The Impact of Feed-in Tariff on Green Total Factor Productivity: Cross-country Empirical Evidence

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List of Abbreviations

BaU	Business as usual
CAGR	Compound annual growth rate
CAPEX	Capital expenditure
CO_2	Carbon dioxide
CO_{2eq}	CO_2 equivalent
CUE-GMM	Continuous updating estimator GMM
CVs	Critical values
DDF	Directional distance function
DEA	Data envelopment analysis
DID	Difference-in-differences
DMU	Decision-making unit
EEG	Erneuerbare-Energien-Gesetz (Renewable Energy Sources Act)
FA	Factor analysis
FDI	Foreign direct investment
FEM	Fixed-effects model
FIT	Feed-in tariffs
GHG	Greenhouse gas
GMM	Generalised method of moments
GTFP	Green total factor productivity
HAC	Heteroskedasticity- and autocorrelation-consistent (estimator)
HICs	High-income countries
ICT	Information and communications technology
IMF	International Monetary Fund
KOF	Swiss Economic Institute
LIML	Limited Information Maximum Likelihood
LPI	Luenberger productivity index
MICs	Middle-income countries
MIT	Middle-income trap
MLI	Malmquist-Luenberger productivity indicator
ND-GAIN	Notre Dame Global Adaptation Initiative
NO_x	Nitrogen oxides
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
OPEX	Operating expenditure
PCA	Principal component analysis
PISA	Programme for International Student Assessment
PM_{10}	Particulate matter
POLS	Pooled OLS
PPAs	Purchasing Power Agreements
PPF	Production possibility frontier

PURPA	Public Utility Regulatory Policies Act
PV	Photovoltaic
RE	Renewable energy
REM	Random-effects model
SE	Standard error
SO_x	Sulfur oxides
StreEG	Stromeinspeisungsgesetz (Feed-in Law)
SUTVA	Stable unit treatment value assumption
TECCH	Technological change
TECH	Technical efficiency change
TFP	Total factor productivity
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
V-Dem	Varieties of democracy
WDI	World Development Indicators
WGI	World Governance Indicators
WMO	World Meteorological Organisation

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Abstract

Extensive global climate actions have been implemented through demand- and supply-side initiatives to curb fossil fuel use. Still, GHG emissions continue to rise at an alarming rate, posing threats to economies. Given this context, the present paper focuses on FIT as a market-pull instrument in the RE transition. Despite the positive impact on RE generation and CO_2 emission mitigation, the role of FIT in sustainable development remains understudied. Moreover, TFP growth often emerges as the stimulus for continuous growth, but it ignores environmental impacts. Hence, GTFP credits both desirable and undesirable outcomes, acting as an alternative to TFP. This paper aims to examine the effect of FIT on GTFP growth. Outcomes are built on the non-parametric MLI under the DDF with global PPF, decomposing into TECH and TECCH. To do so, a panel dataset of 56 countries over the 1990-2019 period has been used. The CUE-GMM estimation method with HAC SEs is also integrated to handle endogeneity and heteroskedasticity in the specification. The findings indicate that the FIT has a positive impact on GTFP and TECCH, and a negligible influence on TECH. Heterogeneous results suggest a similar pattern in OECD countries, but counterbalancing effects in non-OECD countries. While generous rates failed to translate into proportionate green performance, the impacts of FIT in mature RE technologies are more pronounced. As a result, a mix of policies, such as carbon taxes and augmenting R&D subsidies, should be considered to complement FIT. This, in turn, facilitates the simultaneous influences of technological diffusion and the frontier shift. FIT remuneration degression is also imperative to reap the full benefits of FIT in GTFP and TECCH.

Relevance to Development Studies

This paper lies at the intersection of environmental and development economics. From the former perspective, it focuses on one of the most prominent demand-pull RE policies, FIT. The scheme is crucial for boosting RE investments and carbon emission reduction. This aligns with the UN Sustainable Development Goal (SDG) 7 on affordable and clean energies. Moreover, GTFP is a crucial metric of green performance, as it integrates CO_2 emissions into the measurement method. Therefore, the impact of FIT on GTFP helps to evaluate operational improvements in the RE transition. From the latter standpoint, GTFP often serves as a precursor for sustainable development. FIT also signals price effects for endogenous R&D investments towards cleaner and resource-saving technologies (Acemoglu *et al.*, 2012, pp. 131–66). As a result, this research sheds light on the impact of price-induced subsidies on technical progress and diffusion along the biased R&D path, leading to long-run growth. Together, research findings establish an empirical bridge from Acemoglu's concept of directed technical changes to GTFP growth in the cross-national setting. This, in turn, enables a deeper understanding of the continuous growth patterns in development theories.

Keywords

Feed-in tariffs; Malmquist-Luenberger productivity indicator; green total factor productivity; technological progress; technical efficiency.

Chapter 1. Introduction

Climate change is defined as the "long-term shifts in temperatures and weather patterns" arising from both natural factors and human activities (UN, 2025). Still, burning fossil fuels has been the main driver of this phenomenon since the 1800s. This leads to the alarming rate of GHG emissions and rising temperatures on Earth. WMO (2025) reported that atmospheric CO_2 levels reached 420 ppm in 2023, up 2.3 ppm from 2022 and 151% of the pre-industrial level. Meanwhile, the mean near-surface temperature in 2024 was 1.55 °C above the 1850-1900 baseline, marking the highest point in the 175-year observational period. Ocean heating content also registered at 11.2–12.1 ZJ per annum over the last two decades, more than double the rate observed from 1960 to 2005. Sea-level rise also set a new annual record of 4.7 mm between 2014 and 2015, over twice the figure for 1993-2002. The advent of El Niño and La Niña acts as an amplification mechanism behind such heat extremes and sea-level anomalies. These factors contribute to an increasing number of prolonged extreme weather events, including droughts, floods, heatwaves, and wildfires. As a result, millions of people worldwide contend with food crises, economic losses, environmental degradation, casualties, and displacement. Overall, climate change has become one of the most pressing issues of our time.

Numerous global efforts have been made to address climate change since the first World Climate Conference in 1979 (UNFCCC, 2025). In 1988, the WMO and the UN Environment Programme set up the Intergovernmental Panel on Climate Change, providing scientific assessments as the foundation for international negotiations. In 1990, the UN introduced the Intergovernmental Negotiating Committee for the UNFCCC, involving over 150 states. The Convention was then opened for signature at the Rio Earth Summit in 1992 and entered into force in 1994, with the involvement of 198 parties to date. Still, the 1995 Berlin Mandate highlighted inadequate commitments in comparison to its objectives, charting the course for strengthened negotiations on the responsibilities of developed countries. As a result, the Kyoto Protocol was adopted in 1997 and ratified in 2005, serving as the first legal document on GHG emissions reduction. Several subsequent Conferences of the Parties convened to establish the groundwork for greater ambition and climate action at all levels, including developing countries. Combined with the 2014 Lima Call for Action, in-depth discussions under the 2012-2015 Ad Hoc Working Group on the Durban Platform for Enhanced Action culminated in the approval of the 2015 Paris Agreement, aiming to limit global warming to 1.5 °C. It was a historic milestone as all nations came together for the first time to take concerted actions and make investments towards a sustainable, resilient, and low-carbon future. Still, the temperature goal of the Agreement might give a misleading impression due to natural climate variability (WMO, 2025).

On the other hand, Shue's (2015, pp. 7–31) argument that "neither bad intentions nor foresight is necessary to causal responsibility" for causing climate change provides a fundamental moral insight into the responsibility in the North-South relationship. Following the principle in the camel narrative, advanced economies should be the main contributor to current climate actions, given their unintentional historical high emissions. Still, transforming these ethical intentions into practice might confront challenges arising from high-polluting industrial development in developing economies. It is impractical to force Global South countries to shut down their manufacturing sectors in pursuit of climate action without financial benefits (Sharma *et al.*, 2025, p. 124639). The majority of existing policies have focused on diminishing the use of fossil fuels. Meanwhile, a moratorium on oil extraction in some resource-rich developing countries has been in place since the 1990s. Pellegrini and Arsel (2022, pp. 1–14) argued that supply-side initiatives began to gain attention and acceptance due to the ineffectiveness of demand-side counterparts. Pursuing these policies together can reinforce commitments to abate GHG emissions and address weaknesses in demand interventions. These demand-side challenges include intercountry and intertemporal leakages arising from arbitrage in fossil fuels.

Nonetheless, moratoria and compensation mechanisms might struggle with financial and distributive constraints. Orta-Martínez *et al.* (2022, pp. 15–27) found that $5.4 trillion is needed to compensate rights holders for leaving oil and gas in the ground. In addition, there is a mismatch between the rhetoric, intentions, and actions of international donors in fulfilling financial obligations towards owners of fossil fuel reserves, leading to the so-called bullshit governance (Stevenson, 2021, pp. 86–102). This can be seen in the case of the Yasuní-ITT initiative, where $3.6 billion was committed to compensate for the unburnable 0.85 billion barrels of crude oil. However, a fraction of $34 million had been disbursed to the Yasuní-ITT trust fund, and therefore, Ecuador abandoned the project (Orta-Martínez *et al.*, 2022, pp. 15–27). Hence, it is imperative to revisit demand-side policies, but under the transition to RE sources, rather than cutting fossil fuel use. FITs emerge as one of the most effective and prominent demand-pull policies in accelerating the deployment of RE technologies. As of 2022, 83 jurisdictions had implemented the instrument worldwide (REN21, 2023). The FIT scheme provides a secured remuneration for RE investments, thus reducing financial risks and attracting more new entrants.

A considerable amount of literature has been published on the environmental and economic impacts of the programme. These studies support its beneficial role in RE installations and CO_2 emissions, while the effects on GDP growth and job creation remain complicated. Meanwhile, productivity is considered the "ultimate engine of growth in the global economy" (OECD, 2015). As a result, enhancing productive power has become a fundamental concern for countries to sustain their growth performance. Under the Cobb-Douglas production function, TFP refers to an unexplained component of economic output, owing to advances in production and process technologies (Kim and Park, 2017). Since 1947, a significant portion of economic expansion has been attributed to TFP growth. TFP disparities in different income groups have also elucidated productivity gaps between them. Hence, TFP growth serves as an effective measure for productivity changes. In HICs, sustained long-term growth depends on enhancements in TFP/MFP, focusing on continuous investments in knowledge-based capital and the diffusion of innovations (OECD, 2015). Supporting this view, TFP growth acts as a precursor for MICs to overcome the MIT, a sharp slowdown after GDP reaches around $15,000-$16,000 (Agénor, Canuto and Jelenic, 2012). This trap can be attributed to high debt, an ageing population, fierce competition from lower-wage economies and adoption challenges of advanced technologies. Among standard methods of measurement, a non-parametric TFP index using a linear programming approach provides a more flexible estimation, facilitating the decomposition into innovation effect and catching-up effect. Still, the traditional TFP growth fails to capture the environmental impacts of productivity improvements (Hulten, 2001, pp. 1–54).

GTFP is an environmentally sensitive measure of TFP, crediting both desirable and undesirable outputs. Sharma *et al.* (2025, p. 124639) argued that a large and growing literature has signalled a shift in cognisance to sustainable productive power since 2017. China positions itself as a pioneer in this field as a result of the public emphasis on environmental regulations and green finance. Findings from Zhou *et al.* (2023, p. 129042) highlight the positive role of FITs on GTFP and its components. Still, there is little empirical evidence on such causal paradigms outside China, let alone between the developed and developing countries, different RE technologies, and remuneration levels. Given the dearth of empirical studies, this paper aims to examine the impact of the FIT on GTFP growth and its components using a cross-national panel dataset from 1990 to 2019. This paper seeks to answer the main research question: "To what extent does the FIT affect GTFP growth?" To answer that question, the following five sub-questions will be explored:

- To what extent does the FIT affect TECH?
- To what extent does the FIT affect TECCH?
- How much does the FIT affect GTFP growth and its components between OECD and non-OECD countries?
- How much does the FIT affect GTFP growth and its components among FIT rate levels?
- How much does the FIT affect GTFP growth and its components among RE sources?

From an academic perspective, the paper attempts to illuminate the connection between Romer's (1990, pp. S71–S102) endogenous growth model and Acemoglu *et al.*'s (2012, pp. 131–66) concept of directed technical changes under environmental constraints, facilitating the examination of the FIT-GTFP causal pattern. This theoretical linkage provides a framework for assessing how instrument-induced price effects shape the technical changes along the biased path for sustainable development. From a practical viewpoint, it is expected to propose more effective pro-growth FIT designs that enhance GTFP growth, TECH, and TECCH. From a development standpoint, the research lies at the intersection of environmental and development economics. It provides insights into how demand-pull RE policies can serve as a stimulus for green performance, leading to both higher GDP per capita and lower CO_2 emissions. As a result, developing countries stand a higher chance of transitioning from polluting, input-driven to cleaner, innovation-driven growth.

The remainders of the study are organised as follows. Theories of change and empirical studies on the causal relationships between FITs and GTFP growth, TECH and TECCH are reviewed in Chapter 2. Data description and research methodology are outlined in Chapter 3. Research findings are presented in Chapter 4. Discussions of the results and their implications are provided in Chapter 5.

Chapter 2. Literature review

This chapter first introduces two crucial theories of change in the endogenous green innovation domain. Examining these views, empirical studies shed light on the historical development of FITs and GTFP. Later evidence highlights the environmental and economic impacts of the former, as well as the measurement methods and determinants of the latter. The literature on the linkage between these two concepts is further discussed at the end of the chapter.

2.1. Theoretical framework

2.1.1. Endogenous technological change

Endogenous technological change provides a framework for long-term economic growth as an outcome of the intentional actions of profit-maximising agents (Romer, 1990, pp. S71–S102). This approach diverges from neoclassical growth concepts, where exogenous technological progress enters the production function as an unexplained residual (Solow, 1956, pp. 65–94). In the Romer model, technological change is derived from purposeful R&D investments of private firms. These companies respond to market incentives and allocate human capital devoted to research activities to produce innovations. The model assumes that knowledge is a nonrival and partially excludable production input. Hence, a new design can be utilised repeatedly without depletion. Much as legal or technical means might limit its use in the production of new producer durables, these restrictions cannot deprive an engineer from adopting it in the research sector. Producing new knowledge often generates reusable innovations without additional marginal costs, leading to nonconvexities in the aggregate production function. As a result, it eliminates price takers and defines an equilibrium that allows for monopolistic competition and spillover externalities.

Romer conceptualised these phenomena with a model of three sectors: research, intermediate goods production, and final goods production. The research sector transforms human capital and the existing stock of knowledge into new designs. Each new design, combined with capital, contributes to creating a new intermediate durable available for manufacturing final goods. The generation of innovation also becomes easier as more knowledge accumulates due to a positive feedback loop of R&D activities. A larger stock of knowledge is often associated with more research outputs for production, and therefore, it demonstrates the increasing returns to scale in the research sector. In addition, the long-run economic expansion relies on the allocation of human capital between these sectors. Unlike semi-endogenous growth with the emphasis on the exogenous population growth rate, Romer pointed out that sustained innovation lies in the distribution and level of human capital. Hence, education and skill formation are critical determinants in pursuing long-term development. Nevertheless, there is a market failure in translating research outputs into effective spillover externalities. Private firms often struggle to capture the overall social benefits of innovation due to their business priorities for financial performance. Therefore, these agents often allocate lower-than-optimal investments in R&D efforts. Government interventions might act as feasible solutions to bridge the gap between private and social capital returns and improve overall welfare.

Additionally, the Romer model differs from earlier endogenous works in decision-making. This can be seen from the perspective of Arrow's (1962, pp. 155–173) learning-by-doing, which presents innovation as a passive by-product of capital accumulation. In contrast, firms in the endogenous technological change framework actively participate in R&D activities as profit-maximising activities under monopolistic competition. This allows for a higher marginal product of the research sector associated with an increase in the intermediate varieties, motivating long-term economic growth. Thus, technological change is an economic factor subject to resource allocation decisions and institutional constraints. Romer's (1990, pp. S71–S102) endogenous technological change shifts the focus of growth theories from exogenous forces to market-driven innovation, facilitating the causal paradigms between technological progress, institutional settings, market structures, and human capital formation. With nonrival and partially excludable knowledge as producer durables, the framework also reveals the cumulative and scalable nature of innovation. Hence, it elaborates on the differences in long-run growth rates across countries and provides a theoretical foundation for evaluating innovation-related policies.

2.1.2. Directed technical change

Directed technical change extends the endogenous growth models through the incorporation of the direction of innovation as a choice rather than a fixed outcome. In neoclassical and earlier endogenous perspectives, technological progress improves the marginal product in a uniform manner across sectors or inputs. In contrast, directed technical change considers that innovation can target specific production factors depending on market conditions and relative profitability. Acemoglu (2002, pp. 781–809) argued that firms allocate research efforts towards improving technologies that complement either capital or labour as production inputs. The main mechanism relies on the interaction between relative factor prices and the profits of different research lines. Hence, there is a trade-off in technological advances facing firms, directing innovation towards the scarce or the abundant factor. The model refers to this phenomenon as the tension between the price effect and the market size effect. The former increases the incentive for innovation that complements the scarcer and more expensive factor, where the marginal rate of return is higher. In turn, the latter facilitates technical advances that favour the more abundant factor, as firms can sell to a larger number of users. The directed technical change equilibrium depends on the effect of domination, and therefore, it determines the direction of factor-biased technological progress. As a result, it presents causal paradigms between factor endowments, innovation incentives, and long-run growth.

Moreover, the concept reveals the mechanism by which changes in factor supplies serve as a precursor to the innovation pattern. This can be seen in the case of economies with higher capital accumulation, where private firms are more attracted to promote capital-augmenting technological advances. The feedback loop contributes to a biased path of innovation and reinforces the role of the initial abundant factor. In addition, under standard assumptions, long-run growth requires the innovation process to enhance the factor whose share in output remains stable over time (Acemoglu, 2002, pp. 781–809). This leads to asymptotic factor-augmenting neutrality to prevent one factor's share from collapsing to zero. The direction of innovation, hence, forms the basis for a balanced growth path. Much as there are structural changes, the bias in technological progress persists. Thus, the model provides a framework for understanding the impacts of government interventions on the direction of technological progress. If market outcomes lead to inefficient allocation of research efforts, targeted policies can adjust incentives toward more desirable innovations. This framework is also relevant in the context of environmental performance. Acemoglu *et al.* (2012, pp. 131–66) integrated the competition between clean and pollution-intensive technologies into the initial framework. With profit-maximising goals, market forces tend to encourage polluting innovations due to a higher marginal return in the short run. As a result, environmental policies, such as carbon taxes or environment-related subsidies, act as an effective solution to shift innovation incentives and facilitate sustainable long-run development.

Acemoglu's (2002, pp. 781–809) directed technical change provides a foundation for empirical observations that technological progress has not been neutral, regardless of the factors or sectors involved. Historical events, such as the Industrial Revolution or the ICT era, facilitated innovations that favoured capital or complemented skilled labour in a disproportionate manner. Hence, the model formalises such technical bias and links it to economic fundamentals, such as factor endowments, relative prices and market sizes. It also enriches the Romer model with the rate and direction of innovation as additional endogenous inputs. These insights offer broader implications for income distribution, structural changes, and environmental intervention designs, due to technological advances in labour, capital and fossil-fuel use. Moreover, as innovation evolves along biased paths, the model deepens an understanding of the relationship between innovation incentives, market forces, and long-term development.

2.2. Empirical studies

2.2.1. Environmental and economic impacts of FIT

2.2.1.1. Evolution and design of FIT

FITs represent a command and control instrument that offers guaranteed prices for renewable electrical outputs feeding into the grid over a fixed period. Jacobs (2014, pp. 755–773) described how the law has evolved through targeted upgrades across different jurisdictions since the 1970s. Due to increasing fuel prices and construction costs of new conventional power plants, the U.S. initiated the process with the PURPA of 1978. It mandated state-owned utilities to purchase electricity from smaller-scale generators at avoided cost rates. Despite the capital access for RE projects, the PURPA rates relied on the cost structure of incumbent production. Thus, the government of California refined the regulation with long-term contracts and indexed prices under the Standard Offer No.4 of 1983. Much as the divergence of fuel price forecasts placed a significant financial burden on utilities, it reduced revenue risks for non-utilities. Following success in California, several European countries began to adopt the price-based approach in supporting RE producers in the mid-1980s. To address the drawback of the state-interpretation PURPA 1983, Denmark implemented voluntary agreements to anchor FIT remunerations at around 80–90% of the retail price in 1986. At the same time, Portugal imposed Decree-Law No. 189/88 (DR 1988) to facilitate cogeneration and small-scale renewable power production. The German federal government later enacted the Feed-in Law of 1990 (StreEG 1990) as a result of increased pressure from parliamentarians in support of RE after the Chernobyl nuclear accident in 1986. Instead of voluntary contracts, the legislation offered legal purchase obligations between regional monopolies and non-utilities at 65–90% of the price, depending on the RE technologies.

Nevertheless, building on the value-based approach, the Danish and German indexed prices were subject to the volatile electricity market in the late 1990s. Hence, the Electricity Act 1997 in Spain advanced the tariff calculation with explicit generation costs based on the "cost-covering remuneration" method. This facilitates RE manufacturers to gain reasonable profits relative to capital costs on financial markets. Eventually, the German parliament integrated these principles into the EEG 2000. It codified technology-specific rates for RE investors based on generation costs with a long-term guaranteed period of up to 20 years. The scheme thus serves as a best practice for FIT design, contributing to its rapid global diffusion. Couture and Gagnon (2010, pp. 955–965) further argued that FITs are categorised into two main models: market-independent and market-dependent. With pre-determined prices, the former provides a fixed amount of remuneration under PPAs for each RE kilowatt-hour produced, regardless of market volatility. In contrast, the latter compensates for the premium paid on top of the retail price, known as the feed-in premium, and causes fluctuations in the marginal returns of RE investors. As a result, the market-independent model with a fixed price remains the most widespread FIT in practice. It helps secure legal access to government subsidies, minimises financial risks, and delivers investment certainties for new entrants. Therefore, the initiative can attract more diverse independent power producers to accelerate the cost-effective transition from fossil fuels to renewable sources.

2.2.1.2. Role of FITs in the RE transition and ex-post performance

Empirical evidence shows that FITs are crucial predictors for promoting investment in RE technologies (Smith and Urpelainen, 2014, pp. 367–392; Carley *et al.*, 2017, pp. 397–440). Focusing on advanced economies, Szendrei *et al.* (2025, p. 126102) pointed out the positive effects of the scheme on RE growth in Europe. As the pioneer of FIT adoption, the Danish financing led to the successful penetration of wind power in electric power consumption, at 13 per cent in 2001 (Meyer and Koefoed, 2003, pp. 597–607). However, Munksgaard and Morthorst (2008, pp. 3940–3947) indicated that Denmark experienced a dramatic decline in new onshore wind turbine installations after the electricity market liberalisation due to inefficient spatial planning, high risk aversion and more conducive neighbouring programmes. Despite the volatility of the restructured market, a combination of FIT, anticipatory transmission planning and interconnection costs allocated to loads or end-users provides strong incentives for sustainable RE investments in the U.S., Canada and other European markets (Alagappan, Orans and Woo, 2011, pp. 5099–5104). Proença and St. Aubyn (2013, pp. 176–185) found that the instrument was an effective and cost-efficient means that enabled Portugal to climb 25.8% of RE shares in the power source structure compared to the BaU scenario. Specifically, wind energy recorded the highest rise of 21.9%, almost tenfold the figures for biomass and hydroelectric power. This is similar to the case of Spain, where RE sources accounted for 25% (68.5 TWh) of the total electricity generation in 2012, excluding large hydro (Azofra *et al.*, 2015, pp. 47–56). Nonetheless, López Prol (2018, pp. 1170–1181) indicated the adverse effects of uncertainties in the Spanish programme and solar orchard ownership structure, compared to the stable German EEG. An increase of 1 cent in the EEG was further associated with an increase of 796 MW in wind capacity during 1996-2010 (Hitaj and Löschel, 2019, pp. 18–35). Moreover, the provision of Italian Conto Energia was pivotal to the PV expansion, with an additional 17.6 GW in installed capacity and 157 GWh in commercial generation from 2006 to 2018 (Poponi, Basosi and Kurdgelashvili, 2021, p. 112297). This is similar to the case of Croatia, where the wind FIT facilitated achieving 10% of RE production earlier than the 2020 target (Mikulić, Lovrinčević and Keček, 2018, p. 1881).

On the other hand, the role of FITs in the RE transition in MICs remained controversial. Lin and Xie (2024, p. 130853) stated that the financing support dramatically boosted the RE installed capacity in China, especially in large state-owned enterprises. The solar FITs, in tandem with lower investment costs, were essential drivers of the substantial rise in utility-scale PV investments (Zhang *et al.*, 2022, p. 113044). Zhou, Dong and Li (2023, pp. 37791–37804) also reported that an increase of ¥0.1/kWh in remuneration was associated with an additional 7.4-9.6 GW in wind capacity per annum. Likewise, a 10% increase in Taiwan's FIT rates led to a growth of NT$1.19 billion in the cumulative wind output value in 2020 (Hsu and Ho, 2016, pp. 548–557). Meanwhile, the positive effects of FITs in Thailand and Malaysia were more evident on PV generation, but insignificant on other RE forms (Tantisattayakul and Kanchanapiya, 2017, pp. 260–269; Koerner *et al.*, 2022, p. 112918). However, the effect on residential rooftop PV was negligible compared to large-scale solar utilities. In Vietnam, Do *et al.* (2021, pp. 1–11) noted that generous FIT rates and exemptions for income tax and land lease augmented the investment environment and signalled price effects for RE new entrants. As a result, these factors have been vital to the solar and wind installation boom since 2011. Still, domestic investors struggled with limited transmission infrastructure and complex administrative procedures. In addition, Guild (2019, pp. 417–431) highlighted the crucial contribution of FITs to the massive growth in RE capacity in the Philippines, rather than in Indonesia. This aligns with the findings of Setiawan *et al.* (2022, p. 113164), who asserted that bureaucratic, social and technical factors deterred the beneficial influence of the Indonesian scheme on the geothermal power. Unavailable technical experts and inefficient FIT implementation also dampened the RE uptake in Kenya, leading to 0.66% of the target electric power generation (Ndiritu and Engola, 2020, pp. 593–605). Therefore, the Global Energy Transfer FIT or GETFiT, a top-up result-based cash flow from international donors, is an effective alternative that attracted $453 million in disbursements for 17 small-scale RE projects in Uganda over three years (Probst *et al.*, 2021, p. 105347).

Environmentally, as a stimulus for RE installation, FIT policies cause a significant reduction of greenhouse gas emissions from fossil-fuel combustion. This is evident in the case of Portugal, where the imposition of FIT subsidies resulted in a reduction of over 7.2 million tonnes CO_{2eq} between 2000 and 2010 (Behrens *et al.*, 2016, pp. 309–319). Moreover, Peña, Lima Azevedo, and Ferreira (2014, pp. 353–363) found that wind power avoided 22 million metric tons of CO_{2eq}

during 1990–2013. Therefore, it contributed to achieving the national RE target of 45% in 2010 (Proença and St. Aubyn, 2013, pp. 176–185). In addition, FITs led to the respective avoided CO_2, NO_x, and SO_x values, at \$10/t, \$478/t, and \$1460/t in Spain (Azofra *et al.*, 2015, pp. 47–56). Meanwhile, the German EEG caused more 4% reductions in CO_2, NO_x, SO_x, and PM_{10} emissions than the uniform FIT incentive. In Italy, the PV installations in the Conto Energia programme enabled the avoidance of 77 million tonnes of CO_{2eq} in GHG emissions at a cost of €405/ton over 13 years. This is consistent with the case of Australia, where FIT had long-term influences on diminishing the emission consequences, although challenges exist in the short term (Zakari *et al.*, 2024, pp. 108–125). In China, Zha *et al.* (2023, p. 113782) believed that the mix of RE policies positively and synergistically impacts carbon emission reduction, with the most effective role of FIT. Farias-Rocha *et al.* (2019, pp. 45–56) also argued that the Philippines' utility-scale programme caused a decrease of 102.9 tonnes CO_{2eq} in GHG emissions. Along the same line, the RE remuneration demonstrates potential for significant environmental benefits in Iran under different simulation scenarios. Compared to the BaU scenario, the instrument is expected to cause a reduction of 7% in carbon emissions from 2019 to 2040 (Mostafaeipour *et al.*, 2022, p. 121602). Combined with reducing fossil fuel subsidies and introducing carbon costs, it amplifies the abatement effect to 41% over the same period.

Economically, using the agent-based Eurace model, Ponta *et al.* (2018, pp. 274–300) found that FIT was associated with increased job creation due to higher RE investments under various simulation scenarios. Moreover, as financing costs had little impact on government budgets, there was an upward trend in economic conditions. Still, high remuneration intensities led to a growth in the GDP share of investment sectors, lower consumption, and higher interest rates and prices. Evidence on the economic impacts of FITs is mixed. Szendrei *et al.* (2025, p. 126102) affirmed that the Danish GDP growth rebounded in the long run after a brief short-term decline in exposure to the national-specific shock of FIT-induced RE generation. Nonetheless, Austria and the U.K. experienced a sustained economic contraction. There was also a lower demand in the Austrian, Slovakian and German labour markets during the same period. This aligns with Hillebrand *et al.*'s (2006, pp. 3484–3494) work on the German EEG, where the contractive effect crowded out an initial expansion of 33-thousand jobs due to higher power production costs. In contrast, Behrens *et al.* (2016, pp. 309–319) argued that the Portuguese subsidies led to a growth of €1557 million in GDP and an additional 160-thousand jobs per annum from 2000 to 2010. In the same vein, the Spanish FITs caused an estimated savings of €0.7 billion in emission costs (Azofra *et al.*, 2015, pp. 47–56). Gallego-Castillo and Victoria (2015, pp. 411–420) further found that such savings can compensate for the rates between €50 and €80 per MWh without extra costs for consumers. Otherwise, additional solar generation causes a rise in the industrial retail price, and the effect is greater than that of wind power (Costa-Campi and Trujillo-Baute, 2015, pp. 157–165). Meanwhile, in Croatia, wind FITs generated advantageous socio-economic effects, despite the limited domestic production of turbines and equipment (Mikulić, Lovrinčević and Keček, 2018, p. 1881). The programme stimulated economic activities among foreign suppliers, contractors, installers and maintenance companies. Therefore, over 4000 jobs were supported during peak investments and around 2500 jobs after the planned subsiding quota.

2.2.2. Relationships between GTFP, growth and environmental health

2.2.2.1. Overview of TFP

Productivity has shifted from an implicit part of the circular income flow model to one of the two really great mysteries of economics (Krugman, 1994). In the classical era, Adam Smith, often known as the father of modern economics, emphasised the impact of the division of labour in boosting production efficiency and the wealth of nations in 1776. Later, David Ricardo highlighted the benefits of resource allocation through specialisation in more productive sectors in 1817, leading to the so-called comparative advantage. The concept remained marginal until the continuous growth of advanced economies since the Great Depression (Kim and Loayza, 2019).

In 1939, Hicks highlighted the importance of productivity improvements in social welfare. Schumpeter then established bridges between perpetual firm renewal and creative destruction in 1942, forming the conceptual basis for productive power as an innovation-induced outcome. Literature in the 1950s also supported the growth path based on structural transformation from less to more productive sectors, such as the Lewis dual-sector model or the Kuznets curve.

On the other hand, Tinbergen (1942, pp. 511–549) first tied the aggregate production function to productive studies. Supporting this view, Solow (1956, pp. 65–94) developed a seminal work on the neoclassical growth model, revealing the role of changes in capital accumulation and labour in the growth rate. The model established the groundwork for understanding TFP as the portion of output not explained through these traditional inputs, the so-called Solow residual (hereafter, $\mathfrak{R}_t$). However, Abramovitz (1956, pp. 5–23) argued that $\mathfrak{R}_t$ is a "measure of our ignorance" as it captured desirable technological changes and undesirable aggregation bias, measurement errors or omitted factors. Jorgenson and Griliches (1967, pp. 249–283) adopted careful adjustments for input decomposition and model specification to limit residual noise, advancing the growth-accounting approaches. Still, assuming exogenous TFP, the Solow model failed to elucidate the long-term development with increasing saving rates. To address the theoretical shortcomings, Romer (1990, pp. S71–S102) established the substantial contribution of horizontal technological advances to sustain innovation through R&D investments, the existing stock of ideas, and knowledge spillover effects.

In contrast, Aghion and Howitt (1992, pp. 323–351) described the role of vertical innovation in continuous growth under the creative destruction mechanism. This, in turn, complements the Romer model with the business-stealing effects. Together, these endogenous theories conceptualised TFP as an outcome of intentional research activities. However, Solow's (1987, p. 36) comment on computers emphasised the missing effects of the ICT-driven opportunities on TFP, leading to the so-called Solow paradox. The New Economy also criticised the productivity statistics for omitting changes in product quality, thus understating the actual gains in output per capita (Hulten, 2001, pp. 1–54). More recent attention on TFP has shifted to the roles of human capital, tax-financed public goods, trade openness, institutions, and FDI (Haider, Kunst,(Haider, Kunst and Wirl, 2021, pp. 283–327). Still, it has drawn further criticism for neglecting several crucial dimensions of sustainability. For example, Hsiang (2010, pp. 15367–15372) found that the production efficiency of labour-intensive industries starts to fall as the average surface temperature exceeds 26 °C. This resulted in an estimated 2.5% drop in economic output for each additional degree Celsius. As a result, these critiques raised concerns about conventional TFP as an environmentally undistorted and neutral measure of productivity.

2.2.2.2. Patterns and determinants of GTFP

Measuring and decomposing TFP and GTFP

Heshmati and Rashidghalam (2020, pp. 21–36) pointed out that methods for traditional TFP measurements are divided into four groups: exact index numbers, parametric estimations, non-parametric indices, and linear programming approaches. The first cluster originates from Copeland's (1937, pp. 3–63) paper, where the "output per unit input" index laid the foundation for using index numbers as an efficiency measure. However, it is subject to substitution bias arising from consumer responses to changes in relative prices, as Friedman noted (Hulten, 2001, pp. 1–54). Denison then proposed chain-indexing procedures to mitigate the chronic measurement issues of fixed-weighted indices in 1962. Later, Ahn and Abt (2006, pp. 323–335) advocated using the Fisher price index number due to its self-duality property. This means the direct quantity index is identical to the indirect price-deflated one. Building on the Solow model and the Cobb-Douglas production function, the second cluster, parametric estimations, measures $\mathfrak{R}_t$ growth based on the growth accounting pattern of Jorgenson and Griliches (1967, pp. 249–283). Given a set of inputs, the frontier approach assumes the existence of production boundaries corresponding to the maximum attainable output levels, in contrast to the non-frontier counterpart. This method is advantageous for the panel data and the investigation of heterogeneous and temporal effects. Still, it is sensitive to assumptions on functional form, returns to scale and equilibrium conditions. In addition, growth accounting mismeasures environmental externalities and resource depletion (Hulten, 2001, pp. 1–54). Using market quantities and prices, it ignores the costs of growth arising from the degradation of natural capital, including forests, parks, and clean air and water. Hence, the method overstates real improvements in social welfare.

On the other hand, the third cluster, non-parametric indices, adopts the input-output approach to measure TFP growth and its components. These indicators are often categorised into two major branches: the Malmquist index and the Luenberger index. The former non-parametric index conceptually traces back to the microeconomics work of Malmquist (1953, pp. 209–242), who first defined price and quantity indices on indifference surfaces to enable comparisons at the same utility level. In the same vein, Caves, Christensen, and Diewert (1982, pp. 1393–1414) linked the Malmquist concept to the Shephard output distance function, leading to the so-called CCD formula. This helps compare input, output, and productive power between two DMUs operating under the same production frontier. Using observed data on price and quantities, the empirical Törnqvist output and input indices are equivalent to the geometric mean of two Malmquist indices, conditional on two translog underlying functions with separate parameters. The scale-adjusted Törnqvist productivity index also equals the geometric mean of two Malmquist productivity indices. Meanwhile, the latter non-parametric index was first introduced in Luenberger (1992a, pp. 461–481), who developed a benefit function to generalise the willingness-to-pay concept. The function measures changes in utility level relative to a reference bundle in terms of quantities. It also reflects the sign of preference and allows for additive aggregation across individuals. In a production setting, the benefit function transforms into the shortage function to measure the directional distance of vector g from an inefficient production plan towards the PPF (Luenberger, 1992b, pp. 221–264).

Furthermore, the fourth cluster, linear programming approaches, is derived from the work of Aigner and Chu (1968, pp. 826–839), who established the boundary from observed data to estimate industrial efficiency in Yugoslavia. Charnes, Cooper and Rhodes (1978, pp. 429–444) formalised the method with DEA, which builds the frontier without assumptions on functional forms and residual distribution, thus mitigating bias in equating price and marginal product. Still, these indices are prone to outliers and have no validating statistical tests (Heshmati and Rashidghalam, 2020, pp. 21–36). Färe *et al.* (1994, pp. 66–83) extended the literature on the DEA-based Malmquist index and its components: TECH and TECCH. The former presents how much the world frontier shifts due to a mix of inputs in each nation, known as the innovation effect. The latter demonstrates how much a nation moves closer to the world frontier, known as the catching-up effect. Haider, Kunst and Wirl (2021, pp. 283–327) credit the first mention of this phenomenon to Gerschenkron in 1962, who observed the convergence in economic growth of backward European countries during the Industrial Revolution in the 18^{th} and 19^{th} centuries. Using the Malmquist output index approach, Färe *et al.* (1994, pp. 253–272) found technical inefficiency and technological regress in 17 Swedish hospitals from 1970 to 1985. Nevertheless, with an assumption of all positive output prices, Pittman (1983, pp. 883–891) argued that the non-parametric CCD formula failed to account for bad outputs, whose prices are often negative or negligible. Hence, the Pittman enhancement incorporated shadow prices for undesirables into adjusted revenue shares and collapsed to the CCD formula without them, subject to data constraints.

Along the same line, Färe *et al.* (1989, pp. 90–98) introduced a piecewise linear framework that models the reduction of undesirable outputs at the cost of lower desirable ones, highlighting the environment-economic trade-off. Later, Chung, Färe, and Grosskopf (1997, pp. 229–240) proposed the non-parametric MLI based on the DEA. The approach jointly addresses the absence of shadow prices and satisfies the weak disposability of undesirable outputs. In addition, integrating the Malmquist concept and the DDF enables simultaneous credit for increases in good outputs and reductions in bad ones. This helps to achieve both economic and environmental goals, contributing to sustainable growth (Sharma *et al.*, 2025, p. 124639). Hence, the MLI provides an environmentally sensitive measure of TFP, the so-called GTFP, and its components (TECH and TECCH) across different DMUs. Using a panel data set of OECD members from 1985 to 1998, Yörük and Zaim (2005, pp. 401–420) found that Ireland and Norway are the best performers for MLI. Furthermore, the positive impact of technological progress dominates that of technical efficiency changes, acting as the main contributor to GTFP growth. This aligns with the findings of Kumar (2006, pp. 280–293) on a sample of 41 countries over the 1973-1992 period, who also found that Annexe I parties to the UNFCCC performed better than their Non-Annexe I counterparts. Still, the multiplicative averaging form of contemporaneous MLI is prone to linear programming infeasibilities for cross-period DDFs. Pastor and Lovell (2005, pp. 266–271) explained that the geometric mean Malmquist index is not circular, and therefore, the measure of productivity changes can differ across adjacent periods. To mitigate this problem, several variants have been suggested to adjust the PPF corresponding to different types of production technology, including global, sequential and biennial sets (Oh, 2010, pp. 183–197; Oh and Heshmati, 2010, pp. 1345–1355; Pastor, Asmild and Lovell, 2011, pp. 10–15).

Determinants of TFP and GTFP growth

There is a large volume of published studies describing determinants of TFP growth. Isaksson (2007) classified them into two categories: proximate determinants and deep determinants. The first group refers to medium-term sources, including knowledge creation, diffusion, and absorption, as well as factor supplies and efficient allocation. The second group shapes the long-term incentives and capabilities that enable these proximate factors to improve the productive power. These comprise integration, institutions and invariants.

In terms of proximate determinants, R&D investments often emerge as the main contributor to TFP growth. Still, exploiting new knowledge is more crucial than the input into its creation, as strong institutions enhance returns to research efforts. In addition to institutional quality, technology transfer depends on the absorptive capacity of home countries, irrespective of FDI or imports. The capacity depends on the level of capital intensity and human capital. Although the former is often taken for granted as a determinant of TFP growth, the beneficial role of human capital remains a controversial matter. Since inadequate health support prevents efficient learning, prioritising health over education helps to ensure the causal link in emerging economies. Furthermore, investments in infrastructure act as an essential amplification mechanism for productivity enhancement if public capital is well-managed. Specifically, the distribution of public expenditure is preferred to increasing public debt. Financial development also benefits capital accumulation, thus boosting convergence speed in late-coming countries. Despite much literature on the economic impacts of structural change, its effects on TFP growth remain indirect through intra-industry and within-plant efficiency gains. Market frictions even hinder the efficient allocation of inputs and outputs across firms.

Regarding deep determinants, integration through trade liberalisation increases competitive pressure, thus forcing market participants to either boost TFP growth or exit. This effect is more substantial for less productive firms, while more productive ones are shielded under buffer effects. Openness also enables access to foreign capital and technologies at lower costs. In addition, imports are more decisive in TFP growth than exports, whose learning effects appear negligible or non-existent. Nevertheless, the impacts of political and economic institutions remain divergent. The political institution is subject to political ideologies. Empirical evidence suggests that a democratic regime or economic freedom benefits productive power but impedes capital accumulation. In contrast, the economic institution enhances both the level and growth of TFP through better institutional effectiveness. Still, if powerful groups benefit from the poor institution, these elites might be more motivated to persist. Meanwhile, geographical conditions have both direct and indirect effects on TFP growth. For instance, landlocked countries face high transport costs, weak technology diffusion and limited access to large economic markets. These challenges can be mitigated through agreements with coastal partners, highlighting the mediating role of institutions in the invariants-TFP relation.

More recent empirical studies affirmed several determinants of TFP growth in both groups, including innovation, education, market efficiency, infrastructure, finance and institutions (Kim and Loayza, 2019; Heshmati and Rashidghalam, 2020, pp. 21–36). Danquah, Moral-Benito, and Ouattara (2014, pp. 227–251) also believed that trade openness and country-specific unobserved heterogeneity are the most robust factors affecting TFP components. Considering the sustainable dimensions, agglomeration, industrial structure, environmental regulation, and green finance are candidate determinants of GTFP (Sharma *et al.*, 2025, p. 124639). Cheng and Jin (2022, p. 101003) found that the specialised and diversified economies contributed to improving green productive power in China from 2005 to 2017. While the former has the most potent effects under the industrial complementarity, the latter improved GTFP through narrowed efficiency gaps and expanded technological progress. In addition, Porter (1991, p. 168) laid the foundation for the relationship between industrial competitiveness and environmentalism. Well-designed environmental standards can stimulate technological innovation and offset the compliance costs (Porter and van der Linde, 1995, pp. 97–118). This, in turn, contributes to more efficient resource allocation, thus improving GTFP. Findings of Tong *et al.* (2022, p. 134930) lend credence to the Porter hypothesis, where strict environmental legislation caused a significant rise of 1.826 beta value in China's GTFP from 2010 to 2021. Furthermore, more emphasis on green finance, investments in green technologies, and FDI contribute to the expansion of green manufacturing. Such findings are consistent with the work of Zhou *et al.* (2019, p. 3776), who found that higher levels of financial development enable Chinese provinces to attract high-tech and low-carbon inflow FDI, thus promoting GTFP. Therefore, it is crucial to integrate coordinated industrial, environmental, and financial policies to enhance green economic performance.

2.2.3. Causal paradigm between FIT and GTFP growth

Zhou *et al.* (2023, p. 129042) first investigated the impact of FIT reduction on GTFP growth. Using a panel data set of 31 Chinese provinces from 2013 to 2020, the global MLI was estimated based on the Epsilon-Based Measure, a variant of the non-parametric linear programming approach (DEA). Using the quasi-experimental DID approach, the paper found that the FIT reduction in PV and wind energies had a significant and beneficial impact on GTFP growth, at 0.054 and 0.055 units, even without considering covariates. Controlling for income per capita, population, public revenue, trade openness and industrial structure, a further increase of 0.073 and 0.053 units of GTFP was observed during the same period. This highlights the advantageous contribution of FIT reduction to GTFP growth in areas with little wind and PV resources. As MLI components, the scheme contributed to simultaneous increases in TECH and TECCH for the PV source. Still, the effect exerts a positive influence on the former and an insignificant impact on the latter for the wind power. This aligns with the findings of Xie, Jiang, and Chen (2022, p. 116232), who computed and decomposed the global Malmquist index for the environmental performance. Their findings also indicated that FIT contributed to TECH in 30 Chinese provinces, excluding Tibet, Taiwan, Hong Kong, and Macao, from 2011 to 2020. Considering the mediation effect, the main positive outcome of FIT reduction was attributed to its negative influence on PV and wind generation. This means that excessive RE consumption might translate into lower efficiency. These findings highlight that FIT reduction fostered GTFP growth and technological progress across solar and wind sources. It also helps to optimise resource allocation and eliminate inefficient RE projects.

Focusing on the GTFP components, much of the current literature has paid particular attention to the effect of FITs on TECH, rather than TECCH. Building on the seminal work of Acemoglu *et al.* (2012, pp. 131–66), Nakada (2022, pp. 765–785) described the relationship between FIT and deregulation in directing technological progress. The former generates a price effect for new RE entrants, causing a biased technical change toward resource-saving technologies. Meanwhile, the latter increases market competition in the resource-intensive sector. This promotes a scale effect due to expanding demand for resource-intensive technologies. Therefore, if the positive price effect exceeds the negative scale effect, the FIT-induced technical change is reinforced, as deregulation lowers the marginal returns of R&D investment in the resource-intensive sector. Still, empirical studies show that the directed role of FIT programmes in technical changes remained complicated. Johnstone, Haščič, and Popp (2010, pp. 133–155) argued that, as targeted subsidies, these programmes are an essential driver of technological progress in more expensive sources, such as solar power. This can be seen in the case of German EEG, where the scheme had a positive demand-side effect, directing technical changes towards green ideas. Still, it could not transform much higher remuneration levels into proportionately higher induced-innovation impacts than the previous StreEG programme (Böhringer *et al.*, 2017, pp. 545–553). Along the same line, Lin and Chen (2023, pp. 29–46) found that FIT boosted patenting activities in wind power during the implementation period, but the effect diminished over time in China. Rising FIT rates are also associated with an increase in patents in PV technologies. In contrast, Zhao, Zhou and Wen (2021, p. 112453) claimed that FIT harmed provincial wind power innovation in China from 2008 to 2017. The RE subsiding programme is implemented under the demand-pull mechanism, and therefore, it promotes innovative activities at the diffusion phase through technological learning (Lindman and Söderholm, 2016, pp. 1351–1359). Without the existing stocks of knowledge, FIT might not even be implemented to support innovative activities in an effective manner. Moreover, firms are often reluctant to invest in RE due to the high installation costs and associated risks. As a result, local government interventions, such as policy stringency in renewables and augmenting R&D investments, can mitigate the adverse effects of FIT on innovation.

2.3. Research gaps

With pre-determined prices under long-term PPAs, FIT diminishes investment risks for independent RE generators. This, in turn, helps promote RE shares in the power source structure and alleviates the dependence on extracting fossil fuels from the soil. There is a subsequent decrease in GHG emissions and abatement costs. Hence, FIT implementors reap the benefits of either GDP growth or additional job creation. Still, the Global South is sensitive to governance, technical, infrastructure and social barriers. In addition, as a revenue-raising instrument, FIT offers higher marginal returns on R&D activities in clean technologies. It thus signals price effects for RE producers and shapes the technical changes along a biased path towards green innovation, aligning with the findings of Acemoglu *et al.* (2012, pp. 131–66). Empirical studies demonstrate the merits of FITs on technological progress, conditional on the existing stocks of knowledge. Otherwise, the programme appears more effective in the diffusion phase through learning processes from frontier to non-frontier DMUs.

Nonetheless, as components of non-parametric GTFP, far too little attention has been paid to the impact of FITs on TECCH, compared to the extensive literature on TECH. There is also insufficient cross-national evidence on the direct effect of FITs on the GTFP growth, TECH and TECCH. This is more apparent in the cases between developed and developing countries and across RE technologies. In addition, generous FIT rates might lead to excessive RE installations, disproportionate economic benefits, and substantial burdens on end-user surcharge bills. As a frontrunner in the green domain, empirical evidence shows that FIT reduction exerts a positive impact on GTFP growth and TECH, but an insignificant impact on TECCH in Chinese provinces. Still, the effect of different FIT remuneration levels on GTFP growth and its components is understudied outside China. This study aims to fill these gaps and provide comprehensive evidence on the FIT-GTFP causal paradigm.

Chapter 3. Research methodology

This chapter describes the characteristics and measurement methods of all variables. Econometric models are then identified for the panel data, restricted to OLS assumptions. Given the suspected endogenous treatment, the static panel IV estimators are discussed to provide unbiased and consistent estimates. Heterogeneous effects and robustness checks are further considered to support the main causal paradigm, while acknowledging some limitations.

3.1. Data description

The adoption of the UNFCCC at the Rio Earth Summit 1992 is recognised as the first major international effort with the near-universal membership to address climate change. The Convention established the institutional foundation for subsequent multilateral treaties on mitigating GHG emissions. Therefore, the current research first intends to collect data from 218 countries and jurisdictions between 1990 and 2019. Nevertheless, data constraints exist for some subcomponent-level indicators of the overall TFP determinant index. Hence, the paper utilises the panel dataset of 56 countries for the period 1990-2019 to investigate the impact of FITs on the growth of GTFP and its components. The dataset is consistent across baseline effects, heterogeneous effects, and robustness checks. Description of all variables is demonstrated in Appendix I.

3.1.1. Outcome variable (Y)

Following the seminal work of Chung, Färe and Grosskopf (1997, pp. 229–240), the present paper adopts the non-parametric MLI approach based on DEA as the method for measuring GTFP growth. Capital stocks, the total labour force, and energy use act as inputs, whereas the respective desirable and undesirable outputs include GDP at constant 2015 US dollars and CO_2 emissions. Almost all variables are gathered from WDI, excluding the capital stock. This input is collected from the IMF Investment and Capital Stock Dataset, which is constructed using the perpetual inventory method in the local currency unit. It is then adjusted for inflation using the GDP deflator and converted into constant 2015 US dollars. Let inputs $x \in \mathbb{R}_{+}^{N}$, desirable outputs $y \in \mathbb{R}_{+}^{M}$, undesirable outputs $b \in \mathbb{R}_{+}^{L}$. The output sets are defined as:

$$P(x) = \{(y, b): x \text{ can produce } (y, b)\}$$

In addition, the radial DDF is constructed as the maximum feasible expansion (or contraction) of a scalar β. It involves a proportional adjustment of all inputs and outputs along direction g toward the production frontier T:

$$\overrightarrow{D_r}(x, y, b; g) = \sup\{\beta:(y, b) + \beta\vec{g} \in P(x)\}$$

Under the homogeneous degree of distance functions, if the vector $\vec{g} = (y, b)$ is plugged into the vector $\overrightarrow{D_r}$, the relationship between the Shephard distance function and DDF is:

$$D_r(x, y, b) = \frac{1}{1 + \vec{D}_r(x,y,b;\, y,b)}$$

Still, the output-oriented Malmquist index based on DDF or MLI is constructed in the direction $\vec{g} = (y, \text{-}b)$ to address undesirable pollution b. As a result, substituting the DDF into the Shephard distance function is described as:

$$\mathrm{GTFP}_t^{t+1} = \left[\frac{(1 + \overrightarrow{D_r^t}\,(x^t,y^t,b^t;\, y^t,-b^t))}{(1 + \overrightarrow{D_r^t}\,(x^{t+1},y^{t+1},b^{t+1};\, y^{t+1},-b^{t+1}))} . \frac{(1 + \overrightarrow{D_r^{t+1}}\,(x^t,y^t,b^t;\, y^t,-b^t))}{(1 + \overrightarrow{D_r^{t+1}}\,(x^{t+1},y^{t+1},b^{t+1};\, y^{t+1},-b^{t+1}))}\right]^{1/2}$$

The geometric mean is used to handle an arbitrary choice of the base year. Therefore, if the $\mathrm{GTFP}_t^{t+1} > 1$, it indicates a simultaneous improvement in GDP growth and CO_2 emissions mitigation between t and t+1; otherwise, the opposite holds. In addition, similar to the traditional Malmquist index, the MLI can be decomposed into TECH and TECCH, corresponding to innovation and catch-up effects as follows:

$$\mathrm{TECH}_t^{t+1} = \left[\frac{(1 + \overrightarrow{D_r^{t+1}}\,(x^t,y^t,b^t;\,y^t,-b^t))}{(1 + \overrightarrow{D_r^{t}}\,(x^t,y^t,b^t;\,y^t,-b^t))} \cdot \frac{(1 + \overrightarrow{D_r^{t+1}}\,(x^{t+1},y^{t+1},b^{t+1};\,y^{t+1},-b^{t+1}))}{(1 + \overrightarrow{D_r^{t}}\,(x^{t+1},y^{t+1},b^{t+1};\,y^{t+1},-b^{t+1}))}\right]^{1/2}$$

$$\mathrm{TECCH}_t^{t+1} = \frac{1 + \overrightarrow{D_r^{t}}\,(x^t,y^t,b^t;\,y^t,-b^t)}{1 + \overrightarrow{D_r^{t+1}}\,(x^{t+1},y^{t+1},b^{t+1};\,y^{t+1},-b^{t+1})}$$

Furthermore, this paper adopts the global PPF that incorporates all contemporaneous benchmark technologies into a single reference frontier, based on a panel dataset of the inputs and outputs of relevant DMUs (Oh, 2010, pp. 183–197). This approach facilitates overcoming the non-circularity of the geometric mean form and potential linear programming infeasibilities in cross-period comparisons. Multiplicative outcome indicators are then transformed into additive growth rates (subtracting one) to facilitate more straightforward estimations.

To summarise, Figure 1 illustrates the changes in the production frontier, technological level, and technical efficiency level of an inefficient unit C between t and t+1. Following the direction vector $\vec{g}$ = (y, -b), TECH and TECCH are illustrated as BB' and CC' in that order. Hence, the total movement from C = (y_t, -b_t) to C' = (y_{t+1}, -b_{t+1}), the sum of BB' and CC', represents GTFP growth during the period examined.

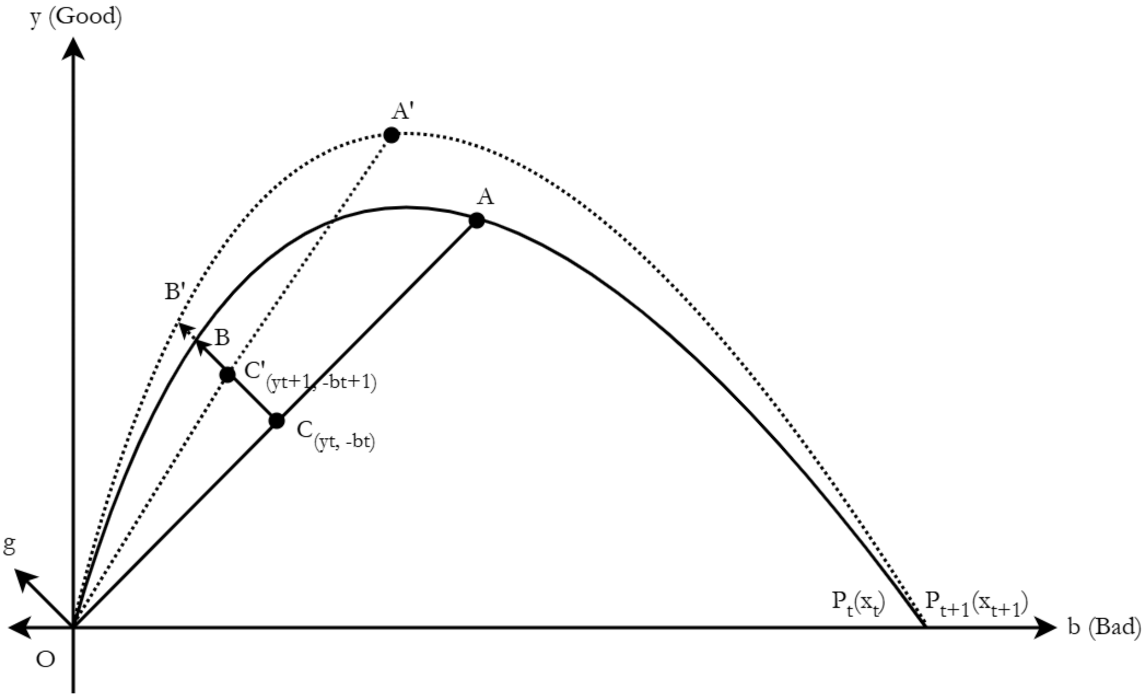


Figure 1. A graphical illustration of DDFs

Source: Author's compilation from Chung, Färe and Grosskopf (1997, pp. 229–240)

3.1.2. Treatment variable (T)

Data on the treatment are drawn from the OECD dataset on RE FITs (hereafter, REFITs) and the Climate Actions and Policies Measurement Framework (hereafter, CAPMF) dataset. The former provides enactment status from 2000 to 2019 across different technologies, while the latter complements the coverage for the 1990–2000 period. The REFITs dataset focuses on industrial, commercial, or large-scale projects. Installations below 1MW are then omitted from the mean FIT calculation, except for onshore wind power. Still, the use of FIT rates as the main regressor has been excluded due to insufficient data from CAPMF. Therefore, the treatment enters the model as a binary variable, indicating whether a jurisdiction adopted the FIT for RE investments. It equals one after the scheme was imposed and collapses to zero if it was not or never in place. Due to the success of EEG 2000, the German FIT design acts as a role model in this domain (Jacobs, 2014, pp. 755–773). Cost-based rates for each RE power, conditions of participation, dispatcher obligations, and grid-connected rules tend to follow a similar template. Hence, the remaining disparities often affect the rate level or the guarantee period, rather than the FIT mechanism. This means the treatment remains identical across different jurisdictions.

3.1.3. Control variables (X)

Following the pioneering work of Zhou *et al.* (2023, p. 129042), GDP per capita at constant 2015 US dollars, total population, public revenue-to-GDP ratio, and trade openness are included to isolate the effect of the treatment and control for unobservable characteristics. Still, low-carbon FDI inflow is crucial for promoting GTFP as an additional vital source of technology transfer. Therefore, the research utilises the KOF economic globalisation index from Gygli *et al.* (2019, pp. 543–574), an extension of Dreher (2006, pp. 1091–1110). It provides a composite of trade and financial globalisation, acting as a more comprehensive control for technological dissemination. Moreover, the 9.0 magnitude earthquake and subsequent tsunami triggered the Fukushima Daiichi nuclear accident in 2011, promoting the FIT imposition in 2012 (Huenteler, Schmidt and Kanie, 2012, pp. 6–11), a similar case to the German StreEG 1990. Hence, the ND-GAIN vulnerability index serves as a covariate on the exposure of each nation to climate-related risks. It influences the stringent level of environmental policies, including the adoption of FITs.

On the other hand, as an environment-sensitive TFP variant, GTFP growth might be sensitive to the same determinants, let alone green features. Controlling for these factors also reduces the likelihood of omitting essential variables. Kim and Loayza (2019) categorised TFP determinants into five groups, including innovation, education, market efficiency, infrastructure, and institutions. Each group comprises several indicators that represent a common feature. The list of indicators is presented in Appendix II. If an indicator has missing values, it will be imputed based on income levels or time trends to maximise the panel coverage. The imputation method relies on the existing data and the characteristics of the indicators. For instance, if a nation has an indicator with available data for more than 10 out of 30 years from 1990 to 2019, missing values are estimated using linear trend projection. Otherwise, these values are replaced with a median of both income and regional groups. Still, a different procedure is applied to the PISA score, as less than one-third of the sample period is available for all countries. Given a significant correlation of 0.653 between PISA scores and a 5-year lag of the log of GDP per capita (Appendix III), the former is regressed on the latter, controlling for time effects, in a POLS model. Predicted scores are then adjusted to the median of each income–region group to fill in gaps. Furthermore, the earliest available observations of minimum wage and severance are extended backwards to the previous period due to limited coverage and time trends.

Furthermore, FA is applied to extract the maximum amount of common variance among the relevant indicators within each group, thus producing five subcomponent indices (Mulaik, 2009). These indices are then combined using PCA to construct an overall TFP determinant index. It helps to capture as much of the total variance of each index as possible in a single component measure (Jolliffe, 2002). However, Mohammadi and Khabbazan (2022, p. 3973) noted that a passive society, arising from a centrally planned economy and fossil fuel subsidies, hindered the RE transition in Iran. In contrast, the German corporatist tradition and strong advocacy coalitions generated political incentives for substantial RE deployment. Hence, the V-Dem core civil society index (Bernhard, Nordstrom and Reenock, 2001, pp. 775–803) is integrated into the institution subcomponent to account for the strengths and autonomy of civil society. Setting the value of 2015 equal to one, the present research also carried out backwards and forward fillings for the levels of GTFP, TECH, and TECCH based on their annual additive growth rates.

3.2. Econometric estimation

The present paper utilises a 5-year lag of regressors to address the endogeneity problem due to reverse causation between the overall TFP determinant index and GTFP growth. This aligns with the method of Kim and Loayza (2019), who argued that using lagged observations is a “more straightforward and less biased" approach than the instrumental variable (hereafter, IV). Hence, the treatment and control variables are also used with a 5-year lag in the model. Furthermore, such a long time lag allows for smoothing the GTFP growth and its components. This eliminates, or at least diminishes, the impacts of business-cycle fluctuations at shorter frequencies (Beck, Levine and Loayza, 2000, pp. 261–300; Khan and Senhadji, 2000, p. 13). The paper employs the CAGR method to estimate the growth of GTFP, TECH, and TECCH over the periods t-5 and t.

$$\text{CAGR } (\%) = \left(\frac{X_t}{X_{t-5}}\right)^{1/5} - 1$$

Where X_t is the level of GTFP, TECH and TECCH in year t.

The 5-year CAGR provides a consistent measure of the annualised growth rate, as it accounts for the compounding effects of growth over time. This accords with the cumulative nature of most economic data, which evolves through multiplicative processes rather than additive changes. CAGR is also less sensitive to outliers, and therefore, it is a preferable measure compared to arithmetic linear growth.

3.2.1. Model design

An unbalanced panel dataset of 56 countries from 1990 to 2019 is adopted to evaluate the impact of FIT on GTFP growth and its components. Using the method of OLS, the intuitive panel data specification is described as:

$$Y_{it} = \alpha + \beta T_{it} + \gamma X_{it} + \varepsilon_{it}$$

Where α is an identical unobserved effect, T_{it} is the treatment in country (i) at time (t), X_{it} is a vector of time-varying controls in country (i) at time (t), and ε_{it} is the error term.

POLS is a common estimator due to its simple estimation and ease of interpretation. However, it assumes that there are no individual effects, leading to the same unobserved characteristics (α) across different countries. As a result, this model might suffer from heterogeneity bias.

$$Y_{it} = \alpha_i + \beta T_{it} + \gamma X_{it} + \tau_t + \varepsilon_{it}$$

Where α_i is the country fixed effects, and τ_t is year fixed effects.

To address the drawbacks of POLS, the FEM is adopted to account for country-specific effects through heterogeneous slopes, α_i. Kim and Loayza (2019) reported that the composite index in the vector X_{it} fails to control for all possible TFP growth determinants, including both broad subcomponents and specific indicators. Hence, country fixed effects α_i help control for time-invariant unobserved factors, such as geographic conditions or workforce demographics. Year fixed effects τ_t are also included to absorb the global shocks to GTFP growth and its components over time, leading to the so-called two-way FEM (hereafter, TWFE). Still, the specification cannot accommodate time-invariant regressors due to the within-demeaning transformation.

$$Y_{it} = \alpha_0 + \alpha_i + \beta T_{it} + \gamma X_{it} + \tau_t + \mu_{it}$$

Where $\alpha_i \sim N(0, \sigma_\alpha^2)$ is the country random effects, $\mu_{it} \sim N(0, \sigma_\mu^2)$ is the idiosyncratic error.

Under the method of generalised least squares, the REM retains between-unit variation of variables. Therefore, it allows for the estimation of regressors that are persistent over time. However, the REM estimate is sensitive to the assumption on the α_i–X_{it} correlation. The choice between FEM and REM is examined through the Hausman specification test, as discussed in Section 3.2.2.

3.2.2. Statistical tests

Several crucial tests should be considered for the composition index, sample size and panel data models. Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (hereafter, KMO) test for sampling adequacy provide the criterion validity of subcomponent indices in FA and the overall TFP determinant index in PCA. The former assesses the correlation matrix of constitutive indicators, and rejection of H_0 indicates a significant correlation among them. The latter evaluates the magnitude of common variance shared among indicators. A KMO value above 0.5 means that the dataset is suitable for extracting latent factors from observed variables. It is also pivotal to investigate the statistical power of the existing sample size in the FIT-GTFP causation. Setting the power at 0.8, an acceptable rate of Type II error is 20%, while the two-sided significance level (α) is fixed at 0.1. Following the paper of Zhou *et al.* (2023, p. 129042), the noise (σ) of GTFP is collected from its within-sample standard deviation of 0.092. Using 911 observations (N), these parameters cause a minimum detectable effect (MDE) of 0.015. This threshold is lower than the estimated impacts of FIT reduction on GTFP in Chinese provinces, 0.054 to 0.073. Hence, the available sample size is sufficient to capture meaningful changes in the main outcome.

On the other hand, t-tests are used to examine whether the differences in the mean values of $GTFP_{t-5}$, $TECH_{t-5}$, and $TECCH_{t-5}$ between FIT adopters and non-adopters are statistically significant or attributed to random sampling variation. For OLS assumptions, the correlation matrix among regressors indicates the sign of multicollinearity, while the variance inflation factor (hereafter, VIF) helps to diagnose its presence. In addition, as a dataset spans multiple countries and time periods, the model might encounter issues of individual heteroskedasticity and autocorrelation in the error term. This is particularly true when economic performance often fluctuates across different income and regional groups. As a result, the modified Wald test is utilised to detect groupwise heteroskedastic variance, while the Wooldridge statistic allows for inspecting serial correlation. Moreover, Baltagi (2021, pp. 89–98) noted that FEM enables individual-specific effects to correlate with regressors, whereas REM assumes there is no relationship between them. REM estimates, thus, become inconsistent if this assumption is violated. Assuming both FEM and REM are consistent, the Hausman specification test is adopted to determine the most suitable panel data model for this sample. Rejection of H_0 indicates that REM estimates are inconsistent, and therefore, FEM should be the main estimator for the specification; otherwise, REM is better.

3.2.3. Identification strategy

3.2.3.1. Panel estimations

The effect of FITs on GTFP growth and its components is investigated using panel data models, restricted to the assumptions of the OLS method. A combination of different countries across various periods allows for mitigating the multicollinear relationships between regressors in the dataset. In addition, the robust SEs are utilised instead of the standard structure $\sigma^2(X'X)^{-1}$, built on the "sandwich" variance-covariance matrix of coefficients $VCV(\hat{\beta}) = (X'X)^{-1}X'\sigma X(X'X)^{-1}$. This enables observation to have its own error variance, thus addressing biased SEs arising from arbitrary heteroskedasticity (White, 1980, pp. 817–838). However, White-Huber SEs remain sensitive to within-group correlation, leading to biased SEs and significance levels. To address this econometrics limitation, Newey and West (1987, pp. 703–708) developed a HAC estimator of the disturbance covariance matrix, constructed based on a finite Bartlett-weighted sum of sample autocovariances. The resulting positive semi-definite estimator $\hat{S}$ acts as an alternative middle matrix to the homoskedastic error covariance matrix $\sigma^2 I$ in White's $VCV(\hat{\beta})$, thus achieving the HAC SEs. Furthermore, Newey and West (1994, pp. 631–653) proposed a formula for lag selection parameters using Bartlett, Parzen, or Quadratic Spectral kernels used to smooth the sample autocovariance function. The bandwidth selection under the Bartlett kernel is as follows:

$$m(T) = \left[4.\left(\frac{T}{100}\right)^{2/9}\right]$$

Where T is the number of time observations

In this paper, due to the 5-year lags of regressors, the usable time dimension T reduces to 25 out of 30 years over the 1990-2019 period. As a result, the truncation lag plugged into the HAC estimator is 2. This means autocovariances up to lag 2 enter the HAC estimators, providing SEs robust to both groupwise heteroskedastic variance and serial correlation in the residuals. Meanwhile, the time-lagged variables allow for mitigating the likelihood of endogeneity due to reverse causation. The inclusion of both panel and time fixed effects also helps isolate the impact of time-invariant unobservables and global temporal shocks within the central causal paradigm. However, endogeneity concerns persist due to a lack of control for unobservable heterogeneous characteristics that can change over time, such as national climate targets and other environmental regulations. Nachtigall *et al.* (2024, pp. 191–217) introduced the CAPMF database to monitor and evaluate climate actions worldwide. The database structure categorises green policies into three groups: sectoral, cross-sectoral, and international policies. Belonging to market-based instruments, FIT is one of the RE supports, alongside auctions and the renewable portfolio standard. These intra-group policies, let alone non-market-based instruments, might act as confounding factors for the implementation of FIT. Moreover, if the government enacts a mix of FIT and green innovation policies, such as augmenting local R&D investments, the causal impact on GTFP growth and its components can be distorted. As a result, it is necessary to adopt the IV approach to tackle the endogeneity problem arising from omitted time-variant unobservable factors.

3.2.3.2. IVs and validity conditions

There are two crucial conditions for a valid IV in the literature, including relevance and exclusion restriction. The former indicates that the instrument is correlated with the suspected endogenous regressors, and therefore, it is not weak. Assuming the good IV, the latter demands that the instrument is uncorrelated with the residuals and is excluded from the second-stage regression. Still, there is little published research on the valid IVs for FITs to date. Söderholm and Sundqvist (2007, pp. 2559–2578) first investigated the impact of FITs on investment costs in four European countries from 1986 to 2000. Due to the reverse causation, the FIT price was instrumented with a set of IVs, including electricity prices, the existing age structure of fossil fuel plants, and coal prices. Still, there is limited information on these variables in the cross-national setting outside the EU. In contrast, Smith and Urpelainen (2014, pp. 367–392) examined the influence of FITs on RE generation in 26 industrialised countries over the 1979-2005 period. Once again, owing to the simultaneous causalities, both internal and external IVs were used to instrument the FIT rates, addressing the endogeneity issue.

First, the internal temporal instrumental variable is a 4-year lag of its own FIT. Due to the inherent time-series properties of economic indicators, lagged FITs have a strong predictive power on current FITs. Still, past programmes have not improved the profits of existing RE generation. Therefore, there is no direct channel for its impact on the existing RE share, rather an indirect one through current FITs. Second, the external spatial instrument variable is the mean FIT remuneration of proximate nations. The adjacent FIT design is a strong projection of the home programme. This is evident in the case of the German EEG, which serves as a role model for the FIT scheme in the EU through policy diffusion. However, the regulation is designed to attract more domestic RE producers, instead of foreign counterparts. Therefore, FITs in adjacent countries are not likely to influence investments in the internal RE market. Moreover, the mean number of RE patents filed in neighbours is used to control for possible technological spillovers. As a result, the 4-year lag of FIT and average FIT in contiguous jurisdictions are valid IVs for current domestic FITs.

Considering these principles, this paper employs a 9-year lag of the FIT and a 5-year lag of the number of bordering countries enacting FITs as valid instruments for the domestic treatment variable lagged 5 years. (1) With strong anticipation capabilities, both variables are expected to correlate with the 5-year lag of treatment, thus fulfilling the relevance condition. Although the 9-year lag of FIT can mitigate CO_2 emissions at that time, it fails to translate the effect into a lower atmospheric CO_2 concentration 4 years later, even if there are positive net emissions. (2) Therefore, the temporal IV cannot impact the GTFP growth and its components over t-5 and t without its own lag of 5 years. Controlling for green knowledge transfer, the spatial IV also fails to exert a direct influence on domestic outcomes. Together, these IVs meet the exclusion restriction condition. Concerns about the spillover effects of bordering FIT adoption on the home GTFP growth and its components will be discussed in Section 3.2.3.5.

3.2.3.3. Panel IV estimations

Given the endogeneity risks, POLS, FEM and REM yield biased and inconsistent estimates. Therefore, 2SLS and GMM estimation methods emerge as appropriate alternatives in the static longitudinal dataset, provided that valid instruments are used. The former is the IV estimator, which replaces the endogenous regressor with its fitted values obtained from the first stage. The second-stage estimates remain consistent even when the first-stage functional form is nonlinear (Kelejian, 1971, pp. 373–374; Angrist and Krueger, 2001, pp. 69–85). However, Hausman et al. (2011, pp. 45–57) reported that it is sensitive to over-identification and substantial finite-sample bias under weak instruments in the first stage. The latter refers to a 2SGMM estimator where an initial non-optimal matrix in the first step is used to construct the weighting matrix for the more efficient second step (Hansen, 1982, pp. 1029–1054). In the first step, the GMM criterion function is minimised using a unit matrix (I) to obtain residuals (ε). Such residuals are then used to estimate VCV $(\widehat{\Omega})$, whose inverse serves as the weighting matrix (W). Later, in the second step, the matrix W is plugged into the GMM criterion function $\frac{1}{T}\sum_{t=1}^{T} g_t\,(\beta)'\widehat{\Omega}^{-1}\frac{1}{T}\sum_{t=1}^{T} g_t\,(\beta)$ to get the updated estimates (β). Still, Hausman *et al.* (2011, pp. 45–57) noted that 2SGMM suffers from finite-sample bias that increases with the number of moments. It might also become inconsistent when several weak moments are present (Hansen, Heaton and Yaron, 1996, pp. 262–280).

To mitigate these econometric problems, the CUE-GMM estimation method integrates the 2SGMM estimator into the iteration process of minimising the advanced objective function $\frac{1}{T}\sum_{t=1}^{T} g_t\,(\beta)'\widehat{\Omega}(\beta)^{-1}\frac{1}{T}\sum_{t=1}^{T} g_t\,(\beta)$. This, in turn, allows for updating both the estimates (β) and VCV until convergence, contributing to reduced finite-sample bias and improved robustness under numerous weak moments. Still, the estimation presents several limitations, including potential computational infeasibilities, dependence on initial parameter values in the optimisation procedure, and difficulties in IV selection. Hence, this paper employs several post-estimation diagnostic tests to validate the instruments. First, the Kleibergen-Paap rk LM statistics (hereafter, KP LM) test whether the model is under-identified. The rejection of H_0 indicates that the instrument is sufficiently correlated with the suspected endogenous regressor, and the model is identified. Second, using the HAC SEs for individual heteroskedastic variance and serial correlation in the residuals, the Kleibergen-Paap rk Wald F statistic (hereafter, KP Wald F) tests whether the IV is weak. If the statistic exceeds the Stock-Yogo CVs at the chosen maximal LIML size (hereafter, mLIML), the instrument is strong and satisfies the relevance condition. Third, the Hansen J statistic (hereafter, Hansen J) is used to test for overidentification of all instruments. Failure to reject the H_0 highlights that the instrument is not correlated with the error term in the second stage, and therefore, it satisfies the exclusion restriction condition. A small p-value of the Durbin-Wu-Hausman χ^2 statistic (hereafter, DWH χ^2) also confirms that the suspected variable is endogenous as expected.

3.2.3.4. Heterogeneous effects

To address the sub-questions, this paper examines the impact of FITs on GTFP growth and its components through the lens of three separate sub-samples. First, the empirical results distinguish between OECD and non-OECD countries, highlighting the different stages of development. The former consists of HICs with advanced economic growth, deep accumulated knowledge stocks, and high historical CO_2 emissions. The latter represents MICs with rapid industrialisation, reliance on technological spillovers, and significant current atmospheric release. Second, the FIT remuneration level acts as a precursor for the marginal returns of RE investments. It amplifies or diminishes the price-induced incentives for directed technical changes. FIT rates are thus divided into three groups based on the distribution percentile, including cluster 1 (FIT < q25), cluster 2 (q25 < FIT < q75), and cluster 3 (FIT > q75). Third, REs experience divergent development patterns arising from differences in the national renewable targets. Hence, some technologies, including solar and wind, are more mature and often account for a substantial share of commercial generation, even crowding out other power sources. Waste and geothermal plants are also more reliant on the natural resource characteristics, leading to challenges in resource allocation. These opposing settings facilitate an insight into the heterogeneous effects in the FIT-GTFP relationship.

3.2.3.5. Robustness checks

Econometrically, the control function method is an efficient alternative to handle nonlinear endogenous regressors. Instead of fitted values, this approach obtains the residual from the first stage and uses it as an additional covariate in the second stage to absorb unobservable factors (Wooldridge, 2015, pp. 420–445). A significant residual thus confirms the endogeneity problem in the main model. In addition, much as Angrist and Krueger (2001, pp. 69–85) support the use of 2SLS regardless of the first-stage functional form, it is more efficient to estimate it using the Probit model in the first stage to avoid fitted values outside the range of 0 and 1. Still, it is sensitive to the "forbidden regression" phenomenon, in which the first-stage nonlinear fitted values are plugged into the second stage to mimic 2SLS (Wooldridge, 2010). To handle this issue, Angrist and Pischke (2009) proposed a nonlinear fit-as-instruments approach, which utilises the nonlinear fitted values from the first stage as an instrument for the endogenous regressor in the second stage. This aligns with the method of Windmeijer and Santos Silva (1997, pp. 281–294), who even use the first-stage predicted values as an additional instrument, alongside existing IVs, in the second-stage estimation.

On the other hand, DID is an alternative identification strategy to the main causal paradigm. Still, Callaway and Sant'Anna (2021, pp. 200–230) argued that the traditional TWFE is prone to the negative weight problem as the treatment is rolled out over time. Such an issue is associated with the estimates (β) due to the weighted average of all cohorts. In contrast, the staggered DID identifies causal effects at the group-time level, avoiding negative weights. The placebo test is also examined for the spillover effect of the treatment on the GTFP growth of bordering countries, thus providing more consistent estimates. Moreover, the 7-year lag structure for both regressors and time-lagged IVs helps to assess the temporal robustness of the findings. Finally, the multiplicative MLI is replaced with the additive LPI to test for the sensitivity of the treatment effect to the different GTFP growth measures. Building on the DDF, the LPI measures the GTFP growth and its components using the arithmetic mean, instead of the geometric mean. Therefore, it can signal a sign of changes in the main outcomes without non-circularity risks. A positive LPI indicates higher GTFP growth, technological progress, and technical efficiency improvements of DMUs; otherwise, the opposite holds.

Taken together, the present study employs the FEM or REM using CUE-GMM with HAC SEs as an estimation method. All data management and econometric estimations are performed under Stata 18.0, and a p-value < 0.1 is considered statistically significant.

3.3. Limitations

Despite the large number of estimations, certain limitations remain. First, data constraints on the subcomponent indicators bound the cross-national coverage, raising potential concerns about the external validity. Second, the radial MLI measure imposes proportionate contraction (or expansion) of all inputs (or outputs) when projecting DMUs onto the production frontier. Nevertheless, at the frontier efficient point, some inputs (or outputs) can be further expanded (or shrunk), leading to the so-called slack. Non-radial slack-based measures, thus, account for these non-proportional gaps, relaxing the constant returns to scale assumption. Third, much as the adjacent mean RE patents variable is used to capture neighbouring innovation, knowledge diffusion is unlikely to be confined to contiguous countries. In addition, potential spillovers of GTFP growth may serve as an implicit confounding factor in the main causal paradigm.

Chapter 4. Empirical results

This chapter presents the multivariate estimates for the composite index and descriptive statistics for all variables of interest, including mean-comparison t-tests for outcomes and statistical tests for panel data models. In the baseline results, the CUE-GMM estimation method and diagnostic tests for the IVs are presented, facilitating heterogeneous discussions later. Robustness checks are provided at the end of the chapter.

4.1. Multivariate results

For the FA, there is one latent factor with an eigenvalue greater than 1 for each subcomponent. All subcomponent indices also survived tests for the factorability of the correlation matrix, with a small Bartlett p-value and a KMO value above the acceptable threshold of 0.5. Such latent factors also represented over 50% of the total and unique variance in their constitutive indicators. The specific weights for the factor score computation are presented in Appendix II.

On the other hand, PCA generated a single composite index through orthogonal varimax rotation. With an eigenvalue of 3.923, the component has sufficient power to extract meaningful dimensions of subcomponent indices. It is also likely to explain 78.5% cumulative variance, alongside a KMO value of 0.878. The overall TFP determinant index is constructed with subcomponent weights as follows:

TFP index = 0.434*z(innov) + 0.439*z(edu) + 0.460*z(effic) + 0.461*z(infra) + 0.440*z(inst)

Where $z(X_i)$ is standardised $X_i = \frac{X_i - \mu}{\sigma}$

Although the component captures various conventional TFP drivers, it fails to account for environmentally sensitive factors due to data constraints. Hence, the overall determinant index tends to reflect resource-intensive attributes associated with potentially high carbon emissions.

4.2. Descriptive statistics

Table 1. Descriptive statistics[1]

Variable	N	Mean	SD	Min	Max
$GTFP_{t-5}$	1323	.336	.6	-4.328	5.444
$TECH_{t-5}$	1323	-.295	2.629	-12.028	11.432
$TECCH_{t-5}$	1323	.701	2.683	-10.011	13.863
FIT_{t-5}	1400	.308	.462	0	1
TFP $index_{t-5}$	1400	.498	.283	0	1
ln(GTFP $level_{t-5}$)	1323	-.043	.061	-.373	.158
ln(TECH $level_{t-5}$)	1323	.036	.123	-.517	.536
ln(TECCH $level_{t-5}$)	1323	-.079	.125	-.56	.501
ln($GDPpc_{t-5}$)	1400	9.461	1.109	6.534	11.63
ln(Pop_{t-5})	1400	16.622	1.518	12.853	21.039
Rev_{t-5}	1094	29.546	9.488	2.93	51.828
ln(Glo_{t-5})	1389	4.121	.261	2.857	4.533
ln($Vuln_{t-5}$)	1120	3.576	.153	3.23	3.946
Pat_{t-5}	1400	.267	.771	0	9.63
FIT_{t-9}	1176	.242	.429	0	1
Adj_{t-5}	1400	1.036	1.436	0	8

Source: Author's calculations

Table 1 shows descriptive statistics for the main variables. Almost all log-transformed continuous variables follow the 3-sigma rule of the normal distribution, except for the economic globalisation

[1] Almost all variables are log-transformed, except those containing percentage or zeros.

index and the MLI groups[2]. The former is outside the lower bound and thus indicates the presence of countries with limited openness, weak FDI attraction, or exposure to international sanctions. The latter suggests that GTFP and its components experience substantial fluctuations in terms of size and growth rate. This highlights heterogeneous effects across panels and time periods. The level heatmap reveals the initial dispersions in the 1990s and the subsequent σ-convergence in the late 2010s in all indices (Appendix IV). While the global technological level remained stable, cumulative gains in technical efficiency enabled late-coming countries to move closer to the existing production frontier. Hence, TECCH (0.7%) prevails over TECH (0.18%) to become the main driver of GTFP growth, in contrast to Kumar (2006, pp. 280–293). Ireland and Luxembourg exhibited the best performance during the examined period.

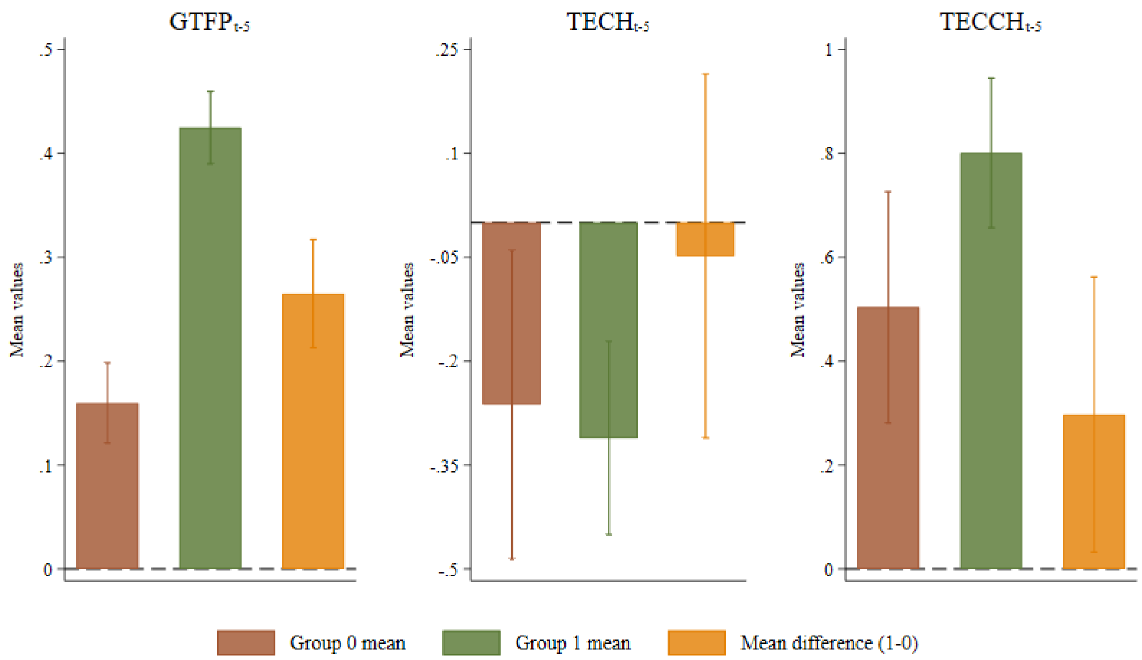


Figure 2. Mean-comparison t-tests

Source: Author's calculations

On the other hand, Figure 2 compares the average mean of MLI group indicators over t-5 and t between FIT-adopters and non-adopters. Introducing the scheme is associated with higher $GTFP_{t-5}$ and $TECCH_{t-5}$, but exerts an insignificant effect on frontier-shifting technological progress ($TECH_{t-5}$). In addition, as illustrated in Appendix V, each pair of variables in the Pearson correlation matrix has an absolute value less than 0.8, while no regressor indicates a VIF exceeding 5. As a result, the specification has no perfect multicollinearity and satisfies the full rank OLS assumption for panel data. Furthermore, with a p-value < 0.1 of the χ^2 statistic, the H_0 of the Hausman test on FEM and REM is rejected (Appendix VI). Therefore, FEM estimates are consistent, and it is an appropriate estimator for $GTFP_{t-5}$, $TECH_{t-5}$ and $TECCH_{t-5}$ models. Under the FEM specification, a small p-value indicates statistically significant Wald χ^2 and Wooldridge F statistics. This means there remains groupwise heteroskedastic variance and serial correlation in the residuals, and it is thus imperative to use HAC SEs to handle these econometric problems.

[2] MLI groups include the annualised growth rate and the level of GTFP and its components.

4.3. Baseline results

Table 2. Coefficient estimates with CUE-GMM estimation methods

Variables	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
FIT_{t-5}	0.545^{***}	-0.700	1.772^{***}
	(0.174)	(0.514)	(0.556)
TFP $index_{t-5}$	-0.477^{***}	-0.247	-0.559
	(0.182)	(0.593)	(0.634)
ln(GTFP $level_{t-5}$)	-8.147^{***}		
	(1.349)		
ln(TECH $level_{t-5}$)		-18.307^{***}	
		(0.992)	
ln(TECCH $level_{t-5}$)			-19.122^{***}
			(1.112)
ln($GDPpc_{t-5}$)	-1.144^{***}	2.265^{**}	-3.713^{***}
	(0.215)	(0.906)	(0.987)
ln(Pop_{t-5})	0.014	4.707^{***}	-5.034^{***}
	(0.377)	(1.683)	(1.366)
Rev_{t-5}	0.000	-0.054^{*}	0.046
	(0.007)	(0.031)	(0.031)
ln(Glo_{t-5})	0.452^{*}	0.594	-1.087
	(0.254)	(1.202)	(1.177)
ln($Vuln_{t-5}$)	-2.494	-3.765	0.023
	(1.861)	(4.839)	(5.098)
Pat_{t-5}	-0.087^{***}	-0.132	-0.010
	(0.025)	(0.101)	(0.089)
N	911	911	911
KP LM	34.716***	34.105***	34.510***
KP Wald F	32.345	31.192	31.729
Stock-Yogo CVs			
• 10% mLIML		8.68	
• 15% mLIML		5.33	
• 20% mLIML		4.42	
• 25% mLIML		3.92	
Hansen J	0.412	0.023	0.063
DWH χ^2	5.311**	1.513	9.139***

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Source: Author's calculations

Table 2 reports the regression results for $GTFP_{t-5}$, $TECH_{t-5}$, and $TECCH_{t-5}$, using the CUE-GMM estimation method and post-estimation tests for IV conditions.

For the treatment variable, the 5-year lag of FIT exerts a significant positive difference of 0.545 percentage points in the annualised GTFP growth between the treated and control groups, ceteris paribus. Combining guaranteed prices and grid access, the scheme reduced revenue risks for RE investments, thus eliminating barriers for new entrants. This, in turn, promoted operational learning and the diffusion of best practices, facilitating improvements in technical efficiency. Supporting this view, there was a significant divergence in the TECCH over t-5 and t between countries adopting FIT and their non-participating counterparts, at 1.722 percentage points. This is consistent with Acemoglu *et al.*'s (2012, pp. 131–66) concept of directed technical change, where the price effect-induced government interventions, including carbon taxes or RE subsidies, tend to countervail the market-size advantages of fossil fuels. As a result, innovation is steered along the biased path toward cleaner, resource-saving technologies. Still, as a demand-pull instrument, the FIT failed to translate these benefits into shifts in the production frontier among the implementing parties during the examined period. The finding aligns with those of Lindman and Söderholm (2016, pp. 1351–1359), who argued that the benefit of FIT lies in the diffusion stage rather than in knowledge creation.

For the control variables, a 1% increase in the initial level of GTFP, TECH, and TECCH was associated with their respective decreases in the annualised growth rate 5 years later, at 0.08, 0.18, and 0.19 percentage points[3]. This indicates a phenomenon of the so-called conditional β-convergence in all indices, consistent with Kim and Loayza (2019). Still, without considering green factors, a one-standard-deviation (hereafter, SD) increase in the 5-year lag of the TFP determinant index resulted in a 0.477 percentage point reduction in the $GTFP_{t-5}$. Following the addition of 1% in GDP per capita, there was a significant drop of 0.01 and 0.04 percentage points in $GTFP_{t-5}$ and $TECCH_{t-5}$, but a climb of 0.02 percentage points in $TECCH_{t-5}$. Such patterns highlight a dilemma between innovation and catch-up effects, where higher-income countries often act as innovation leaders but position closer to the production frontier. As a result, there remained limited room for performance improvements, which even offset the effects of innovation. While an approximate 0.05-percentage-point augmentation in $TECH_{t-5}$ occurred with a 1% increase in population, the associated abatement of 0.05 percentage points in $TECCH_{t-5}$ due to inefficient resource allocation neutralised such merits. In contrast, the 5-year lag of the economic globalisation index contributed to the persistent growth of $GTFP_{t-5}$.

For the diagnostic tests of valid IVs, (1) with a small p-value, the KP LM statistics are significant, rejecting the null hypothesis. Hence, the instruments are sufficiently correlated with the suspected endogenous treatment, and the specification is identified. (2) KP Wald F-statistics are also greater than the Stock-Yogo CVs at the 10% mLIML, and hence, the H_0 is rejected. Therefore, these IVs are not weak and fulfil the relevance condition. (3) In addition, the insignificant Hansen J statistic (p-value > 0.1) allows for the rejection of the H_0. Thus, the instruments are unlikely to be correlated with the residuals and correctly excluded from the principal regression. This means IVs are valid, thereby satisfying the exclusion restriction condition. (4) Nonetheless, the DWH χ^2 statistics indicate the statistical significance for $GTFP_{t-5}$ and $TECCH_{t-5}$, neither for $TECH_{t-5}$. As a result, the FIT is endogenous as expected, except for the model of innovation effects. Nevertheless, the insignificant impact of FIT_{t-5} on TECH during the ensuing five years remains unchanged in the FEM estimator, as illustrated in Appendix VI.

[3] The exact marginal effect of continuous regressors in the lin-log functional form equals to β x ln(1.01)

4.4. Heterogeneity results

4.4.1. OECD and non-OECD countries

Table 3. OECD and non-OECD countries

Variables	OECD countries			Non-OECD countries		
	$GTFP_{t-5}$	**$TECH_{t-5}$**	**$TECCH_{t-5}$**	**$GTFP_{t-5}$**	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
FIT_{t-5}	0.701***	-0.087	1.154*	-0.286	-4.170**	3.468**
	(0.207)	(0.662)	(0.691)	(0.298)	(1.748)	(1.539)
TFP $index_{t-5}$	-0.349	0.740	-1.565*	-0.425***	-1.946**	1.402
	(0.253)	(0.734)	(0.812)	(0.138)	(0.961)	(0.933)
ln(GTFP $level_{t-5}$)	-8.652***			-15.088***		
	(1.731)			(1.847)		
ln(TECH $level_{t-5}$)		-18.547***			-18.520***	
		(1.115)			(1.429)	
ln(TECCH $level_{t-5}$)			-18.967***			-19.781***
			(1.175)			(1.611)
ln($GDPpc_{t-5}$)	-1.831***	0.265	-2.099	0.006	2.701*	-3.020**
	(0.354)	(1.320)	(1.487)	(0.271)	(1.415)	(1.419)
ln(Pop_{t-5})	0.510	10.216***	-7.996***	-0.876*	-2.700	1.022
	(0.765)	(2.037)	(2.304)	(0.524)	(2.313)	(2.150)
Rev_{t-5}	-0.035***	-0.069	0.016	-0.008	-0.163***	0.158***
	(0.011)	(0.045)	(0.043)	(0.005)	(0.051)	(0.051)
ln(Glo_{t-5})	0.616	5.551***	-6.260***	0.420**	-2.687*	3.043**
	(0.389)	(1.732)	(1.781)	(0.204)	(1.551)	(1.454)

Variables	OECD countries GTFP$_{t-5}$	TECH$_{t-5}$	TECCH$_{t-5}$	Non-OECD countries GTFP$_{t-5}$	TECH$_{t-5}$	TECCH$_{t-5}$
ln(Vuln$_{t-5}$)	-2.599	-2.307	-1.159	3.043	18.304	-13.200
	(2.081)	(5.889)	(6.159)	(2.238)	(12.969)	(11.357)
Pat$_{t-5}$	-0.157***	-0.303***	0.060	0.098**	0.871***	-0.766**
	(0.024)	(0.083)	(0.087)	(0.048)	(0.327)	(0.298)
N	621	621	621	290	290	290
KP LM	26.061***	26.049***	26.275***	8.590**	8.657**	8.621**
KP Wald F	20.247	20.744	20.961	6.843	6.995	6.971
Hansen J	1.798	0.011	0.442	0.823	1.078	1.093

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)
Source: Author's calculations

Table 3 presents the heterogeneous effects of FIT in the North-South relationship. Among OECD countries, FIT implementers experienced increases of 0.701 and 1.154 percentage points in the annualised growth rate of GTFP and TECCH during the subsequent five years, except for TECH. Hence, technical diffusion remains the pivotal driver of improved green performance in developed RE markets, owing to strong knowledge stocks and specialised human capital. In contrast, there was a negligible effect on GTFP growth over t-5 and t in non-OECD countries associated with the adoption of FIT. This is attributed to a significant decrease of 4.170 percentage points in TECH$_{t-5}$, impeding the incremental 3.468 percentage points in TECCH$_{t-5}$. As price incentives, the programme also encourages the imitation of existing technologies to maximise marginal returns, more evident for those without disposable financial buffers. This led to a significant decline in innovation desire in the Global South, alongside an increasing dependence on globalisation for technological learning and thus a 0.03-percentage-point addition in TECCH$_{t-5}$. Furthermore, a one-percentage-point increase in public revenue caused a significant 0.163 percentage-point decrease in TECH$_{t-5}$. Ineffective fiscal procedures, therefore, further deterred the frontier shift, similar to the cases of Vietnam and Indonesia (Do *et al.*, 2021, pp. 1–11; Setiawan *et al.*, 2022, p. 113164).

4.4.2. FIT remuneration levels

Table 4. FIT remuneration levels

Variables	25th percentile			25th-75th percentile			75th percentile		
	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
FIT_{t-5}	0.955***	-0.780	2.726**	0.573**	-0.712	1.569**	1.078**	0.613	0.866
	(0.357)	(1.297)	(1.360)	(0.246)	(0.533)	(0.639)	(0.454)	(0.895)	(0.741)
TFP $index_{t-5}$	-0.322*	0.465	-1.027	-0.312	0.246	-0.991	-0.214	0.730	-1.023
	(0.191)	(0.777)	(0.842)	(0.217)	(0.755)	(0.787)	(0.155)	(0.795)	(0.810)
ln(GTFP $level_{t-5}$)	-9.420***			-9.009***			-15.138***		
	(1.611)			(1.825)			(1.236)		
ln(TECH $level_{t-5}$)		-20.103***			-19.166***			-20.448***	
		(1.434)			(1.034)			(1.356)	
ln(TECCH $level_{t-5}$)			-20.074***			-19.586***			-20.946***
			(1.478)			(1.162)			(1.213)
$\ln(GDPpc_{t-5})$	-0.918***	3.963***	-5.201***	-1.056***	1.713	-2.849**	-0.530*	2.871***	-3.572***
	(0.342)	(1.272)	(1.469)	(0.267)	(1.221)	(1.304)	(0.292)	(1.093)	(1.127)
$\ln(Pop_{t-5})$	-0.334	5.075**	-6.238***	-0.040	3.505**	-4.260***	-0.662	3.813*	-4.425**
	(0.473)	(2.322)	(2.153)	(0.521)	(1.785)	(1.588)	(0.414)	(2.037)	(1.776)
Rev_{t-5}	-0.015*	-0.122***	0.101**	0.006	-0.060	0.069*	-0.004	-0.114**	0.123***
	(0.009)	(0.042)	(0.045)	(0.008)	(0.037)	(0.037)	(0.008)	(0.044)	(0.044)
$\ln(Glo_{t-5})$	0.799**	-1.213	1.298	0.077	0.132	-1.273	0.090	0.185	-0.368
	(0.319)	(1.567)	(1.718)	(0.267)	(1.439)	(1.469)	(0.258)	(1.695)	(1.607)
$\ln(Vuln_{t-5})$	-2.303	0.916	-6.968	-3.601*	-3.632	0.043	-3.598*	-8.392	4.243

Variables	25th percentile			25th-75th percentile			75th percentile		
	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
	(2.481)	(8.015)	(8.761)	(2.118)	(5.470)	(5.517)	(2.125)	(6.349)	(6.022)
Pat_{t-5}	-0.006	0.568*	-0.606*	-0.101***	-0.215**	0.076	0.391*	-0.076	0.660
	(0.080)	(0.342)	(0.354)	(0.027)	(0.084)	(0.088)	(0.202)	(0.510)	(0.528)
N	533	533	533	675	675	675	553	553	553
KP LM	13.128***	12.657***	12.690***	28.617***	28.348***	28.391***	10.475***	9.439***	9.432***
KP Wald F	10.934	10.209	10.733	23.795	23.036	23.003	7.444	7.728	7.732
Hansen J	0.694	0.006	0.027	0.086	1.384	2.394	2.413	0.453	2.187

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)
Source: Author's calculations

As seen in Table 4, FIT_{t-5} has a significant and positive impact on implementing parties, regardless of remuneration levels. It contributed to increases of 0.955, 0.573, and 1.078 percentage points in $GTFP_{t-5}$ at the lower 25th percentile (small), the 25th to 75th percentiles (medium), and the higher 75th percentile (high) of FIT rates[4]. The most potent effect of the high cluster indicates that the higher the subsiding amount, the stronger the price effect can direct technical changes, attracting more new RE producers. This, in turn, can reduce higher CO_2 emissions and create additional jobs, leading to additional beneficial green performance. Decomposing the growth pattern, the 5-year lag of FIT exerts a positive impact of 2.726 and 1.569 percentage points in $TECCH_{t-5}$ for small and medium clusters, but insignificant effects for the remainder. This means that excessive remuneration cannot be translated into corresponding performance outcomes, aligning with the findings of Böhringer *et al.* (2017, pp. 545–553) on the German EEG. Together, much as the generous FIT rate can cause explosive price effects, it fails to generate technical diffusion due to diminishing marginal returns on (semi-)monopolistic knowledge. Therefore, the remuneration gap of almost threefold between small and high clusters caused a disproportionate 0.12-percentage-point rise in GTFP within the 5-year window.

[4] 25th percentile ($r < 0.056$ US$/kWh), 25th-75th percentile (0.056 US$/kWh $< r <$ 0.150 US$/kWh), and 75th percentile ($r > 0.150$ US$/kWh) (Appendix VII).

4.4.3. RE technologies

Table 5. RE technologies

Variables	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
$FIT_{s,t-5}$	-0.064	-0.889	1.176^{**}
	(0.244)	(0.600)	(0.597)
$FIT_{w,t-5}$	0.583^{***}	-0.733	1.773^{***}
	(0.180)	(0.509)	(0.530)
$FIT_{b,t-5}$	0.417^{*}	-0.734^{*}	1.428^{***}
	(0.216)	(0.443)	(0.475)
$FIT_{h,t-5}$	0.601^{**}	-0.966^{*}	1.848^{***}
	(0.280)	(0.515)	(0.539)
$FIT_{ws,t-5}$	0.346	0.284	0.248
	(0.211)	(0.524)	(0.514)
$FIT_{g,t-5}$	-0.130	0.098	0.243
	(0.191)	(0.534)	(0.514)
$FIT_{m,t-5}$	0.657^{*}	-0.239	1.263^{***}
	(0.349)	(0.444)	(0.480)
N	911	911	911

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)
Source: Author's calculations

Controlling for each FIT as an additional confounding factor, Table 5 illustrates the performance impact through the lens of different RE technologies. A rise in $GTFP_{t-5}$ occurred with the introduction of FIT for some power sources, including wind, biomass, small hydro, and marine. This is ascribed to an increase in $TECCH_{t-5}$, consistent with the baseline diffusion. Although wind and marine sources incur high CAPEX for infrastructure construction, both sources benefit from fuel-free generation, thus reducing financial burdens on R&D activities. In contrast, biomass suffers from high OPEX due to the continuous procurement of fuel and logistics, while small hydro struggles with exorbitant maintenance costs arising from stringent dam regulations. As a result, FIT_{t-5} in these capital-intensive technologies led to significant reductions of 0.734 and 0.966 percentage points in $TECH_{t-5}$. Substantial CAPEX and OPEX costs, such as well drilling or incineration, even cancelled out the positive impacts of waste and geothermal FITs on all indices, consistent with Setiawan *et al.* (2022, p. 113164). In addition, mature PV failed to transform FIT-induced advantageous $TECCH_{t-5}$ gains into positive impacts on $GTFP_{t-5}$, indicating operational drawbacks from curtailment and price cannibalisation.

4.5. Robustness checks

4.5.1. Control function method

Table 6. Second-stage control function method

Variables	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
FIT_{t-5}	0.645***	-0.697*	1.786***
	(0.078)	(0.381)	(0.299)
TFP $index_{t-5}$	-0.492**	-0.245	-0.576
	(0.211)	(0.467)	(0.565)
ln(GTFP $level_{t-5}$)	-7.819***		
	(2.635)		
ln(TECH $level_{t-5}$)		-18.297***	
		(2.635)	
ln(TECCH $level_{t-5}$)			-19.094***
			(2.532)
ln($GDPpc_{t-5}$)	-1.209***	2.272**	-3.741***
	(0.155)	(1.073)	(1.298)
ln(Pop_{t-5})	0.150	4.674***	-5.001***
	(0.442)	(0.896)	(0.925)
Rev_{t-5}	-0.000	-0.054**	0.046*
	(0.004)	(0.022)	(0.024)
ln(Glo_{t-5})	0.436**	0.564	-1.055*
	(0.168)	(0.656)	(0.603)
ln($Vuln_{t-5}$)	-3.488***	-3.919	0.122
	(1.204)	(3.809)	(3.093)
Pat_{t-5}	-0.096***	-0.132*	-0.011
	(0.010)	(0.069)	(0.060)
Residuals	-0.458***	0.596	-1.554***
	(0.107)	(0.414)	(0.345)
N	912	912	912
Panel FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Driscoll-Kraay SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Table 6 presents the control function method as the first alternative econometric estimation on the impact of FIT_{t-5} on the annualised growth rate of GTFP growth and its components over t-5 and t. The first-stage regression shows that FIT_{t-9} and Adj_{t-5} are significant, and therefore, these instruments fulfil the relevance condition (Appendix IX). In the second stage, the 5-year lagged treatment exerts a positive and significant influence on $GTFP_{t-5}$ and $TECCH_{t-5}$. The significant residuals also confirm the presence of endogeneity in these specifications. In contrast, FIT_{t-5}

significantly hurts $TECH_{t-5}$ (p-value < 0.1), but the insignificant residual relaxes the treatment as an endogenous regressor in this model. Such results are consistent with the baseline estimates.

4.5.2. First-stage probit model

Table 7. Second-stage CUE-GMM with first-stage probit model

Variables	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
FIT_{t-5}	0.462^{***}	-0.629	1.539^{***}
	(0.165)	(0.496)	(0.496)
TFP $index_{t-5}$	-0.398^{**}	-0.229	-0.616
	(0.174)	(0.592)	(0.629)
ln(GTFP $level_{t-5}$)	-8.584^{***}		
	(1.336)		
ln(TECH $level_{t-5}$)		-18.363^{***}	
		(0.988)	
ln(TECCH $level_{t-5}$)			-19.313^{***}
			(1.097)
ln($GDPpc_{t-5}$)	-1.089^{***}	2.204^{**}	-3.523^{***}
	(0.210)	(0.898)	(0.969)
ln(Pop_{t-5})	-0.099	4.625^{***}	-5.009^{***}
	(0.361)	(1.659)	(1.356)
Rev_{t-5}	0.002	-0.051^{*}	0.041
	(0.007)	(0.031)	(0.031)
ln(Glo_{t-5})	0.454^{*}	0.512	-1.079
	(0.243)	(1.199)	(1.173)
ln($Vuln_{t-5}$)	-1.741	-4.219	1.164
	(1.827)	(4.756)	(4.924)
Pat_{t-5}	-0.078^{***}	-0.129	0.014
	(0.024)	(0.102)	(0.084)
N	911	911	911
KP LM	37.807***	39.854***	43.990***
KP Wald F	24.258	24.779	28.287
Hansen J	3.016	0.458	1.530

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* p < 0.1, ** p < 0.05, *** p < 0.01)
Source: Author's calculations

As illustrated in Table 7, using the nonlinear fit-as-instruments approach modified with the method of Windmeijer and Santos Silva (1997, pp. 281–294), there is a beneficial effect of FIT_{t-5} on $GTFP_{t-5}$ and $TECCH_{t-5}$, instead of $TECH_{t-5}$, aligning with the main findings. Considering probit post-estimation tests (Appendix X), the rejection of H_0 for the likelihood ratio (hereafter, LR) χ^2 statistics for overall significance indicate that at least one of the slope coefficients is different from zero. The small p-value of the LR χ^2 statistics of ρ also supports the use of REM probit in the first stage. In addition, LR χ^2 statistics for the joint significance of two IVs allow for rejecting the H_0. This means at least one instrument is correlated with the treatment and satisfies the relevance condition.

4.5.3. Staggered DID

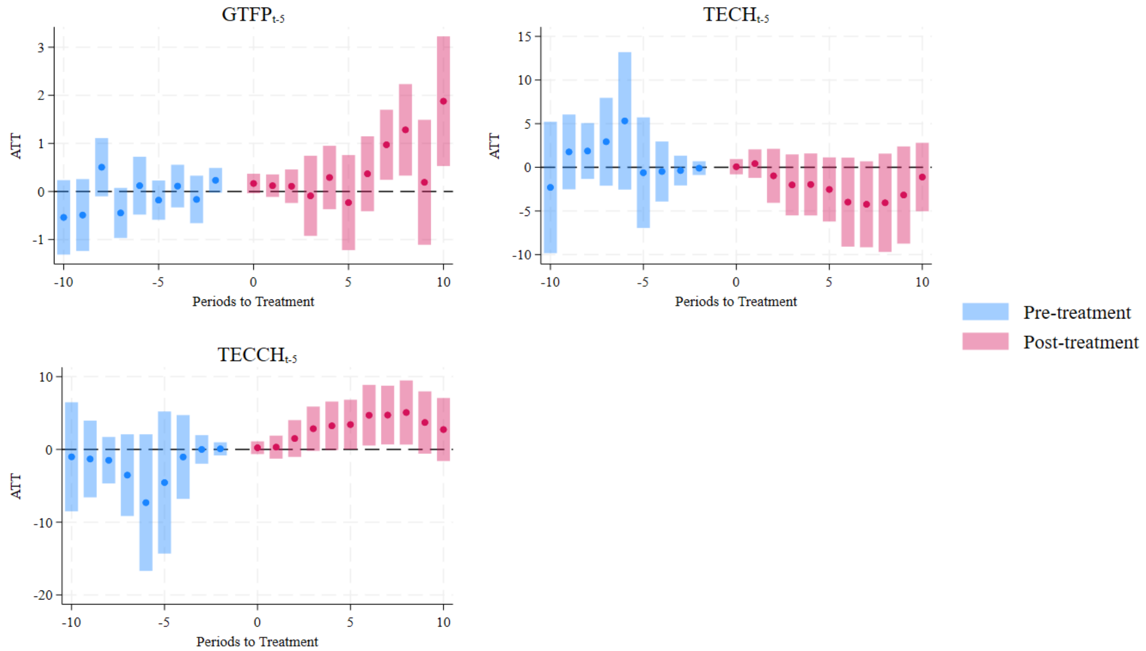


Figure 3. Event study plots on the main estimate

Source: Author's calculations

Due to the outcome measurement over the t-5 and t periods, the treatment timing was aligned at five years after FIT adoption. This enables the outcome window to lie post-treatment, avoiding overlap with pre-treatment periods. In addition, as the scheme was rolled out at different times across countries, this temporal shift does not change the staggered DID identification. Hence, the ATT represents the five-year exposure effects, indicating an addition in $GTFP_{t-5}$ and $TECCH_{t-5}$ as the main results (Appendix XI). Event study plots confirm the parallel trend assumption of this causal paradigm, as seen in Figure 3. Furthermore, the insignificant ATT in the placebo test suggests that there is no spillover effect of the treatment on the outcomes of neighbouring countries. This supports the validity of the SUTVA assumption.

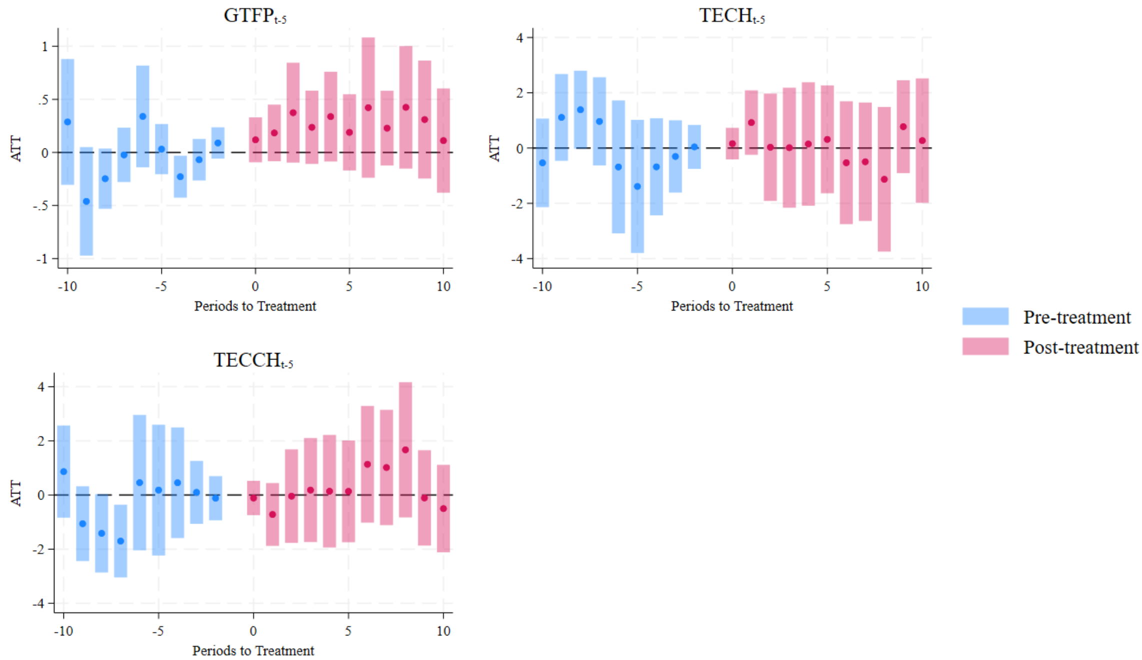


Figure 4. Event study plots on the placebo test

Source: Author's calculations

4.5.4. 7-year lag structure

Table 8. 7-year lag structure

Variables	GTFP$_{t-7}$	TECH$_{t-7}$	TECCH$_{t-7}$
FIT$_{t-7}$	0.469***	-0.302	1.114**
	(0.167)	(0.415)	(0.444)
TFP index$_{t-7}$	-0.291**	-0.227	-0.189
	(0.132)	(0.435)	(0.450)
ln(GTFP level$_{t-7}$)	-7.281***		
	(1.102)		
ln(TECH level$_{t-7}$)		-15.322***	
		(0.573)	
ln(TECCH level$_{t-7}$)			-15.849***
			(0.659)
ln(GDPpc$_{t-7}$)	-1.175***	0.558	-1.764***
	(0.218)	(0.670)	(0.671)
ln(Pop$_{t-7}$)	-0.361	2.535	-2.945**
	(0.373)	(1.703)	(1.369)
Rev$_{t-7}$	-0.003	-0.024	0.012
	(0.007)	(0.023)	(0.022)
ln(Glo$_{t-7}$)	0.200	0.541	-1.067

	(0.230)	(1.072)	(1.066)
$\ln(Vuln_{t-7})$	-3.741^{**}	-8.553^{**}	4.527
	(1.814)	(4.200)	(4.457)
Pat_{t-7}	-0.067^{**}	-0.121	0.017
	(0.027)	(0.087)	(0.068)
N	811	811	811
KP LM	26.110***	26.490***	26.701***
KP Wald F	22.696	22.781	22.984
Hansen J	0.486	0.862	1.889

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)
Source: Author's calculations

Table 8 describes the causation between FIT and GTFP, as well as its components, at another lag level (7 years). Therefore, IVs are redesigned with an 11-year lag of its own FIT and the 7-year lag of the mean number of RE patents in contiguous countries. The results illustrate that FIT_{t-7} continues to exert a significant and positive impact on the annualised growth rate of GTFP and TECCH over t-7 and t, but not on the $TECH_{t-7}$. Post-estimation diagnostic tests also affirm the validity of the restructured IVs. This means the main findings are independent of the lag structure.

4.5.5. Alternative outcome measure

Table 9. Alternative outcome measure LPI

Variables	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
FIT_{t-5}	0.721^{***}	-0.573	2.954^{***}
	(0.248)	(0.787)	(0.888)
TFP $index_{t-5}$	-0.678^{***}	-0.065	-0.468
	(0.235)	(0.946)	(0.938)
$\ln(GTFP\ level_{t-5})$	-9.165^{***}		
	(1.106)		
$\ln(TECH\ level_{t-5})$		-15.686^{***}	
		(1.063)	
$\ln(TECCH\ level_{t-5})$			-17.871^{***}
			(1.643)
$\ln(GDPpc_{t-5})$	-1.650^{***}	-0.765	-9.606^{***}
	(0.304)	(1.570)	(1.455)
$\ln(Pop_{t-5})$	-0.171	5.183^{**}	-5.999^{***}
	(0.526)	(2.629)	(1.690)
Rev_{t-5}	-0.001	-0.104^{**}	0.015
	(0.010)	(0.052)	(0.051)
$\ln(Glo_{t-5})$	0.759^{**}	1.081	-1.888
	(0.367)	(2.043)	(2.006)

$\ln(Vuln_{t-5})$	-3.681	-9.960	-9.484
	(2.554)	(7.285)	(7.379)
Pat_{t-5}	-0.119***	-0.451***	-0.259
	(0.037)	(0.114)	(0.234)
N	911	911	911
KP LM	34.322***	33.939***	35.055***
KP Wald F	31.579	31.204	32.003
Hansen J	0.167	0.642	1.872

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* p < 0.1, ** p < 0.05, *** p < 0.01)
Source: Author's calculations

Using the additive LPI as an alternative to the multiplicative MLI, Table 9 presents the sensitivity analysis for the FIT-GTFP relationship. The 5-year lagged FIT led to an increase in $GTFP_{t-5}$ and $TECCH_{t-5}$ and no significant changes in $TECH_{t-5}$. IVs also survive the diagnostic tests and fulfil both relevance and exclusion restrictions conditions, similar to the main results.

To summarise, these robust checks demonstrate that the baseline results are consistent across different identification strategies, lag structure and outcome measurement methods.

Chapter 5. Conclusion

This paper examines the impact of FIT adoption on GTFP growth and its components in a cross-national setting from 1990 to 2019. The non-parametric MLI is used to estimate outcomes based on the DEA method. Building under the DDF, global PPF enables the addressing of linear programming infeasibilities and the decomposition into TECH and TECCH. Meanwhile, Jacobs (2014, pp. 755–773) reported that the German FIT has become the role model for global adoption since the EEG 2000, and thus, the treatment design remains relatively unchanged across implementors. In addition, multivariate statistics is adopted to estimate the composite determinant index, while the lag structure helps handle reverse causation due to short-term fluctuations. Given the remaining time-variant unobservable factors, both internal and external instruments are used to address the endogenous risks associated with omitted variables. The CUE-GMM estimation method with HAC SEs is also considered due to its superior efficiency in mitigating finite-sample bias in 2SLS and 2SGMM.

The findings reveal that average annual MLI changes benefit from both TECCH and TECH in general, though the former prevails. Ireland and Luxembourg stand out as the top performers. For the baseline results, FIT has a positive and significant impact on GTFP and TECCH, but not on TECH, within the five-year window. The scheme thus operates as a diffusion- rather than frontier-pushing instrument. Following Acemoglu *et al.*'s (2012, pp. 131–66) concept of directed technical change, endogenous R&D investments are not neutral. These activities often steer along a biased path, depending on government interventions. In this case, as a price-induced incentive, FIT diminishes the revenue risks to attract more new RE producers. This, in turn, facilitates operational gains through mutual technological learning, leading to improved performance. Still, the FIT mechanism rewards renewable generation rather than R&D, and hence, it failed to cause technological progress. This indicates that regulation design is crucial for translating these directed technical changes into shifts in the production frontier.

Regarding heterogeneous lenses, OECD countries follow a similar baseline pattern due to existing knowledge stocks and human capital. Their non-OECD counterparts, however, observe an opposite effect, where TECH and TECCH offset each other. Furthermore, generous FITs resulted in substantial growth in GTFP, but had an insignificant impact on the remaining outcomes. This can be attributed to the limited technological diffusion arising from knowledge appropriability and diminishing returns. In contrast, moderate remuneration credits an increase in both GTFP and TECCH, contributing to more sustainable development. This aligns with the findings of Zhou *et al.* (2023, p. 129042) on the positive impact of FIT reduction in China. Moreover, the RE-specific programme shows the potential moderating role of different costs in the central causal paradigm. While wind and marine FITs led to consistent positive effects as expected, technological changes are sensitive to OPEX from biomass and small hydro. Waste and geothermal FITs even exerted no significant impact on GTFP or its components, whereas curtailment and price cannibalisation are potential main hindrances to PV performance. Robustness checks confirm the unbiased and consistent estimates of the baseline panel IV model across specifications and lag structure.

Together, these findings highlight that the effectiveness of FIT on GTFP growth is achieved through operation-oriented diffusion channels, aligning with its market-pull design. Hence, the government can take these steps to utilise the FIT benefits. First, a mix of policies, such as carbon taxes or augmenting R&D investments, should be implemented alongside FIT to reap the benefits of both technological progress and operational efficiency. This is critical for developing countries, where FIT-induced diffusion alone is insufficient. Targeted technical training and enhanced grid management are also imperative to improve absorptive capacity. Second, generous FIT remuneration can be applied in the initial short periods, given its limited impact on TECH and TECCH. This, in turn, allows for achieving the most significant price effects on the RE transition, CO_2 emission mitigation, and GTFP growth. Still, there should be a subsequent FIT degradation mechanism, or even auctions, to boost TECCH and reduce surcharge bills on end-users. Third, mature RE power sources, including wind and marine, are the most advantageous entities for FIT adoption. These sources often have standardised global value chains for turbines and other equipment to utilise operational technologies. In contrast, biomass and small hydro remain cost-sensitive, and therefore, additional OPEX-reducing instruments need to be considered to support FITs. Countries should also replace FITs for waste and geothermal energies with auctions or concessional finance to overcome the expensive CAPEX. Storage and load balancing will be of most concern for PV in the post-FIT era. Future research could further investigate how R&D-oriented policies shape technological progress, complementing the diffusion effects of FITs. Studies at the subnational or sectoral levels should also be taken into account due to heterogeneous disparities in resource endowments, grid infrastructure and industrial composition.

Appendices

Appendix I. Summary of variables

Variable	Description	Abbreviation	Unit
Outcome variable	Annualised GTFP growth rate over t-5,t	$GTFP_{t-5}$	%
	Annualised TECH growth rate over t-5 and t	$TECH_{t-5}$	%
	Annualised TECCH growth rate over t-5 and t	$TECCH_{t-5}$	%
Treatment variable	FIT enactment status t-5 (1 = FIT enacted)	FIT_{t-5}	-
Control variable	Overall TFP determinant index t-5	TFP $index_{t-5}$	[0;1]
	GTFP level t-5	GTFP $level_{t-5}$	-
	TECH level t-5	TECH $level_{t-5}$	-
	TECCH level t-5	TECCH $level_{t-5}$	-
	GDP per capita t-5 at constant 2015 US$	$GDPpc_{t-5}$	US$
	Total population	Pop_{t-5}	person
	Revenue, excluding grants (% of GDP)	Rev_{t-5}	%
	KOF economic globalisation index t-5	Glo_{t-5}	[0;100]
	ND-GAIN vulnerability index t-5	$Vuln_{t-5}$	[0;1]
	Mean RE patents of adjacent countries t-5 (in thousands)	Pat_{t-5}	patents
Instrumental variable	FIT enactment status t-9 (1 = FIT imposed)	FIT_{t-9}	-
	Number of adjacent countries enacting FIT t-5	Adj_{t-5}	nation

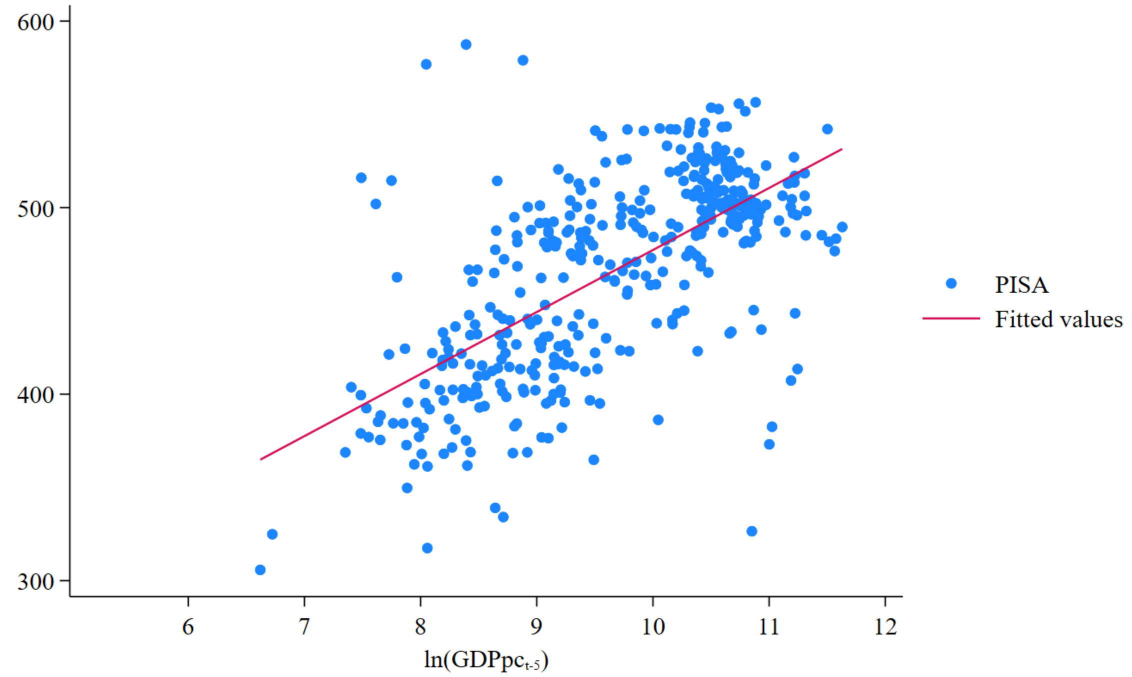
Appendix II. List of indicators in the FA

Indicators	Factor loadings	Sources
Innovation index (Eigenvalue = 2.271; Bartlett p-value = 0.000; KMO = 0.633; Cumulative = 0.757)		
Research and development expenditure (% of GDP) (R&D)	0.935	WDI
Scientific and technical journal articles (article)	0.888	WDI
Patent applications (patent)	0.780	WDI
• Patent applications = Patent applications, non-residents + Patent applications, residents	-	-
⇨ *innov = 0.412*z(R&D) + 0.391*z(article) + 0.343*z(patent)*		
Education index (Eigenvalue = 2.034; Bartlett p-value = 0.000; KMO = 0.694; Cumulative = 0.509)		
Government expenditure on education, total (% of GDP) (eduexp)	0.586	WDI
PISA: Mean performance on average (pisa)	0.807	Education Statistics
• PISA = (Mean performance on the reading scale + Mean performance on the mathematics scale + Mean performance on the science scale)/3	-	-
Proportion of population aged 25 and over with completed secondary education (secondary)	0.614	Barro and Lee (2013, pp. 184–198)
Proportion of population aged 25 and over with completed tertiary education (tertiary)	0.814	Barro and Lee (2013, pp. 184–198)
⇨ *edu = 0.288*z(eduexp) + 0.397*z(pisa) + 0.302*z(secondary) + 0.400*z(tertiary)*		
Market efficiency index (Eigenvalue = 1.867; Bartlett p-value = 0.000; KMO = 0.621; Cumulative = 0.622)		
Financial development index (financial)	0.858	IMF
Ease of doing business score (business)	0.786	Doing Business
Labour market index (labour)	-0.716	-
• Ratio of minimum wage to value added per worker (minwage)	0.662	Employing Workers
• Severance pay for redundancy dismissal (in weeks of salary) (severance)	0.749	Employing Workers
• Share of women employed in the non-agricultural sector (% of total non-agricultural employment) (women)	-0.632	WDI

→ *labour = 0.474*z(minwage) + 0.535*z(severance) - 0.451*z(women)*		
⇨ *effi = 0.460*z(financial) + 0.421*z(business) - 0.383*z(labour)*		
Infrastructure index (Eigenvalue = 3.471; Bartlett p-value = 0.000; KMO = 0.799; Cumulative = 0.578)		
Fixed telephone subscriptions (per 100 people) (tele)	0.846	WDI
Mobile cellular subscriptions (per 100 people) (mobile)	0.531	WDI
Rail lines[5] (total route-km) (rail)	0.658	WDI
Proportion of population using improved sanitation facilities (water)	0.826	WDI
Proportion of population using improved drinking water sources (sanit)	0.857	WDI
Total electricity production (kWh) (elec)	0.789	WDI
• Total electricity production[6] = (Electricity production from renewable sources, excluding hydroelectric (kWh) / Electricity production from renewable sources, excluding hydroelectric (% of total)) * 100	-	-
⇨ *infra = 0.243*z(tele) + 0.153*z(mobile) + 0.190*z(rail) + 0.238*z(water) + 0.247*z(sanit) + 0.227*z(elec)*		
Institutions index (Eigenvalue = 5.491; Bartlett p-value = 0.000; KMO = 0.876; Cumulative = 0.784)		
Control of Corruption: Estimate (cc)	0.934	WGI
Government Effectiveness: Estimate (ge)	0.949	WGI
Political Stability and Absence of Violence/Terrorism: Estimate (ps)	0.802	WGI
Regulatory Quality: Estimate (rq)	0.946	WGI
Rule of Law: Estimate (rl)	0.967	WGI
Voice and Accountability: Estimate (va)	0.915	WGI
Core civil society index[7] (cs)	0.638	V-Dem
⇨ *inst = 0.170*z(cc) + 0.173*z(ge) + 0.146*z(ps) + 0.172*z(rq) + 0.176*z(rl) + 0.167*z(va) + 0.116*z(cs)*		

[5] Alternative to the indicator "Paved roads (km per 100 people)"
[6] Alternative to the indicator "Electricity production (kWh per 100 people) " (author's calculation)
[7] New indicator of the Institutions subcomponent index

Appendix III. Relationship between PISA scores and ln($GDPpc_{t-5}$)
Appendix III-a. Scatter plot between PISA scores and ln($GDPpc_{t-5}$)



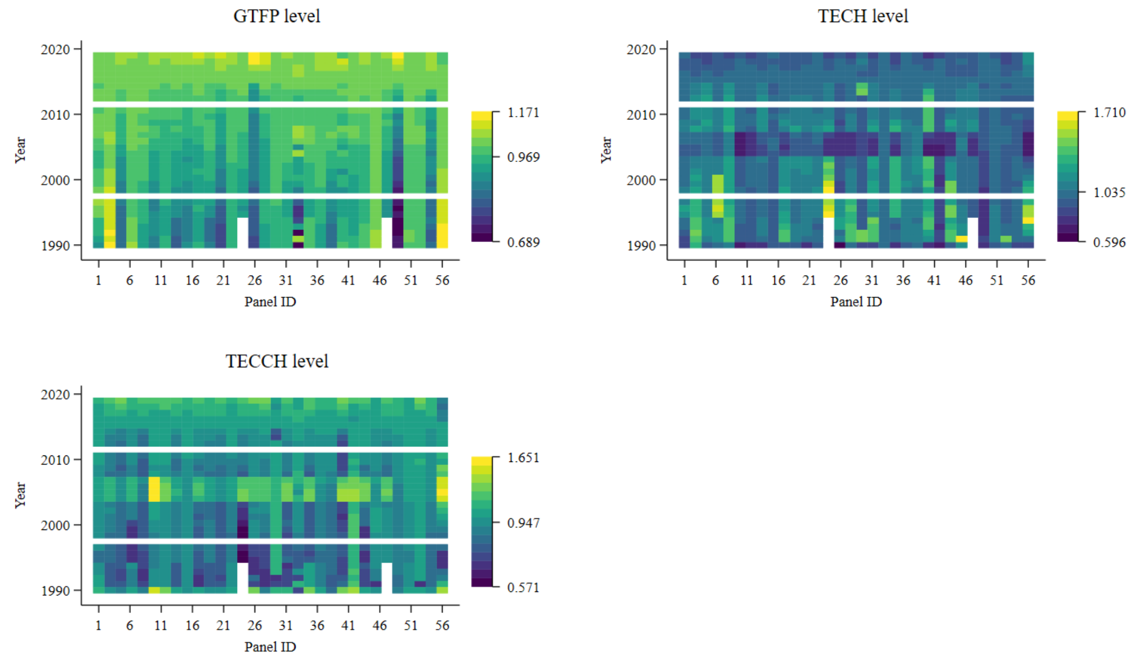
Appendix III-b. Estimated coefficients of ln($GDPpc_{t-5}$) on PISA scores

	PISA
ln($GDPpc_{t-5}$)	33.057***
	(1.894)
Constant	153.218***
	(19.263)
R^2	0.440

SEs in parentheses
Year FE: Yes
(* p < 0.1, ** p < 0.05, *** p < 0.01)

Appendix IV. Changes in GTFP and its components: 1990 to 2019

Appendix IV-a. Heatmaps of GTFP and its component levels



Appendix IV-b. Average annual growth rates of GTFP and its components

No	Code	Country	GTFP	TECH	TECCH	Rank
1	ALB	Albania	1.0031	1.0039	1.0001	26
2	ARE	United Arab Emirates	0.9951	0.9846	1.0111	56
3	ARG	Argentina	1.0011	1.0055	1.0042	43
4	AUT	Austria	1.0052	1.0015	1.0050	15
5	BEL	Belgium	1.0060	0.9983	1.0107	11
6	BGR	Bulgaria	1.0018	0.9810	1.0325	36
7	BRA	Brazil	1.0001	0.9996	1.0011	51
8	CAN	Canada	1.0020	0.9970	1.0075	35
9	CHE	Switzerland	1.0064	1.0000	1.0064	10
10	CHL	Chile	1.0016	1.0253	0.9959	38
11	CHN	China	1.0015	1.0012	1.0002	40
12	CRI	Costa Rica	1.0029	1.0095	1.0030	30
13	CZE	Czechia	1.0029	0.9994	1.0050	29
14	DEU	Germany	1.0075	1.0059	1.0048	9
15	DNK	Denmark	1.0094	1.0050	1.0045	5
16	DZA	Algeria	0.9998	0.9992	1.0007	53
17	ESP	Spain	1.0031	1.0042	1.0051	28
18	EST	Estonia	1.0034	1.0047	1.0032	20
19	FIN	Finland	1.0048	1.0011	1.0047	17
20	FRA	France	1.0051	1.0007	1.0056	16
21	GBR	United Kingdom	1.0108	1.0089	1.0050	3
22	GRC	Greece	1.0025	0.9950	1.0104	33

No	Code	Country	GTFP	TECH	TECCH	Rank
23	HRV	Croatia	1.0025	1.0018	1.0009	31
24	HUN	Hungary	1.0035	0.9846	1.0280	19
25	IDN	Indonesia	1.0000	1.0163	1.0028	52
26	IRL	Ireland	1.0186	1.0140	1.0076	1
27	ISR	Israel	1.0080	0.9995	1.0141	8
28	ITA	Italy	1.0032	0.9993	1.0066	23
29	JPN	Japan	1.0015	0.9981	1.0035	39
30	KAZ	Kazakhstan	1.0013	1.0314	1.0177	42
31	KOR	Korea, Rep.	1.0017	1.0044	1.0034	37
32	LTU	Lithuania	1.0055	1.0065	1.0154	13
33	LUX	Luxembourg	1.0139	1.0000	1.0139	2
34	LVA	Latvia	1.0053	0.9910	1.0333	14
35	MAR	Morocco	1.0002	1.0024	1.0004	49
36	MYS	Malaysia	1.0005	1.0002	1.0005	45
37	NLD	Netherlands	1.0055	1.0026	1.0039	12
38	NOR	Norway	1.0082	0.9992	1.0097	6
39	NZL	New Zealand	1.0032	1.0003	1.0035	22
40	PAN	Panama	1.0002	1.0064	1.0072	48
41	PER	Peru	1.0022	1.0038	1.0001	34
42	PHL	Philippines	1.0014	1.0073	0.9962	41
43	POL	Poland	1.0032	0.9873	1.0333	25
44	PRT	Portugal	1.0025	1.0029	1.0035	32
45	RUS	Russian Federation	1.0003	1.0099	1.0099	47
46	SAU	Saudi Arabia	0.9987	0.9938	1.0057	54
47	SVK	Slovak Republic	1.0048	1.0034	1.0050	18
48	SVN	Slovenia	1.0034	0.9971	1.0106	20
49	SWE	Sweden	1.0106	1.0053	1.0054	4
50	THA	Thailand	1.0002	1.0001	1.0004	50
51	TUN	Tunisia	1.0009	1.0009	1.0002	44
52	TUR	Türkiye	1.0032	0.9862	1.0189	24
53	UKR	Ukraine	1.0004	1.0030	1.0027	46
54	URY	Uruguay	1.0031	1.0010	1.0029	27
55	USA	United States	1.0080	1.0017	1.0066	7
56	VNM	Viet Nam	0.9974	1.0095	0.9933	55
		All	1.0036	1.0018	1.0070	

Appendix V. Pairwise correlation and VIFs

Appendix V-a. GTFP growth over t-5 and t

Variables	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
(i) $GTFP_{t-5}$	1.000									
(ii) FIT_{t-5}	0.208*	1.000								
(iii) TFP $index_{t-5}$	0.148*	0.467*	1.000							
(iv) ln(GTFP $level_{t-5}$)	-0.565*	0.064*	0.233*	1.000						
(v) ln($GDPpc_{t-5}$)	0.353*	0.348*	0.291*	-0.371*	1.000					
(vi) ln(Pop_{t-5})	-0.156*	0.053*	-0.015	0.195*	-0.301*	1.000				
(vii) Rev_{t-5}	0.225*	0.253*	0.218*	-0.190*	0.428*	-0.430*	1.000			
(viii) ln(Glo_{t-5})	0.368*	0.315*	0.453*	-0.323*	0.658*	-0.434*	0.497*	1.000		
(ix) ln($Vuln_{t-5}$)	-0.354*	-0.323*	-0.295*	0.332*	-0.739*	0.208*	-0.468*	-0.510*	1.000	
(x) Pat_{t-5}	0.042	0.145*	0.207*	0.007	0.133*	0.027	-0.059*	0.132*	-0.150*	1.000

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

Appendix V-b. TECH over t-5 and t

Variables	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
(i) $TECH_{t-5}$	1.000									
(ii) FIT_{t-5}	-0.053*	1.000								
(iii) TFP $index_{t-5}$	-0.039	0.467*	1.000							
(iv) ln(TECH $level_{t-5}$)	-0.711*	0.067*	-0.020	1.000						
(v) ln($GDPpc_{t-5}$)	-0.007	0.348*	0.291*	0.130*	1.000					
(vi) ln(Pop_{t-5})	0.008	0.053*	-0.015	-0.047*	-0.301*	1.000				
(vii) Rev_{t-5}	-0.036	0.253*	0.218*	0.140*	0.428*	-0.430*	1.000			
(viii) ln(Glo_{t-5})	0.038	0.315*	0.453*	-0.038	0.658*	-0.434*	0.497*	1.000		
(ix) ln($Vuln_{t-5}$)	-0.010	-0.323*	-0.295*	-0.113*	-0.739*	0.208*	-0.468*	-0.510*	1.000	
(x) Pat_{t-5}	0.001	0.145*	0.207*	-0.004	0.133*	0.027	-0.059*	0.132*	-0.150*	1.000

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

Appendix V-c. TECCH over t-5 and t

Variables	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
(i) $TECCH_{t-5}$	1.000									
(ii) FIT_{t-5}	0.090*	1.000								
(iii) TFP $index_{t-5}$	0.068*	0.467*	1.000							
(iv) ln(TECCH $level_{t-5}$)	-0.667*	-0.035	0.132*	1.000						
(v) $\ln(GDPpc_{t-5})$	0.075*	0.348*	0.291*	-0.308*	1.000					
(vi) $\ln(Pop_{t-5})$	-0.045	0.053*	-0.015	0.141*	-0.301*	1.000				
(vii) Rev_{t-5}	0.086*	0.253*	0.218*	-0.230*	0.428*	-0.430*	1.000			
(viii) $\ln(Glo_{t-5})$	0.039	0.315*	0.453*	-0.120*	0.658*	-0.434*	0.497*	1.000		
(ix) $\ln(Vuln_{t-5})$	-0.062*	-0.323*	-0.295*	0.250*	-0.739*	0.208*	-0.468*	-0.510*	1.000	
(x) Pat_{t-5}	0.008	0.145*	0.207*	0.007	0.133*	0.027	-0.059*	0.132*	-0.150*	1.000

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

Appendix V-d. VIFs

	$GTFP_{t-5}$			$TECH_{t-5}$			$TECCH_{t-5}$	
	VIF	1/VIF		VIF	1/VIF		VIF	1/VIF
$\ln(GDPpc_{t-5})$	3.601	.278	$\ln(GDPpc_{t-5})$	3.288	.304	$\ln(GDPpc_{t-5})$	3.367	.297
$\ln(Vuln_{t-5})$	2.613	.383	$\ln(Vuln_{t-5})$	2.617	.382	$\ln(Vuln_{t-5})$	2.613	.383
$\ln(Glo_{t-5})$	2.291	.436	$\ln(Glo_{t-5})$	2.265	.442	$\ln(Glo_{t-5})$	2.223	.45
Rev_{t-5}	1.729	.578	Rev_{t-5}	1.763	.567	Rev_{t-5}	1.779	.562
TFP $index_{t-5}$	1.627	.614	$\ln(Pop_{t-5})$	1.458	.686	$\ln(Pop_{t-5})$	1.458	.686
ln(GTFP $level_{t-5}$)	1.596	.627	FIT_{t-5}	1.41	.709	FIT_{t-5}	1.403	.713
$\ln(Pop_{t-5})$	1.465	.683	TFP $index_{t-5}$	1.304	.767	TFP $index_{t-5}$	1.378	.726
FIT_{t-5}	1.44	.694	Pat_{t-5}	1.148	.871	ln(TECCH $level_{t-5}$)	1.191	.84
Pat_{t-5}	1.144	.874	ln(TECH $level_{t-5}$)	1.079	.926	Pat_{t-5}	1.148	.871
Mean VIF	1.945	.		1.815	.		1.84	.

Appendix VI. Panel estimations

Appendix VI-a. Dependent variable: $GTFP_{t-5}$

Variables	POLS	FEM	REM
FIT_{t-5}	0.189^{***}	0.236^{***}	0.101^{***}
	(0.062)	(0.058)	(0.032)
TFP $index_{t-5}$	0.257^{**}	-0.538^{**}	-0.667^{*}
	(0.121)	(0.206)	(0.373)
ln(GTFP $level_{t-5}$)	-6.790^{***}	-7.593^{**}	-7.617^{***}
	(1.112)	(2.656)	(1.357)
$\ln(GDPpc_{t-5})$	-0.009	-1.076^{***}	-0.001
	(0.041)	(0.138)	(0.032)
$\ln(Pop_{t-5})$	-0.013	-0.018	-0.003
	(0.011)	(0.443)	(0.013)
Rev_{t-5}	-0.004^{**}	-0.004	-0.001
	(0.001)	(0.004)	(0.001)
$\ln(Glo_{t-5})$	0.286^{*}	0.462^{**}	0.296^{***}
	(0.139)	(0.166)	(0.074)
$\ln(Vuln_{t-5})$	-0.276^{*}	-1.824	-0.453^{***}
	(0.156)	(1.156)	(0.134)
Pat_{t-5}	-0.011	-0.070^{***}	-0.030^{**}
	(0.013)	(0.014)	(0.013)
N	912	912	912
Panel FE	No	Yes	No
Year FE	No	Yes	Yes
Hausman χ^2		137.763***	
Wald χ^2		44899.940***	
Wooldridge F		13.233***	

Driscoll-Kraay SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix VI-b. Dependent variable: $TECH_{t-5}$

Variables	POLS	FEM	REM
FIT_{t-5}	-0.040	-0.166	-0.057
	(0.145)	(0.121)	(0.058)
TFP $index_{t-5}$	-0.276	-0.183	0.913
	(0.853)	(0.459)	(0.566)
ln(TECH $level_{t-5}$)	-15.967^{***}	-18.422^{***}	-13.796^{***}
	(2.524)	(2.667)	(1.734)
$\ln(GDPpc_{t-5})$	0.185	2.123^{*}	0.103
	(0.135)	(1.094)	(0.125)
$\ln(Pop_{t-5})$	0.040	4.943^{***}	0.037
	(0.033)	(0.961)	(0.042)
Rev_{t-5}	0.014^{**}	-0.049^{**}	0.003
	(0.005)	(0.021)	(0.004)
$\ln(Glo_{t-5})$	-0.047	0.518	0.455
	(0.405)	(0.632)	(0.319)
$\ln(Vuln_{t-5})$	-0.972	-6.116^{*}	-0.741^{*}
	(0.577)	(3.413)	(0.416)
Pat_{t-5}	-0.067	-0.164^{***}	-0.061
	(0.063)	(0.053)	(0.043)
N	912	912	912
Panel FE	No	Yes	No
Year FE	No	Yes	Yes
Hausman χ^2		194.285***	
Wald χ^2		47202.625***	
Wooldridge F		609.984***	

Driscoll-Kraay SEs in parentheses
(* p < 0.1, ** p < 0.05, *** p < 0.01)

Appendix VI-c. Dependent variable: $TECCH_{t-5}$

Variables	POLS	FEM	REM
FIT_{t-5}	0.348*	0.405***	0.239***
	(0.168)	(0.139)	(0.038)
TFP $index_{t-5}$	1.520**	-0.749	-1.491***
	(0.717)	(0.593)	(0.442)
ln(TECCH $level_{t-5}$)	-16.358***	-19.384***	-15.593***
	(2.404)	(2.582)	(1.854)
ln($GDPpc_{t-5}$)	-0.455*	-3.344**	-0.312
	(0.218)	(1.308)	(0.207)
ln(Pop_{t-5})	-0.085**	-5.714***	-0.070
	(0.038)	(0.974)	(0.049)
Rev_{t-5}	-0.022***	0.033	-0.006
	(0.006)	(0.023)	(0.007)
ln(Glo_{t-5})	-0.197	-0.974	-0.681*
	(0.364)	(0.572)	(0.352)
ln($Vuln_{t-5}$)	0.448	5.873**	0.163
	(0.597)	(2.743)	(0.491)
Pat_{t-5}	0.068	0.072	0.047
	(0.058)	(0.050)	(0.038)
N	912	912	912
Panel FE	No	Yes	No
Year FE	No	Yes	Yes
Hausman χ^2		75.898***	
Wald χ^2		604570.08***	
Wooldridge F		843.443***	

Driscoll-Kraay SEs in parentheses
(* p < 0.1, ** p < 0.05, *** p < 0.01)

Appendix VII. Distribution percentile of the FIT remuneration rate

Variables	N	Mean	SD	Min	25th	50th	75th	Max
FIT rate (US$/kWh) (constant 2015 prices)	621	.302	1.739	.001	.056	.094	.150	20.02

Appendix VIII. Heterogeneous effects for RE technologies

Appendix VII-a. Solar PV, Wind and Biomass

Variables	Solar PV			Wind			Biomass		
	GTFP$_{t-5}$	**TECH$_{t-5}$**	**TECCH$_{t-5}$**	**GTFP$_{t-5}$**	**TECH$_{t-5}$**	**TECCH$_{t-5}$**	**GTFP$_{t-5}$**	**TECH$_{t-5}$**	**TECCH$_{t-5}$**
FIT$_{s,t-5}$	**-0.064**	**-0.889**	**1.176^{**}**	0.066	0.604^{*}	-0.821^{***}	0.037	0.075	-0.500
	(0.244)	**(0.600)**	**(0.597)**	(0.121)	(0.315)	(0.302)	(0.182)	(0.304)	(0.330)
FIT$_{w,t-5}$	0.287^{***}	0.829^{**}	-0.589^{*}	**0.583^{***}**	**-0.733**	**1.773^{***}**	0.187	0.596^{*}	-0.156
	(0.104)	(0.335)	(0.313)	**(0.180)**	**(0.509)**	**(0.530)**	(0.159)	(0.329)	(0.351)
FIT$_{b,t-5}$	-0.223^{**}	-0.279	-0.069	-0.279^{**}	-0.077	-0.305	**0.417^{*}**	**-0.734^{*}**	**1.428^{***}**
	(0.106)	(0.370)	(0.397)	(0.110)	(0.341)	(0.391)	**(0.216)**	**(0.443)**	**(0.475)**
FIT$_{h,t-5}$	0.085	0.255	-0.046	0.154	0.320	0.054	-0.009	0.189	0.021
	(0.120)	(0.332)	(0.321)	(0.134)	(0.331)	(0.347)	(0.139)	(0.311)	(0.309)
FIT$_{ws,t-5}$	-0.062	-1.168^{***}	1.266^{***}	-0.098	-1.102^{***}	1.175^{***}	-0.166	-1.154^{***}	1.140^{***}
	(0.125)	(0.293)	(0.288)	(0.110)	(0.298)	(0.316)	(0.117)	(0.290)	(0.294)
FIT$_{g,t-5}$	-0.049	0.841^{***}	-1.046^{***}	-0.095	0.626^{**}	-0.880^{***}	-0.088	0.689^{**}	-0.981^{***}
	(0.093)	(0.285)	(0.285)	(0.094)	(0.263)	(0.271)	(0.107)	(0.279)	(0.287)
FIT$_{m,t-5}$	0.221	0.041	-0.080	0.119	-0.076	0.048	-0.077	-0.066	-0.135
	(0.202)	(0.335)	(0.389)	(0.142)	(0.312)	(0.336)	(0.131)	(0.312)	(0.317)
TFP index$_{t-5}$	-0.491^{***}	0.128	-1.023	-0.425^{**}	-0.132	-0.630	-0.484^{***}	0.088	-1.003
	(0.179)	(0.576)	(0.622)	(0.180)	(0.589)	(0.619)	(0.182)	(0.585)	(0.620)
ln(GTFP level$_{t-5}$)	-7.478^{***}			-8.343^{***}			-8.356^{***}		
	(1.447)			(1.251)			(1.336)		
ln(TECH level$_{t-5}$)		-18.718^{***}			-18.553^{***}			-18.670^{***}	

Variables	Solar PV $GTFP_{t-5}$	Solar PV $TECH_{t-5}$	Solar PV $TECCH_{t-5}$	Wind $GTFP_{t-5}$	Wind $TECH_{t-5}$	Wind $TECCH_{t-5}$	Biomass $GTFP_{t-5}$	Biomass $TECH_{t-5}$	Biomass $TECCH_{t-5}$
		(0.959)			(0.955)			(0.917)	
ln(TECCH $level_{t-5}$)			-19.803***			-19.621***			-20.110***
			(1.040)			(1.055)			(0.973)
ln($GDPpc_{t-5}$)	-1.129***	1.941**	-3.408***	-1.277***	2.010**	-3.621***	-1.139***	1.838**	-3.330***
	(0.218)	(0.867)	(0.908)	(0.219)	(0.881)	(0.943)	(0.222)	(0.863)	(0.926)
ln(Pop_{t-5})	-0.057	4.873***	-5.387***	0.011	5.003***	-5.282***	-0.170	4.784***	-5.800***
	(0.387)	(1.836)	(1.406)	(0.383)	(1.802)	(1.397)	(0.392)	(1.789)	(1.479)
Rev_{t-5}	-0.010	-0.065**	0.047	-0.005	-0.067**	0.052*	-0.002	-0.064**	0.051*
	(0.007)	(0.030)	(0.031)	(0.007)	(0.031)	(0.031)	(0.007)	(0.030)	(0.030)
ln(Glo_{t-5})	0.555**	0.707	-1.010	0.626**	0.781	-1.004	0.613**	0.390	-0.857
	(0.241)	(1.177)	(1.131)	(0.263)	(1.177)	(1.118)	(0.254)	(1.209)	(1.171)
ln($Vuln_{t-5}$)	-2.049	-2.794	1.489	-2.974	-3.201	-0.118	-0.605	-5.451	3.881
	(2.052)	(5.138)	(5.012)	(2.012)	(4.969)	(4.839)	(2.213)	(4.589)	(4.811)
Pat_{t-5}	-0.082***	-0.092	-0.025	-0.102***	-0.097	-0.054	-0.078**	-0.102	-0.037
	(0.027)	(0.093)	(0.085)	(0.029)	(0.095)	(0.086)	(0.033)	(0.087)	(0.079)
N	911	911	911	911	911	911	911	911	911
KP LM	27.679***	26.592***	26.875***	36.013***	37.056***	37.371***	50.756***	50.608***	50.235***
KP Wald F	16.813	16.130	16.376	28.756	29.835	30.308	51.368	50.420	49.325
Hansen J	1.337	0.232	0.016	0.275	0.305	0.320	1.833	0.740	0.055

Appendix VII-b. Small hydro and waste

Variables	Small hydro			Waste		
	$GTFP_{t-5}$	**$TECH_{t-5}$**	**$TECCH_{t-5}$**	**$GTFP_{t-5}$**	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
$FIT_{s,t-5}$	-0.163	0.135	-0.590*	-0.193	-0.024	-0.489
	(0.162)	(0.301)	(0.332)	(0.180)	(0.275)	(0.323)
$FIT_{w,t-5}$	0.479***	0.694**	0.009	0.462***	0.735**	-0.046
	(0.175)	(0.351)	(0.381)	(0.166)	(0.349)	(0.368)
$FIT_{b,t-5}$	-0.274**	-0.217	-0.124	-0.313***	-0.550	0.204
	(0.131)	(0.340)	(0.376)	(0.115)	(0.360)	(0.369)
$FIT_{h,t-5}$	**0.601****	**-0.966***	**1.848*****	0.057	-0.148	0.349
	(0.280)	**(0.515)**	**(0.539)**	(0.136)	(0.332)	(0.313)
$FIT_{ws,t-5}$	-0.059	-1.016***	1.151***	**0.346**	**0.284**	**0.248**
	(0.119)	(0.285)	(0.295)	**(0.211)**	**(0.524)**	**(0.514)**
$FIT_{g,t-5}$	-0.095	0.866***	-1.026***	-0.061	0.650**	-0.798***
	(0.103)	(0.249)	(0.260)	(0.090)	(0.283)	(0.263)
$FIT_{m,t-5}$	0.119	-0.074	-0.046	0.126	-0.506*	0.511
	(0.143)	(0.305)	(0.322)	(0.166)	(0.288)	(0.330)
TFP $index_{t-5}$	-0.577***	0.172	-1.180*	-0.509***	-0.137	-0.617
	(0.189)	(0.590)	(0.630)	(0.174)	(0.590)	(0.612)
ln(GTFP $level_{t-5}$)	-8.372***			-8.388***		
	(1.343)			(1.361)		
ln(TECH $level_{t-5}$)		-18.602***			-18.793***	
		(0.961)			(0.972)	

Variables	Small hydro GTFP$_{t-5}$	Small hydro TECH$_{t-5}$	Small hydro TECCH$_{t-5}$	Waste GTFP$_{t-5}$	Waste TECH$_{t-5}$	Waste TECCH$_{t-5}$
ln(TECCH level$_{t-5}$)			-19.711***			-19.967***
			(1.054)			(1.029)
ln(GDPpc$_{t-5}$)	-1.224***	1.854**	-3.337***	-1.118***	2.006**	-3.349***
	(0.236)	(0.833)	(0.898)	(0.224)	(0.838)	(0.892)
ln(Pop$_{t-5}$)	0.257	4.353**	-4.805***	0.025	5.733***	-6.095***
	(0.483)	(1.714)	(1.430)	(0.397)	(1.796)	(1.366)
Rev$_{t-5}$	-0.009	-0.055*	0.039	-0.005	-0.040	0.026
	(0.008)	(0.030)	(0.030)	(0.007)	(0.031)	(0.031)
ln(Glo$_{t-5}$)	0.528*	0.501	-0.899	0.356	0.255	-0.702
	(0.277)	(1.203)	(1.161)	(0.251)	(1.248)	(1.183)
ln(Vuln$_{t-5}$)	-4.631*	-2.692	-1.079	-3.149	-9.372*	7.054
	(2.726)	(4.942)	(4.952)	(2.120)	(5.156)	(5.025)
Pat$_{t-5}$	-0.121***	-0.071	-0.078	-0.099***	-0.137	0.006
	(0.037)	(0.097)	(0.091)	(0.030)	(0.100)	(0.089)
N	911	911	911	911	911	911
KP LM	32.409***	34.383***	34.293***	27.622***	28.123***	27.812***
KP Wald F	21.511	24.054	23.847	18.851	19.264	18.912
Hansen J	0.264	0.327	0.908	0.011	0.646	1.629

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix VII-b. Geothermal and marine

Variables	Geothermal			Marine		
	$GTFP_{t-5}$	**$TECH_{t-5}$**	**$TECCH_{t-5}$**	**$GTFP_{t-5}$**	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
$FIT_{s,t-5}$	-0.213	0.277	-0.853**	-0.110	0.124	-0.586**
	(0.213)	(0.288)	(0.356)	(0.179)	(0.279)	(0.296)
$FIT_{w,t-5}$	0.438**	0.527	0.177	0.429**	0.673**	-0.023
	(0.175)	(0.337)	(0.366)	(0.180)	(0.331)	(0.349)
$FIT_{b,t-5}$	-0.246**	-0.206	-0.190	-0.358***	-0.296	-0.211
	(0.112)	(0.345)	(0.371)	(0.129)	(0.360)	(0.386)
$FIT_{h,t-5}$	0.136	0.475	-0.307	0.145	0.249	0.097
	(0.126)	(0.298)	(0.294)	(0.134)	(0.316)	(0.320)
$FIT_{ws,t-5}$	-0.074	-1.170***	1.364***	-0.023	-1.240***	1.376***
	(0.126)	(0.310)	(0.307)	(0.128)	(0.270)	(0.274)
$FIT_{g,t-5}$	**-0.130**	**0.098**	**0.243**	-0.044	0.687***	-0.835***
	(0.191)	**(0.534)**	**(0.514)**	(0.097)	(0.267)	(0.262)
$FIT_{m,t-5}$	0.196	-0.118	0.052	**0.657***	**-0.239**	**1.263*****
	(0.177)	(0.326)	(0.354)	**(0.349)**	**(0.444)**	**(0.480)**
TFP $index_{t-5}$	-0.470***	0.116	-1.018	-0.431***	0.061	-0.895
	(0.175)	(0.589)	(0.630)	(0.166)	(0.584)	(0.616)
ln(GTFP $level_{t-5}$)	-8.609***			-8.683***		
	(1.418)			(1.180)		
ln(TECH $level_{t-5}$)		-18.595***			-18.693***	
		(0.982)			(0.926)	

Variables	Geothermal			Marine		
	$GTFP_{t-5}$	**$TECH_{t-5}$**	**$TECCH_{t-5}$**	**$GTFP_{t-5}$**	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
ln(TECCH $level_{t-5}$)			-19.427^{***}			-19.907^{***}
			(1.020)			(0.966)
ln($GDPpc_{t-5}$)	-1.118^{***}	1.443^{*}	-2.512^{***}	-1.175^{***}	1.587^{**}	-3.181^{***}
	(0.235)	(0.868)	(0.897)	(0.211)	(0.799)	(0.850)
ln(Pop_{t-5})	-0.258	5.051^{**}	-5.473^{***}	-0.156	5.191^{***}	-6.080^{***}
	(0.403)	(2.042)	(1.588)	(0.377)	(1.885)	(1.492)
Rev_{t-5}	-0.008	-0.062^{*}	0.045	-0.009	-0.060^{**}	0.038
	(0.007)	(0.032)	(0.032)	(0.007)	(0.030)	(0.030)
ln(Glo_{t-5})	0.476^{**}	0.706	-1.186	0.669^{**}	0.645	-0.812
	(0.239)	(1.255)	(1.200)	(0.280)	(1.239)	(1.165)
ln($Vuln_{t-5}$)	-1.663	-6.620	5.835	-3.387	-6.172	2.159
	(2.184)	(4.506)	(4.553)	(2.759)	(4.833)	(5.034)
Pat_{t-5}	-0.086^{***}	-0.172^{*}	0.096	-0.126^{***}	-0.123	-0.070
	(0.031)	(0.091)	(0.084)	(0.046)	(0.092)	(0.080)
N	911	911	911	911	911	911
KP LM	34.224***	33.697***	34.841***	32.161***	31.896***	31.647***
KP Wald F	23.437	21.224	22.375	28.078	27.752	27.614
Hansen J	3.322	0.687	2.161	0.611	0.636	0.017

HAC SEs in parentheses
Panel FE: Yes
Year FE: Yes
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix IX. First-stage control function method

Variables	FIT_{t-5}	FIT_{t-5}	FIT_{t-5}
TFP $index_{t-5}$	-0.058	-0.041	-0.046
	(0.106)	(0.103)	(0.106)
ln(GTFP $level_{t-5}$)	-0.250		
	(0.457)		
ln(TECH $level_{t-5}$)		0.227*	
		(0.111)	
ln(TECCH $level_{t-5}$)			-0.259**
			(0.108)
ln($GDPpc_{t-5}$)	0.294*	0.247	0.242
	(0.165)	(0.159)	(0.152)
ln(Pop_{t-5})	-0.656***	-0.691***	-0.720***
	(0.128)	(0.158)	(0.149)
Rev_{t-5}	-0.010**	-0.010*	-0.010**
	(0.005)	(0.005)	(0.005)
ln(Glo_{t-5})	0.066	0.163*	0.150
	(0.110)	(0.088)	(0.087)
ln($Vuln_{t-5}$)	3.286***	3.271***	3.293***
	(0.517)	(0.516)	(0.512)
Pat_{t-5}	0.047**	0.048**	0.046**
	(0.017)	(0.017)	(0.017)
Adj_{t-5}	-0.083***	-0.082***	-0.083***
	(0.016)	(0.018)	(0.017)
FIT_{t-9}	0.265***	0.261***	0.263***
	(0.068)	(0.066)	(0.067)
N	912	912	912
Panel FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Driscoll-Kraay SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix X. Probit first-stage parameter estimation

Variables	FIT_{t-5}	FIT_{t-5}	FIT_{t-5}
TFP $index_{t-5}$	6.073***	6.367***	6.918***
	(1.148)	(1.278)	(1.154)
ln(GTFP $level_{t-5}$)	40.541***		
	(8.314)		
ln(TECH $level_{t-5}$)		4.200***	
		(1.509)	
ln(TECCH $level_{t-5}$)			-2.502*
			(1.465)
ln($GDPpc_{t-5}$)	4.275***	7.976***	7.522***
	(0.617)	(1.005)	(1.172)
ln(Pop_{t-5})	-0.173	0.418	0.003
	(0.479)	(0.804)	(0.622)
Rev_{t-5}	0.047	0.121**	0.030
	(0.050)	(0.055)	(0.050)
ln(Glo_{t-5})	-0.771	4.679	1.826
	(3.066)	(3.756)	(3.926)
ln($Vuln_{t-5}$)	8.095**	9.447**	12.951**
	(3.346)	(3.801)	(5.697)
Pat_{t-5}	1.777*	2.484**	2.258**
	(0.940)	(1.127)	(1.036)
Adj_{t-5}	1.312***	2.044***	1.719***
	(0.309)	(0.332)	(0.302)
FIT_{t-9}	0.000	0.000	0.000
	(.)	(.)	(.)
Constant	-73.431***	-155.062***	-139.410***
	(20.740)	(28.428)	(31.253)
Log likelihood	-142.857	-152.768	-152.646
AIC	307.714	327.536	327.291
LR χ^2(9)	230.322***	210.500***	210.744***
LR χ^2(rho)	201.658***	179.665***	179.674***
LR χ^2(2)	6.503**	13.632***	18.346***

SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix XI. Staggered DID estimates

Appendix XI-a. ATT for the main estimate and placebo test

	$GTFP_{t-5}$	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
ATT	0.455^{**}	-1.650	2.498^{*}
	(0.193)	(1.562)	(1.402)
ATT	0.193	0.058	0.183
(Placebo test)	(0.146)	(0.853)	(0.807)

Cluster SEs in parentheses

(* p < 0.1, ** p < 0.05, *** p < 0.01)

Appendix XI-b. Dynamic ATT for the main estimate

Main estimate	**$GTFP_{t-5}$**	**$TECH_{t-5}$**	**$TECCH_{t-5}$**
Pre-treatment	-0.095	0.890	-2.243
	(0.177)	(1.480)	(2.096)
Post-treatment	0.459^{*}	-2.143	2.953^{*}
	(0.254)	(1.852)	(1.571)
T–10	-0.539	-2.306	-1.016
	(0.471)	(4.575)	(4.555)
T–9	-0.490	1.764	-1.317
	(0.455)	(2.606)	(3.207)
T–8	0.505	1.866	-1.485
	(0.368)	(1.944)	(1.943)
T–7	-0.446	2.926	-3.537
	(0.316)	(3.059)	(3.416)
T–6	0.120	5.317	-7.312
	(0.366)	(4.786)	(5.710)
T–5	-0.180	-0.613	-4.553
	(0.248)	(3.849)	(5.938)
T–4	0.112	-0.479	-1.038
	(0.269)	(2.088)	(3.498)
T–3	-0.166	-0.373	-0.003
	(0.300)	(1.036)	(1.194)
T-2	0.233	-0.096	0.077
	(0.156)	(0.475)	(0.549)
T+0	0.166	0.071	0.232
	(0.123)	(0.532)	(0.527)
T+1	0.121	0.422	0.311
	(0.142)	(0.992)	(0.961)

Main estimate	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
T+2	0.109	-0.975	1.501
	(0.212)	(1.881)	(1.534)
T+3	-0.091	-2.015	2.849
	(0.506)	(2.125)	(1.851)
T+4	0.291	-1.963	3.246
	(0.401)	(2.158)	(2.026)
T+5	-0.231	-2.536	3.418^{*}
	(0.601)	(2.231)	(2.071)
T+6	0.368	-3.988	4.702^{*}
	(0.473)	(3.097)	(2.534)
T+7	0.972^{**}	-4.236	4.720^{*}
	(0.443)	(2.991)	(2.454)
T+8	1.281^{**}	-4.062	5.072^{*}
	(0.578)	(3.423)	(2.681)
T+9	0.191	-3.175	3.697
	(0.790)	(3.384)	(2.602)
T+10	1.877^{**}	-1.113	2.736
	(0.820)	(2.384)	(2.635)

Cluster SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix XI-c. Dynamic ATT for the placebo test

Placebo test	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
Pre-treatment	-0.031	-0.010	-0.249
	(0.088)	(0.425)	(0.499)
Post-treatment	0.267	0.043	0.255
	(0.200)	(0.932)	(0.894)
T–10	0.287	-0.536	0.864
	(0.360)	(0.975)	(1.034)
T–9	-0.461	1.108	-1.059
	(0.311)	(0.954)	(0.840)
T–8	-0.248	1.387	-1.416
	(0.172)	(0.857)	(0.879)
T–7	-0.023	0.964	-1.701^{**}
	(0.156)	(0.969)	(0.816)
T–6	0.339	-0.683	0.458
	(0.291)	(1.463)	(1.520)

Placebo test	$GTFP_{t-5}$	$TECH_{t-5}$	$TECCH_{t-5}$
T–5	0.031	-1.390	0.183
	(0.144)	(1.464)	(1.469)
T–4	-0.229*	-0.680	0.454
	(0.120)	(1.068)	(1.242)
T–3	-0.069	-0.304	0.098
	(0.119)	(0.795)	(0.707)
T-2	0.089	0.041	-0.118
	(0.090)	(0.483)	(0.496)
T+0	0.119	0.160	-0.110
	(0.129)	(0.347)	(0.385)
T+1	0.184	0.922	-0.719
	(0.162)	(0.709)	(0.705)
T+2	0.375	0.030	-0.041
	(0.286)	(1.181)	(1.050)
T+3	0.237	0.012	0.183
	(0.210)	(1.320)	(1.168)
T+4	0.337	0.146	0.140
	(0.257)	(1.357)	(1.264)
T+5	0.189	0.314	0.136
	(0.218)	(1.187)	(1.144)
T+6	0.422	-0.531	1.136
	(0.402)	(1.351)	(1.310)
T+7	0.229	-0.496	1.017
	(0.214)	(1.303)	(1.294)
T+8	0.425	-1.131	1.670
	(0.351)	(1.591)	(1.519)
T+9	0.310	0.773	-0.107
	(0.338)	(1.021)	(1.071)
T+10	0.111	0.269	-0.501
	(0.298)	(1.368)	(0.982)

Cluster SEs in parentheses
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

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