpha}A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1} = c_E \qquad (A.2.13)$$

Machine Producer Problem

Clean Industry

The FOCs of the maximization problem relative to choice of the number of scientists:

$$S_{cit}: \alpha(1-\alpha)P_{ct}^{\frac{1}{1-\alpha}}L_{ct}A_{ct-1}\lambda\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi}\eta S_{cit}^{\eta-1} - w_t^S = 0$$

$$w_t^S = \alpha(1-\alpha)P_{ct}^{\frac{1}{1-\alpha}} L_{ct} A_{ct-1} \lambda \left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi} \eta S_{cit}^{\eta-1}$$

$$w_t^S = \frac{\alpha x_{cit} \eta \lambda A_{ct-1} \left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi}}{\left(\frac{1}{1-\alpha}\right) S_{cit}^{1-\eta} A_{cit}} \qquad (A.2.14)$$

Dirty industry

The FOCs of the maximization problem relative to choice of the number of scientists:

$$S_{dit}: \alpha_1(1-\alpha_1)\left(P_{dt} E_{dt}^{\alpha_2} L_{dt}^{1-\alpha}\right)^{\frac{1}{1-\alpha_1}} A_{dt-1} \lambda \left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi} \eta S_{dit}^{\eta-1} - w_t^S = 0$$

$$w_t^S = \alpha_1(1-\alpha_1) x_{dit} A_{dt-1} \lambda \left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi} \eta S_{dit}^{\eta-1}$$

$$w_t^S = \frac{\alpha_1 x_{dit} \eta \lambda A_{dt-1} \left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi}}{\left(\frac{1}{1-\alpha_1}\right) S_{dit}^{1-\eta} A_{dit}} \qquad (A.2.15)$$

APPENDIX 4 ROBUSTNESS CHECK RESULTS

NEGATIVE BINOMIAL REGRESSION RESULTS WITH ENERGY PRICE AND ENERGY TAX

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.383*** (0.037)	0.482*** (0.045)	0.488*** (0.047)			
Own Stock Dirty				0.566*** (0.064)	0.751*** (0.069)	0.791*** (0.072)
Energy price	1.649*** (0.230)	1.415*** (0.228)	1.372*** (0.245)	0.062 (0.270)	0.103 (0.261)	0.055 (0.291)
Energy tax	-0.214** (0.083)	-0.144 (0.089)	-0.162* (0.092)	-0.024 (0.120)	0.057 (0.125)	-0.008 (0.129)
Clean R&D	0.123** (0.053)	0.121** (0.052)	0.114** (0.053)	0.049 (0.063)	0.055 (0.062)	0.038 (0.062)
Dirty R&D	-0.005 (0.023)	-0.053** (0.024)	-0.050** (0.024)	-0.0179 (0.032)	-0.122*** (0.032)	-0.110*** (0.033)
Efficiency R&D	-0.051 (0.033)	-0.021 (0.033)	-0.018 (0.033)	-0.039 (0.045)	-0.009 (0.045)	0.001 (0.045)
GDP		0.191 (0.185)	0.160 (0.188)		-0.125 (0.276)	-0.236 (0.296)
Tertiary		-0.949*** (0.223)	-1.093*** (0.245)		-1.869*** (0.274)	-2.126*** (0.303)
CTIMP (Dummy)			0.111 (0.078)			0.270** (0.105)
ETSIMP (Dummy)			0.011 (0.075)			-0.025 (0.093)
Constant	-7.182*** (0.932)	-4.747** (2.196)	-3.650 (2.312)	-0.349 (1.121)	8.116*** (2.821)	10.52*** (3.074)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

NEGATIVE BINOMIAL REGRESSION RESULTS WITH ENERGY PRICE INSTEAD OF ENERGY TAX

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.388*** (0.037)	0.484*** (0.045)	0.485*** (0.047)			
Own Stock Dirty				0.568*** (0.064)	0.748*** (0.069)	0.791*** (0.072)
Energy price	1.565*** (0.228)	1.346*** (0.223)	1.274*** (0.239)	0.054 (0.267)	0.135 (0.253)	0.049 (0.277)
Clean R&D	0.106* (0.053)	0.111** (0.052)	0.101* (0.053)	0.048 (0.062)	0.055 (0.062)	0.038 (0.062)
Dirty R&D	-0.006 (0.023)	-0.055** (0.024)	-0.053** (0.024)	-0.017 (0.032)	-0.123*** (0.032)	-0.110*** (0.033)
Efficiency R&D	-0.037 (0.032)	-0.013 (0.033)	-0.010 (0.033)	-0.038 (0.045)	-0.012 (0.045)	0.002 (0.044)
GDP		0.336** (0.165)	0.329** (0.166)		-0.182 (0.248)	-0.227 (0.256)
Tertiary		-1.020*** (0.221)	-1.154*** (0.247)		-1.836*** (0.264)	-2.130*** (0.296)
CTIMP (Dummy)			0.086 (0.078)			0.269*** (0.103)
ETSIMP (Dummy)			0.037 (0.074)			-0.024 (0.091)
Constant	-7.226*** (0.933)	-5.929*** (2.084)	-4.999** (2.202)	-0.364 (1.115)	8.554*** (2.662)	10.45*** (2.852)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

NEGATIVE BINOMIAL REGRESSION RESULTS WITH ENERGY TAX INSTEAD OF ENERGY PRICE

	Clean Patents			Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.512*** (0.035)	0.621*** (0.040)	0.577*** (0.044)			
Own Stock Dirty				0.572*** (0.059)	0.760*** (0.065)	0.793*** (0.071)
Energy tax	-0.140 (0.087)	-0.0504 (0.092)	-0.0503 (0.094)	-0.020 (0.118)	0.070 (0.120)	-0.0008 (0.123)
Clean R&D	0.135** (0.057)	0.139** (0.055)	0.105* (0.056)	0.0506 (0.062)	0.0595 (0.061)	0.038 (0.062)
Dirty R&D	-0.016 (0.024)	-0.082*** (0.024)	-0.070*** (0.024)	-0.0180 (0.032)	-0.123*** (0.032)	-0.110*** (0.033)
Efficiency R&D	-0.040 (0.035)	-0.001 (0.035)	-0.005 (0.035)	-0.039 (0.045)	-0.009 (0.045)	0.001 (0.045)
GDP		0.210 (0.199)	0.221 (0.199)		-0.102 (0.268)	-0.221 (0.285)
Tertiary		-1.273*** (0.223)	-1.468*** (0.244)		-1.876*** (0.273)	-2.137*** (0.297)
CTIMP (Dummy)			0.132* (0.079)			0.272*** (0.105)
ETSIMP (Dummy)			0.181** (0.071)			-0.017 (0.083)
Constant	-0.851*** (0.253)	1.631 (2.076)	2.573 (2.119)	-0.103 (0.333)	8.287*** (2.772)	10.63*** (3.013)
Observations	298	298	298	298	298	298

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).

CROSS EFFECTS OF PAST CLEAN AND DIRTY INNOVATIONS (2000-2019)

	Dependent Variable: Clean Patents			Dependent Variable: Dirty Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Stock Clean	0.381*** (0.080)	0.357*** (0.079)	0.504*** (0.101)	-0.081 (0.128)	-0.083 (0.134)	-0.034 (0.078)
Own Stock Dirty	-0.072 (0.083)	-0.032 (0.087)	-0.087 (0.102)	0.434*** (0.139)	0.436*** (0.147)	0.415*** (0.128)
Energy price	1.123*** (0.254)	0.981*** (0.245)		0.344 (0.424)	0.357 (0.439)	
Energy tax	-0.256** (0.128)		-0.159 (0.138)	0.116 (0.197)		0.122 (0.197)
Clean R&D	0.165** (0.064)	0.151** (0.064)	0.226*** (0.076)	0.090 (0.057)	0.098 (0.065)	0.095 (0.060)
Dirty R&D	0.010 (0.041)	0.034 (0.037)	0.017 (0.049)	-0.027 (0.063)	-0.040 (0.043)	-0.025 (0.066)
Efficiency R&D	0.053 (0.047)	0.064 (0.047)	0.053 (0.052)	0.041 (0.062)	0.031 (0.072)	0.033 (0.063)
Observations	283	283	283	283	283	283

Robust standard errors in parentheses. ***, ** and * denote p<0.01, p<0.05, p<0.1 respectively. Results of the dependent variable clean patent are in Column. (1) – (3) and the dependent variable dirty patent are in Column. (4) – (6).