Review

Directed Technical Change for Green Economy: The Role of Innovation and Technology Spillovers*

Bilal ÇAYIR[1]

[1] Research Assistant, Hasan Kalyoncu University, bilalcayir2@gmail.com, ORCID: 0000-0001-5340-6635

Abstract: This paper reviews the models of directed technical change in the environmental context, both theoretically and empirically, with a specific emphasis on cross-sector technology spillovers. It is well-established that the direction of technological change is not uniform across production factors and does not progress neutrally. The objective is to assess whether empirical literature aligns with the theoretical insights of the model. Also, we aim to determine whether cross-sector technology spillovers impact the direction of innovations through changes in relative productivity levels during the transition process to a low-carbon economy. Our review suggests that the empirical literature is mainly expanding with research on energy types, cost, and efficiency measures and directed innovations in clean technologies are responsive to environmental policy. A limited number of studies reveal the significant impact of spillovers in directed technical change models, contributing to the advancement of clean energy and the fight against climate change. Overall, the interplay between cross-sector technology spillovers and environmental policies promoting green innovation may provide valuable insights into efforts to fight against climate change.

Keywords: Directed technical change, Environmental policy, Energy, Innovation, Technology spillovers
Jel Codes: O3, Q2, Q5

Yeşil Ekonomi İçin Yönlendirilmiş Teknolojik Değişme: İnovasyon ve Teknoloji Yayılımlarının Rolü

Öz: Bu çalışma, sektörler arası teknoloji yayılımlarına vurgu yaparak, çevresel bağlamdaki yönlendirilmiş teknik değişim modellerini teorik ve ampirik yönden incelemektedir. Teknolojik değişimin yönünün üretim faktörleri arasında tekdüze olmadığı ve tarafsız ilerlemediği bilinmektedir. Çalışmanın amacı, (i) ampirik literatürün modelin teorik içgörüleriyle uyumlu olup olmadığını değerlendirmektir. Ayrıca düşük karbonlu bir ekonomiye geçiş sürecinde sektörler arası teknoloji yayılımlarının, göreli verimlilik seviyelerindeki değişiklikler yoluyla inovasyonların yönünü etkileyip etkilemediği araştırılmaktadır. İncelememiz, ampirik literatürün çoğunlukla enerji türleri, maliyet ve verimlilik ölçümleri üzerine araştırmalarla genişlediğini ve temiz teknolojilerdeki yönlendirilmiş inovasyonların çevre politikasına duyarlı olduğunu göstermektedir. Sınırlı sayıda çalışmanın ise, yönlendirilmiş teknik değişim modellerinde teknolojik yayılımların önemli etkisini ortaya koyarak, temiz enerjinin ilerlemesine ve iklim değişikliğiyle mücadeleye katkıda bulunduğunu ortaya konmuştur. Genel olarak, yeşil inovasyonu teşvik etmeyi amaçlayan sektörler arası teknoloji yayılımları ve çevre politikaları arasındaki etkileşim, iklim değişikliğiyle mücadele çabalarına önemli katkılar sağlayabilir.

Anahtar Kelimeler: Yönlendirilmiş teknolojik değişme, Çevre politikası, Enerji, İnovasyon, Teknoloji yayılımları
Jel Kodları: O3, Q2, Q5

Cite: Çayır, B. (2025). Directed technical change for green economy: The role of innovation and technology spillovers. *Fiscaoeconomia, 9*(1), 53-70. https://doi.org/10.25295/fsecon.1510317

Submitted: 04.07.2024
Accepted: 25.08.2024

* This paper is based on the author's Ph.D. thesis at Hacettepe University.

1. Introduction

High-skilled labor in the job market has consistently increased for many years. The prominence of skilled labor 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 labors, there is a noticeable upward trend in their wage levels (Acemoglu, 1998). 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 mentioned 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 (EoS) and the extent of state dependence on the cost of various types of innovation, shaping what is termed the innovation possibilities frontier. These factors, such as market forces, the profitability of new technologies, EoS, and state dependence on innovation costs, influence the direction of technological change. In economies with a growing supply of skilled labor, these forces often push technological change towards innovations that require and enhance the productivity of these skilled workers, reinforcing the trend of skill-biased technical change.

Following Acemoglu's pioneering studies, the directed technical change (DTC) 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; Li et al., 2016; Fried, 2018; Haas & Kempa, 2018; Kim, 2019; Afonso & Forte, 2023; Hemous & 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 Acemoglu et al. (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 form of the DTC.

In this paper, we aim to review the environment and DTC literature, encompassing theoretical and empirical perspectives, focusing on cross-sector technology spillovers. Exploring the impact of 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 DTC models due to its supportive role in advancing clean energy technologies and implementing environmental policies. However, it is noticeable that these spillovers need to be adequately addressed in studies about the DTC and environment. Therefore, this review seeks to highlight the crucial interaction among technology spillovers, environmental policies, and the direction of innovation.

The following sections of the paper are as follows: Section 2 summarizes the main aspects of the basic DTC model based on Acemoglu (1998; 2002). Section 3 explores the dynamics of the DTC and environment. In section 4, we review the alternative models and extensions of the environmental model of DTC. Then, in section 5, we give special attention to cross-sector technology spillovers in terms of clean and dirty types of technologies. Empirical evidence from related literature is discussed in section 6.

2. Basic DTC Model

Technological change does not diffuse uniformly across all factors of production. Some factors of production or industries may be more biased toward efforts in developing new technologies than others. As Acemoglu (1998, 2002) emphasizes, 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 the dynamics of supply and demand 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 a skilled workforce (Berman et al., 1994; Goldin & Katz, 1996). Acemoglu (1998, 2002) comprehensively explains why such a relationship exists. According to his analysis, the more skilled labor 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.[†]

Acemoglu (1998, 2002) explains this relationship within the DTC 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. Acemoglu (1998) argues that when there is an increase in the supply of skilled labor, the skill-complementary technologies market will expand, leading to the invention of more technologies. Therefore, he suggested that the effect of market size determines the direction of technological change.[‡] The market size effect denotes the broadening of the market for technologies that complement skills, resulting in a rise in skilled workers. Acemoglu (1998) indicates 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.

Acemoglu (2002) systematically formalizes this approach and investigates its effects on income inequality between rich and poor countries. This framework assumes two inputs: Labor, L, and Z for capital, skilled labor, or land. Technological progress is denoted by A. The final good production function is structured in a constant elasticity of substitution (CES) form and can be expressed as follows:

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

In equation 1, Y_L and Y_Z denote the two inputs that are employed for the final good production. 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. The EoS between the two factors is denoted by $\varepsilon \in (0,\infty)$ and implies that two factors are gross complements when $\varepsilon < 1$ and gross substitutes when $\varepsilon > 1$. The EoS of 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.

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

[‡] 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.

The primary objective is to identify the direction of technological change determinants. Profit-maximizing firms are motivated to innovate because they desire greater profits. The price and market size effects determine the relative profitability of new technology in both production factors. 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. Besides the influence of the substitution rate, the degree to which the cost of various innovations depends on past choices (known as the innovation possibilities frontier) can significantly impact the course of technological development. The degree of state dependence suggests that the future costs of innovations can be influenced by the current level of technology (or the current state of research and development).

The results presented by Acemoglu (2002) within the framework of DTC provide crucial insights into the income gap between developed and less developed countries. In the developed countries, referred to as the North, the DTC 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, the DTC is a factor that deepens income inequality.[§]

3. Environmental Model of the DTC

Acemoglu et al. (2012) show the significance of price and market size effects in their Basic DTC model, highlighting their impact on the response of diverse technologies to environmental policies in a two-sector model involving workers. The paper discusses intertemporal endogenous and DTC 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. The study explores how technologies directed in different sectors respond to environmental policies.

Analytical findings suggest that to avoid environmental catastrophe, immediate definitive measures are necessary compared to those proposed by Nordhaus and Stern. (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 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, however, is based on the assumption of a sufficient substitution rate between the clean and dirty sectors; otherwise, permanent intervention becomes inevitable.

An essential 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.

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

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

$$Y_t = \left(Y_{ct}^{(\varepsilon-1)/\varepsilon} + Y_{dt}^{(\varepsilon-1)/\varepsilon}\right)^{\varepsilon/(\varepsilon-1)} \tag{2}$$

where ε denotes the EoS 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:

$$Y_{ct} = L_{ct}^{1-\alpha}\int_0^1 A_{cit}^{1-\alpha}x_{cit}^{\alpha}\,di, \tag{3}$$

$$Y_{dt} = R_t^{\alpha_2}L_{dt}^{1-\alpha}\int_0^1 A_{dit}^{1-\alpha_1}x_{dit}^{\alpha_1}\,di, \tag{4}$$

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.** The innovation side of the economy is as follows:

$$A_{jt} = \left(1 + \gamma\eta_j s_{jt}\right)A_{jt-1}. \tag{5}$$

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 takes the entrepreneurial role in producing the improved machine during that period. If innovation fails, monopoly rights go to a randomly selected entrepreneur using the former technology. The innovation possibilities frontier allows scientists to target a sector rather than a specific machine, ensuring allocation across machines in a sector. The innovation possibilities frontier 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:

$$S_{t+1} = -\xi Y_{dt} + (1+\delta)S_t. \tag{6}$$

Equation 6 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. Precisely, when the right-hand side is 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.

Equation 6 represents a core model for understanding environmental change. It reflects that increased environmental damage negatively impacts the planet's ability to replenish and restore itself. 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.

** 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.

3.1. Non-Exhaustible Resource

The following factors determine the relative profitability of conducting research in the specified intermediate sectors;

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \times \left(\frac{P_{ct}}{P_{dt}}\right)^{1/(1-\alpha)} \times \frac{L_{ct}}{L_{dt}} \times \frac{A_{ct-1}}{A_{dt-1}} \tag{7}$$

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 innovation turns the sector where the average productivity is relatively high.[††]

3.1.1. Substitution case

When there is a substitution relationship between the two inputs, the assumption that the clean technology is relatively backward compared to the dirty one implies that innovations must begin in the more advanced sector, the dirty sector.[‡‡] In this case, while the average efficiency of the sector producing dirty input continues to increase steadily, the efficiency 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 research subsidy financed by a lump-sum tax collected from households to encourage scientists to contribute to the clean sector. According to this approach, when there is a substitution relationship between inputs, temporary incentives applied for a certain period may be enough 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, sufficient substitution will ensure that temporary incentives lead to innovations toward clean technologies.

3.1.2. Complementary Case

Acemoglu et al. (2012) argue that when clean and dirty inputs are complex to substitute for each other, acting more like complements, short-term interventions may not be sufficient to avert an environmental crisis. In a complementary case, temporary intervention facilitates the redirection of research towards the clean sector. However, as shown, the quantity of dirty input will continue to increase.[§§]

3.1.3. Optimal Policy

Acemoglu et al. (2012) emphasize 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, the environmental externality occurs from the dirty input production. Second, there are knowledge externalities arising from research and development activities. Last, there is monopoly distortion in the price of machines subject to monopolistic competition. To eliminate externalities in the form of non-exhaustible resources used in dirty input production, the socially optimal allocation is characterized by recommending lump-sum taxes and transfers. Therefore, Acemoglu et

[††] 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 innovation possibilities frontier.

[‡‡] 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.

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

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 the inefficient use of machines due to monopolistic pricing are addressed with a subsidy for machines. At the same time, environmental damages from dirty input production are mitigated with a carbon tax. Additionally, market failures related to knowledge externalities on the innovation possibilities frontier are addressed with a research subsidy, directing innovation toward the clean sector to address 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 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 a sufficient substitution relationship 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 efficiency level of the clean sector over the dirty sector, making innovation in the clean sector more profitable than in the dirty sector. Subsequently, even without subsidies, innovation will continue in the clean sector.

3.2. Exhaustible Resource

Acemoglu et al. (2012) also characterize the environmental model of DTC, which uses exhaustible resources in the dirty sector. This specification argues that even without intervention, preventing an environmental disaster is possible because using exhaustible resources leads to continuously increasing usage costs due to extraction costs and resource scarcity. First, the model assumes no private ownership of finite resources, and the cost of using them is only based on how much it takes to extract them. Subsequently, the model assumes ownership of resources belongs to long-lasting entities like companies or individuals. As a result, the Hotelling Rule, which considers scarcity and time, governs the price of these resources. Since exhaustible resources are used to produce dirty input, the stock of exhaustible resources now affects the market size and price. Accordingly, as the stock of resources decreases, dirty input productivity decreases, and its price increases.

As resource availability decreases, the cost of using polluting inputs rises. This shrinks the market for these inputs and incentivizes research and development in cleaner alternatives. A substitution elasticity higher than one will reduce the weight of dirty input, preserving environmental quality and enabling positive long-term growth without intervention in the economy. 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 than the baseline model.

3.2.1. Optimal Policy

When non-exhaustible resources are used, the optimal regulation includes a subsidy that corrects monopoly distortions, a carbon tax on dirty input production, and a research subsidy for the clean sector. 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. Here, the pricing of exhaustible resources follows the Hotelling rule. This rule dictates that the resource price rises asymptotically with the interest rate derived from the consumption Euler equation. Under these conditions, if the EoS between the two sectors and the discount rate are sufficiently high, innovation happens in the clean technology. Under laissez-faire, the prevention of environmental disaster is possible. However, if the substitution and discount rates are sufficiently low, avoiding environmental disasters without intervention is impossible. 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.

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 DTC. Table 1 presents the reviewed literature regarding the extensions of the environmental models of DTC. First, Acemoglu et al. (2012) propose some modeling alternatives to the model explained in the previous section. These modeling alternatives that are briefly described 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 Environmental Models of DTC

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, F. J. & Smulders, S.	"Fueling growth when oil peaks: Directed technological change and the limits to efficiency"	Energy efficiency
2017	Lennox, J. A. & 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, T. R. & Rosendahl, K. E.	"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
2023	Kruse-Andersen, P. K.	"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
2024	Casey, G.	"Energy Efficiency and Directed Technical Change: Implications for Climate Change Mitigation"	Energy efficiency

"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 the quality of the environment adversely impacts labor productivity in both sectors. In the absence of intervention, either the productivity loss caused by environmental pollution caused by the increase in the average productivity of the dirty sector will lead to the convergence of total output and consumption to zero, or the decrease in productivity will not be sufficient to balance the increase in the average productivity of the dirty sector, causing 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 increase both the average efficiency of the clean sector and the quantity, decreasing the pollution level of aggregate production. Therefore, this approach suggests that a single type of technical change could reduce pollution in the production process. As supporting evidence, Greaker et al. (2018) discuss whether governments need to direct their innovation efforts toward clean technologies instead of dirty ones and how effective this is compared to carbon pricing. To achieve this, the model incorporates the concept of diminishing returns, where each additional unit of investment in R&D yields progressively more minor benefits. Additionally, the model recognizes that the anticipation of future carbon taxes can influence current R&D choices. The results indicate the need to redirect innovation towards clean technologies to address significant environmental challenges.

"Substitution Between Productivity Improvements and Green Technologies": Acemoglu et al. (2012) suggest eliminating the difference 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.

Apart from the suggestions of Acemoglu et al. (2012), there are also different modeling approaches in the relevant literature. DTC is formalized chiefly through the energy sector in these models, and the literature has developed in this direction. For instance, Andrea & Smulders (2014) address the relationship between energy usage, efficiency improvement, and resource scarcity within the framework of an endogenous growth model. The final product is produced in the model by combining two inputs: Labor services and energy services. The model integrates energy supply influenced by scarcity rent and the DTC motivated by profit, resulting in transitional dynamics that closely match contemporary patterns in energy supply, productivity growth, and extraction costs. The paper highlights the significance of extraction costs in mining and investigates the sustainability of these trends in the long run. Using analytical modeling, this research defines parameter limits to accurately reflect observed trends, including per capita energy supply, energy's share of total costs, energy prices compared to wages, energy efficiency, and growth in per capita income. 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 & Smulders, 2014).

As another example, Witajewski-Baltvilksa et al. (2017) expand on the concept of the DTC by examining how energy-intensive industries, specifically those with products less responsive to price changes, are influenced by technological advancements. The study investigates the determinants of research and development expenditures in energy-intensive sectors and explores the effects of efficiency-enhancing innovations on 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, as mentioned before by Acemoglu et al. (2012). The level of these research efforts in the long term (in a balanced growth path) depends on the growth rate of energy costs.

Similarly, Haas & Kempa (2018) marginally modify the environmental model of DTC by considering heterogeneous energy intensity dynamics in the presence of exhaustible resources. The main novelty of the paper is modeling exogenous energy prices and endogenous energy use. The final good is produced from the combination of labor-intensive and energy-intensive inputs. 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 DTC. 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.

There is also a growing body of literature on the effects of environmental policy measures, such as carbon taxes, within the DTC framework. For instance, Fried (2018) modifies the DTC framework, which assumes that innovation occurs in a single type 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 model produces the final product using three inputs: Fossil, green, and non-energy. Accordingly, limited innovation resources are allocated to fossil, green, and non-energy intermediate inputs. The study also externally accounts for the price of oil imports to model oil shocks. Fried's (2018) research suggests that a consistent carbon tax significantly impacts innovation within 20 years. It finds that this tax leads to a 50% increase in environmentally friendly technology development and a 60% decrease in fossil fuel-based innovation. Casey (2024) constructs an economic growth model that includes the DTC to assess how environmental policies affect energy use. The model considers both the demand side, influenced by technological advancements, and the supply side, constrained by rising extraction costs. Casey (2024) draws attention to the difference between the short-term EoS and the DTC process when examining the effects of environmental policies. Both approaches intend to discourage taxed inputs, but technological advancement happens slower in this scenario. Acemoglu et al. (2023) construct a model economy where energy comes from coal, natural gas, or clean sources. Their research focused on the immediate and long-lasting consequences of a sudden increase in natural gas availability. While a surge in natural gas availability can initially lower carbon emissions by replacing coal, it also hinders the development of clean energy technologies. This delay could make shifting to a carbon-free energy system significantly harder, if not impossible, in the long run. The study adapts the DTC framework, considering these effects tailored explicitly for the energy sector. The findings suggest that shale gas booms decrease societal welfare under a free-market economy but can significantly increase welfare when combined with carbon taxes and more generous green incentives.

Some of the DTC literature deals with cross-country aspects of the direction of innovation. Hemous (2012) integrates the DTC framework into an open economy, examining whether several 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 more than carbon taxation is needed to ensure sustainable growth and environmental quality preservation. However, temporary clean research subsidies and tariffs implemented in one country can lead to sustainable development with high levels of environmental quality. It has been suggested that these findings hold 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 demonstrate that policies in foreign countries, increasing dirty goods production in response to local decreases, also encourage innovation in the dirty sector of the foreign country. The unintended impact of individual policies on innovation can heavily influence the standalone strategies chosen to promote long-term, eco-friendly economic growth.

Finally, some papers examine the DTC approach through concepts such as long-lasting capital investments, carbon capture and storage, and population dynamics.

Lennox & Witajewski-Baltvilks (2017) enhance the DTC model by incorporating the concept of long-lasting capital investments in clean and polluting technologies. Their approach also considers the depreciation costs associated with this capital over time. According to the findings, ongoing innovations in clean technologies embodied in capital also generate depreciation costs borne by clean capital users. These depreciation costs, which have been overlooked in the literature on DTC regarding their impact on the transition speed to clean growth, reveal a negative effect on the demand for clean investment and, hence, on the rate of clean growth.

Durmaz & Schroyen (2019) include a carbon capture and storage sector in the DTC and environment model. 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 & 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 to dirty energy and carbon capture and storage technology.

Kruse-Andersen (2023) develops an economic growth model by associating the DTC approach with population dynamics. Population growth can have contradictory impacts on emissions. On the one hand, more people can mean increased production and, therefore, more emissions. On the other hand, a larger population could boost research capacity, but the effect on emissions would depend on whether research focuses on clean or polluting technologies.

5. Cross-sector Technology Spillovers

The sharing and transfer of technological knowledge, known as technology spillovers, can be a powerful tool in accelerating the shift towards clean energy and mitigating climate change by influencing both the production and use of fossil and clean energy sources. 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 address technology spillovers and their implications for economic growth (Arrow, 1972; Caballero & 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 endogenous technological change framework (Acemoglu, 2002; Acemoglu & Akcigit, 2012; Aghion & Howitt, 1990; Keller, 2004; Keller & 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 the DTC 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 instance of spillovers between environmentally friendly and polluting technologies is the widespread adoption of solar cells. This surge is fueled by oil companies' need for energy to illuminate their offshore rigs. On the other hand, clean technologies also provide a form that can facilitate the spread of innovations to different technologies. Dechezlepretre et al. (2013) demonstrate that innovations emerging in clean energy exhibit a much higher spillover effect and generality than dirty energy.

Technology spillovers are often overlooked in research on 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 DTC 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. Theoretical and computational discoveries suggest that when knowledge spills over, or international innovative firms are involved, a shift towards clean innovation in the global South can be facilitated through policies enacted in the North.

Studies examining the diffusion 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) utilize patent citation data to analyze the extent to which knowledge from clean technologies spreads and influences other innovations compared to knowledge from polluting technologies. They examined this phenomenon in energy production, automobiles, fuel, and lighting. The paper strongly implies the relative advantage of clean patents in all four technologies. It 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, they suggest that clean energy technologies have a greater scientific foundation than other technologies. Additionally, the study highlights that they significantly benefit from scientific and technological knowledge flows from distant places. The study highlights the unique characteristics of clean technologies, setting them apart from other advanced technologies, particularly those involved in traditional energy production.

Using patent citation data, Jee & Srivastav (2022) suggest that the majority of clean technologies do not receive direct knowledge flow from dirty technologies but are indirectly connected. 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) investigated the factors influencing the spread of patented knowledge between renewable energy technologies and other energy sources, like fossil fuels and nuclear power. They used a statistical technique called regression analysis to analyze data on patents filed by companies. Firstly, the findings indicate that patents making more references to the literature and previous patents achieve greater diffusion. 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. Although this research does not cover the scope, foreign direct investments (FDI) are an essential factor that can facilitate the development of clean technologies and benefit from different types of technologies. Investment flows to the host country through FDI have the potential to support sustainable environmental goals by spreading to local firms' clean technology development processes. For example, findings by Tsangyao et al. (2024) reveal that foreign investments directed towards China have raised environmental standards. In other words, this result is also referred to as the Pollution Halo hypothesis.

6. Empirical Literature

After analyzing the foundation laid in 1998 and 2002 within the DTC framework and 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 analyze the environmental model of DTC with a basic application. Subsequently, these analyses have continued with different sector preferences and specifications. This section discusses the numeric and econometric literature findings on the DTC and environment.

Acemoglu et al. (2012) present the findings of a quantitative study of the theoretical model in the context of a non-exhaustible resource setup. The study examined how varying the discount and substitution rates affected the ideal environmental policy and the speed at which society adopts clean technology. The analysis considered five years, and it was assumed that the carbon tax was zero before the optimal policy implication. Based on the substitutability assumption between dirty and clean energy types, the EoS was tested for two different values, 3 and 10. These two values, which are not close to each other, were chosen to emphasize the significant role of the EoS. 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 substitution rate 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. When the substitution rate is 3 and the discount rate is 0.015, the transition to clean technologies occurs within approximately 50 years. When the EoS is 10, it was observed that research subsidies are implemented at a lower level and in a shorter period. With the EoS 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 substitution rate 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 EoS is 10, the temperature increase initially occurs at a small level, then decreases, reaching pre-industrial levels after 90 years. With the EoS 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) demonstrate 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.

Fried (2018) built upon the theoretical insights of Acemoglu et al. (2012) by incorporating parameter calibration to establish connections between energy prices, production, and innovation. The study examines how historical oil shocks caused energy price hikes, using these shocks as stand-ins for energy price increases induced by climate policies. In particular, the oil shocks of the early 1970s serve as relevant historical examples. The analysis sets the EoS at 1.5 between green energy, fossil energy, and oil imports. In the analysis, Fried (2018) follows a two-stage approach in which the first stage uses innovations endogenously, while the second uses exogenously. 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 solid 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 & Kempa (2018) further extend the DTC framework by examining the changes in energy intensity across different sectors in response to energy prices and technical change. They aggregate 32 sectors in 26 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 & Kempa (2018) determine the average energy intensity across sectors, then classify those using more energy than average as "energy-intensive" and those using less as "labor-intensive". The substitution rate between the 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 reduction in energy use per unit of economic output is greater in nations where technological advancements primarily focus on labor-intensive industries. 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 et al. (2020) contribute to this growing literature by using a stochastic frontier model to analyze the DTC in 16 developed and developing countries. Their findings, which showed that technological change tends to be directed towards energy rather than labor, provide empirical support for the sectoral biases observed by Haas & Kempa (2018).

This alignment between studies underscores the importance of considering sector-specific factors when analyzing the broader implications of DTC on energy use and environmental policy. Lanzi & Wing (2011) provide an earlier contribution by developing a two-sector dynamic DTC model that focused on the fossil fuel and renewable energy sectors. Their findings, which established a relationship between relative energy prices and innovation levels, resonate with the insights from Acemoglu et al. (2012) and Fried (2018). The EoS between fossil and renewable sectors, found to be 1.64, suggests a potential for significant shifts in innovation focus as energy prices change, further corroborating the critical role of substitution dynamics highlighted in the literature.

Hou & Song (2022) explore DTC's role in improving China's energy structure. 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 research explores pathways for enhancing China's energy structure, focusing on replacing fossil fuels with electricity and transitioning from thermal power to cleaner alternatives. It also investigates whether directed technical advancements effectively optimize this energy framework. The findings uncover an internal substitution dynamic between thermal power and clean energy. However, technical innovations prioritize fossil fuels over thermal power and clean energy during the external transition, suggesting a dynamic interchange among these three inputs. This suggests that technological progress, in this context, hinders the shift from fossil fuels to electricity as the primary energy source. Therefore, the study suggests that the Chinese government should implement measures such as carbon taxes to eliminate the impact of DTC and optimize the energy structure, similar to the implications discussed in Acemoglu et al. (2012) and Fried (2018). Zhou et al. (2020) investigate the effect of industrial structural rationalization, upgrading, and eco-industrialization processes on energy and environmentally focused technological progress. As industries evolve and technology advances, sectors become more efficient. This attracts resources like labor and capital from less efficient sectors, causing a shift in the economy's makeup. To achieve this, a spatial autoregression model is constructed using panel data covering the years 2000-2016 for the 30 provinces of China. The results demonstrate that the DTC is based on multidimensional industrial structural changes.

As a novel approach, Yang et al. (2020) contribute to the DTC literature with a distinct application. Their research examines how technological advancements driven by big data influence environmental quality. The results suggest that as investments in clean technology research and development become more attractive, big data can further improve environmental conditions. Moreover, while applying 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.

To conclude, the environmental model of DTC literature, inspired by Acemoglu et al. (2012), generally links the model to environmental policies based on energy type, price, and efficiency measures. Nevertheless, although limited, the findings regarding cross-sector technology spillovers provide noteworthy insights.

7. Conclusion and Recommendations

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

Acemoglu et al. (2012) extend the earlier DTC 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 DTC. 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 DTC, impact the direction of innovations during the transition to a low-carbon economy in DTC models? The empirical literature suggests that innovations in clean technologies respond to environmental policy and generally link the DTC model to environmental policy based on energy type, price, and 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.

Several points 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 the DTC. Furthermore, obtaining more empirical evidence could be beneficial since there has yet to be a general consensus on whether clean and dirty technologies have a substitution or complementary relationship. Finally, it is necessary to analyze the effects of cross-sector technology spillovers on productivity levels at the firm level, which result in DTC.

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Conflict of Interest: None.
Funding: None.
Ethical Approval
Author Contributions: Bilal ÇAYIR (100%)

Çıkar Çatışması: Yoktur.
Finansal Destek: Yoktur.
Etik Onay: Yoktur.
Yazar Katkısı: Bilal ÇAYIR (%100)