The Complementary Role of Human Capital in Innovation-Driven Decarbonization

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Abstract

Achieving net-zero emissions requires not only technological innovation but also the capacity to absorb and implement it effectively. This study investigates how absorptive capacity, defined as the interaction between tertiary education and R&D investment, amplifies the impact of innovation on carbon emissions. Using fixed effects and Difference-in-Differences models, the analysis shows that while R&D alone reduces emissions, its effect is significantly stronger in countries with higher levels of education. Mechanism analyses reveal that absorptive capacity enhances environmental outcomes by strengthening policy enforcement, accelerating the diffusion of green technologies, and improving energy efficiency. These findings highlight the importance of aligning education and innovation policies to unlock the full decarbonization potential of climate technologies.

Keywords: Human capital, Innovation, Carbon Emissions, Environmental Policy

JEL Codes: Q55, Q58, O31, O44

1 Introduction

Addressing climate change requires a fundamental shift in how economies grow while reducing carbon emissions. The global challenge of decarbonization has sparked significant policy efforts, particularly in advanced economies, to balance economic expansion with environmental sustainability (Stern, 2008; Fankhauser and Jotzo, 2018). Traditional economic models suggest that as countries develop, emissions initially rise due to industrialization but eventually decline as economies transition toward cleaner energy and advanced technologies (Grossman and Krueger, 1995). However, this pattern is not uniform across countries, and a growing body of research emphasizes that factors beyond economic growth, such as education and technological innovation, play a crucial role in shaping emissions trajectories (Heil and Selden, 2001).

Among these factors, education and R&D stand out as long-term investments that can accelerate decarbonization. Education enhances a society's capacity to absorb and implement new knowledge, while R&D fosters the creation of low-carbon technologies (Balaguer and Cantavella, 2018; Shahbaz et al., 2016). Yet, the effectiveness of R&D in mitigating emissions may depend critically on the presence of a highly skilled workforce. Without the capacity to translate innovation into widespread application, through behavior change, policy enforcement, or institutional adoption, technological advances alone may fall short of delivering sustained emissions reductions.

These dynamics are not only theoretical but are central to major policy frameworks. For example, the European Union's 2020 Strategy explicitly linked education, innovation, and sustainability as pillars of its growth agenda, and the European Green Deal reinforces this by emphasizing skills development and research investments to accelerate the clean energy transition. Similarly, in the United States, large-scale initiatives such as ARPA-E and, more recently, the Inflation Reduction Act illustrate how governments combine R&D support with workforce and institutional capacity to foster green innovation.

This study is motivated by the urgent need to ensure that the large public and private investments in innovation effectively translate into measurable emissions reductions. Despite unprecedented spending on clean technologies, their environmental impact remains uneven across countries (Agency, 2024; Montague et al., 2024). By explicitly analyzing the role of absorptive capacity, this paper provides insights into why some economies succeed in converting innovation into carbon reductions while others lag behind. The results can inform policymakers designing green industrial and education policies, and guide firms investing in R&D to align their innovation strategies with broader societal capabilities.

This study tests the core hypothesis that absorptive capacity, defined as the interaction between education and R&D, plays a central role in reducing CO_2 emissions. The argument is that while R&D expands the technological frontier, its effectiveness in reducing emissions depends critically on a country's capacity to recognize, adopt, and implement new knowledge and practices. Education amplifies this effect by strengthening human capital, institutional readiness, and the societal demand for cleaner technologies. This interaction reflects more than statistical correlation: it captures a theory-driven mechanism grounded in development economics and innovation theory (Cohen et al., 1990; Romer, 1990). To examine this hypothesis, the analysis is guided by three questions: First, does R&D alone reduce carbon emissions, or is its effectiveness conditional on the presence of a highly educated population? Second, do these dynamics vary across income levels and stages of development? Lastly, through which specific mechanisms does absorptive capacity operate to shape emissions outcomes?

While prior research has examined the independent effects of education (e.g., its role in supporting renewable energy adoption, see Zafar et al. 2020) and R&D (e.g., green innovation as a strategic resource, see Khanra et al. 2022) on environmental outcomes, much less is known about how they operate jointly. This represents an important gap, as theory suggests that the effectiveness of R&D in reducing emissions depends critically on the absorptive capacity provided by education. By focusing on this interaction, and by identifying the concrete mechanisms through which it operates, this paper contributes new empirical evidence to a literature that has so far treated education and R&D largely in isolation.

Using cross-country panel data from 91 countries between 1995 and 2019, the analysis first estimates a two-way fixed effects model to isolate the relationship between education, R&D, and carbon emissions while controlling for country-specific and time-specific confounders. Results show that R&D investments alone reduce emissions by approximately 4.9%, but become significantly more effective when combined with higher education levels, amplifying the effect to 6.4%, reflecting the critical role of absorptive capacity in strengthening decarbonization outcomes. To address potential endogeneity concerns, an instrumental variables (IV) strategy is implemented. Lastly, a Difference-in-Differences (DiD) framework leverages the EU 2020 Strategy as a quasi-experimental policy shock. This approach confirms that emissions declined more sharply in countries with stronger education and R&D systems following the reform, supporting the causal interpretation of the interaction effect.

A central contribution of this study lies in uncovering the mechanisms through which education and R&D jointly reduce emissions. Specifically, the analysis highlights three key pathways: technology diffusion, energy efficiency improvements, and environmental policy enforcement. These mechanisms are not merely outcomes. They serve as the channels through which absorptive capacity translates innovation into a measurable environmental impact. The results show that countries with stronger education and R&D systems are significantly more effective at deploying green technologies, achieving energy efficiency gains, and enforcing climate policies, leading to deeper and more sustained emissions reductions.

This paper contributes to the broader decarbonization literature by providing new empirical evidence on how human capital enhances the climate effectiveness of innovation. While prior studies have examined the independent effects of education and R&D on environmental outcomes, this paper is the first to systematically test their interaction and to empirically identify the institutional and technological mechanisms, diffusion, efficiency, and enforcement, through which that interaction reduces emissions. In doing so, the paper emphasizes the role of absorptive capacity as a critical lever for translating innovation into decarbonization at scale.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the empirical strategy. Section 4 presents the main results, followed by robustness checks in Section 5 and mechanism analysis in Section 6. Section 7 concludes.

2 Literature Review and Hypotheses Development

To clarify the conceptual foundations of this study, Section 2 is structured into two parts. Subsection 2.1 reviews the main strands of literature that motivate the analysis, including prior work on decarbonization, education, and innovation. Subsection 2.2 then develops the mechanisms through which absorptive capacity may influence carbon emissions.

2.1 Background Literature

The Environmental Kuznets Curve (EKC) hypothesizes an inverted-U relationship between income per capita and environmental degradation: emissions rise during early development but fall as countries grow richer and adopt cleaner technologies. While some evidence supports this pattern (Shahbaz et al., 2013; Balsalobre-Lorente et al., 2018), the EKC has been widely critiqued.

Ward et al. (2016) argue that observed decoupling trends often reflect outsourcing, financialization, or inequality rather than genuine progress. Vollebergh et al. (2009) show that CO_2 emissions in OECD countries continue to rise, with stabilization better explained by regulatory shifts than income growth. Other studies note N-shaped curves at higher income levels due to rebound effects or technological obsolescence (Balsalobre-Lorente et al., 2018).

Cross-country variation further challenges the EKC's universality. Dinda and Coondoo (2006) and Munir et al. (2020) show that income–emissions relationships vary by region and development stage. Friedrichs and Inderwildi (2013) describes a "carbon curse" in fossil-fuel-rich countries, where growth sustains high emissions due to weak institutions and subsidies.

These critiques highlight a key limitation: the EKC overlooks the structural and institutional mechanisms that translate income into emissions reductions. As Stern (2008) argues, climate stabilization requires deliberate structural shifts, not just economic growth. This motivates the focus on complementary drivers such as education and R&D.

Green R&D and environmental patents are critical to decarbonization, but their effects on emissions are not automatic. Cheng et al. (2019) shows that green patenting in BRIICS countries has a limited impact when diffusion and regulatory support are weak. Secundo et al. (2020) emphasizes that intellectual capital must be embedded in education and governance to advance the Sustainable Development Goals (SDGs). Sectoral studies of steel and cement find that without policy instruments like carbon pricing, uptake of low-carbon technologies remains limited (Van Ruijven et al., 2016). These findings underscore that innovation alone is insufficient and that supportive mechanisms are essential.

Prior research highlights that the effectiveness of R&D in reducing carbon emissions is shaped by several complementary factors. One important condition is the direction of technological change, which responds strongly to policy incentives such as fuel prices and carbon markets. Higher energy prices and the EU Emissions Trading System (ETS), for instance, have been shown to shift innovation away from "dirty" technologies toward cleaner alternatives, thereby increasing low-carbon patenting and reinforcing clean innovation trajectories (Acemoglu et al., 2012; Aghion et al., 2016; Calel and Dechezleprêtre, 2016). Relatedly, clean technologies generate larger knowledge spillovers than fossil-intensive ones, amplifying the case for policy support and absorptive capacity (Popp, 2010; Dechezleprêtre et al., 2014).

The type of R&D also matters. Evidence suggests that disaggregated measures of energy R&D, particularly investments in renewables and efficiency, are more tightly associated with gains in energy and carbon productivity than aggregate R&D measures (Popp, 2019; Mamkhezri and Khezri, 2024). Sector-specific studies reinforce this conclusion: building efficiency standards and power-sector policies have spurred innovation in related technologies, while fuel price increases pushed the auto industry toward cleaner patenting (Noailly, 2012).

At the aggregate level, cross-country evidence suggests that energy-related R&D is associated with reductions in carbon emissions, though effects are heterogeneous across technologies and time horizons. For instance, Verdolini and Galeotti (2011) find that domestic and international energy R&D jointly contribute to emission reductions, with important lags in diffusion. Similarly, Johnstone et al. (2010) show that targeted R&D policies foster renewable energy innovation that ultimately translates into lower emissions. Reviews of energy R&D programs emphasize that while such investments can be effective, their impact is often limited without complementary policies and sufficient absorptive capacity (Popp, 2006; Baker and Adu-Bonnah, 2008). These studies suggest that R&D can reduce emissions under the right conditions, but technological progress also depends on societies' capacity to absorb and apply new knowledge, a role played by education.

Education enhances "absorptive capacity", i.e., the ability to recognize and apply new knowledge, making it a crucial enabler of innovation. It may also influence emissions directly, through changes in individual behavior, environmental awareness, and demand for cleaner technologies. Zafar et al. (2020) find that tertiary education amplifies the emissions-reducing effect of renewable energy in OECD countries. In a long-run study of Australia, Balaguer and Cantavella (2018) document a nonlinear trajectory: education initially raises emissions (via higher consumption) but ultimately lowers them by improving technological uptake and environmental awareness. Camilleri and Camilleri (2020) similarly frame education as essential for equipping individuals and institutions to achieve sustainability goals. Al-Emran and Griffy-Brown (2023) show that technology adoption succeeds only where human capital, institutions, and policies align.

Collectively, this literature positions education not merely as a background variable but as a key driver of decarbonization, both by directly shaping societal behavior and by conditioning the effectiveness of innovation inputs. While education and R&D are widely studied, most empirical work examines them in isolation. A few studies suggest they are complementary. For instance, Secundo et al. (2020) argue that human and structural capital jointly enable green technology diffusion. Khanra et al. (2022) describe them as interdependent resources that support sustainable competitiveness.

Yet, despite these insights, there is little empirical work on their combined effect, especially in the context of emissions. No existing study systematically tests whether education enhances the emissions-reducing impact of R&D across countries. This paper addresses that gap by estimating the interaction between education and R&D, and by identifying the mechanisms, technology diffusion, energy efficiency, and policy enforcement, through which absorptive capacity translates innovation into decarbonization.

2.2 Mechanisms of Absorptive Capacity

While prior work highlights the separate roles of education and R&D in innovation, little is known about how their interaction, absorptive capacity, shapes environmental outcomes. The mechanisms linking absorptive capacity to emissions remain underexplored. Understanding these mechanisms is crucial, since innovation alone does not guarantee decarbonization unless it is diffused, adopted, and embedded in institutions. Guided by this insight and drawing on the literature, I outline several potential mechanisms and formulate corresponding hypotheses.

A first pathway is through the creation of new knowledge. Education raises the stock of human capital and the ability to engage with advanced ideas, while R&D provides the resources and institutional setting to transform these ideas into tangible outputs. In this sense, absorptive capacity may increase the rate of environment-related inventions, which could serve as a channel to reduce emissions.

H1a. Higher absorptive capacity generates more green inventions, which may mediate reductions in CO_2 emissions.

Even when inventions are created, their impact may remain limited unless they spread across borders and industries. Absorptive capacity may facilitate this process by strengthening networks, fostering collaboration, and enhancing the exchange of ideas across institutions and markets. Through greater diffusion, inventions that have already proven effective can contribute to lower emissions.

H1b. Higher absorptive capacity enhances the diffusion of green inventions, which may serve as a channel for reducing CO_2 emissions.

Beyond the exchange of ideas, absorptive capacity may also support the adoption of concrete technologies within production and energy systems. Unlike inventions, which remain abstract until applied, technologies represent practical tools that replace high-carbon processes with low-carbon alternatives. By enabling large-scale technological adoption, absorptive capacity may directly lower emissions.

H1c. Higher absorptive capacity more effectively diffuses green technologies, which may mediate reductions in CO_2 emissions.

Another pathway may arise through the institutional environment. Education and R&D not only generate knowledge but also enhance the design and enforcement of public policies. An educated citizenry can create social and political pressure for ambitious environmental regulations, while strong research systems supply policymakers with the expertise required to craft effective rules. These regulations can, in turn, steer economies toward cleaner production and lower emissions.

H2. Higher absorptive capacity supports stricter environmental regulations, which may provide a pathway to reduce CO_2 emissions.

Absorptive capacity may further contribute by improving how energy is used in the economy. More educated and innovative societies may more readily develop and adopt efficiency-enhancing practices, from cleaner industrial processes to renewable integration and household-level energy savings. By lowering the emissions produced per unit of output, energy efficiency becomes a direct mediator of decarbonization.

H3. Higher absorptive capacity improves energy efficiency, which may mediate reductions in CO_2 emissions.

Finally, absorptive capacity may shape the labor market by shifting employment toward sustainability-related activities. Investments in education and R&D may expand the pool of workers with relevant skills and stimulate the demand for such jobs, leading to structural change in employment patterns. While job creation alone may not directly cut emissions, it may contribute indirectly by supporting the diffusion and adoption of green technologies and policies.

H4. Higher absorptive capacity creates more green jobs, which may act as an intermediary mechanism in lowering CO_2 emissions.

3 Empirical Strategy

This section presents the empirical strategy used to analyze how education and R&D, individually and in combination, affect carbon emissions across countries, and to test whether education amplifies the emissions-reducing effect of innovation. The section is divided into two parts. Subsection 3.1 outlines the empirical model, and Subsection 3.2 describes the data and variables used in the analysis.

3.1 Model Specification

To begin, a baseline fixed effects model is estimated to assess how education and R&D influence carbon emissions across countries over time. This approach is particularly well-suited for macro-level panel data, as it accounts for unobserved, time-invariant country characteristics such as geographic location, institutional history, or long-run development trajectories that could bias the estimated effects. Additionally, time-fixed effects absorb global shocks that affect all countries, such as international oil price fluctuations or coordinated policy responses to climate change. The following equation represents the main estimation framework:

$$
\begin{aligned}
\log\ \mathrm{CO}_{2it} = {} & \beta_1 \log\ \mathrm{GDPpc}_{it} + \beta_2 \log\ \mathrm{GDPpc}^2_{it} + \beta_3 \log\ \mathrm{Educ}_{it} + \beta_4 \log\ \mathrm{Educ}^2_{it} \\
& + \beta_5 \log\ \mathrm{R\&D}_{it} + \beta_6 \log\ \mathrm{R\&D}^2_{it} + \beta_7\ \mathrm{Absorptive\ Capacity}_{it} \\
& + \beta_8 X_{it} + \alpha_i + \delta_t + \varepsilon_{it}
\end{aligned} \tag{1}
$$

where $\log(\mathrm{CO}_2)_{it}$ captures the natural logarithm of carbon emissions per capita measured in metric tons in the country i at time t. The income level is modeled through $\log(\mathrm{GDPpc})_{it}$ and its squared term, capturing the potential nonlinear relationship implied by the EKC. Education effects are introduced via $\log(\mathrm{Education})_{it}$ and its squared term, allowing for diminishing or nonlinear impacts of human capital on emissions. Similarly, $\log(\mathrm{R\&D})_{it}$ and its squared term assess the role of research and development in influencing emissions, with potential nonlinearities.

The inclusion of squared terms for education and R&D is motivated by prior evidence of nonlinearities in both human capital and innovation. Absorptive capacity theory suggests that education enhances the impact of R&D only after a threshold level of skills is reached, while very high levels may face diminishing marginal returns (Cohen et al., 1990; Balaguer and Cantavella, 2018). Likewise, empirical studies on R&D show nonlinear effects on productivity and environmental outcomes, consistent with inverted-U or diminishing return patterns (Popp, 2019). Allowing for these nonlinearities ensures the specification captures these theoretically and empirically grounded dynamics.

In this specification, "Absorptive Capacity$_{it}$" is defined as the interaction between tertiary education and R&D investment: $\mathrm{Absorptive\ Capacity}_{it} \equiv \log(\mathrm{Educ}_{it}) \times \log(\mathrm{R\&D}_{it})$. This term captures the hypothesis that the effect of R&D on emissions reduction depends on a country's level of human capital. In other words, education enhances a country's ability to absorb, implement, and scale up emissions-reducing innovations. This idea is consistent with the concept of absorptive capacity as developed in the innovation literature, where it refers to the ability to recognize the value of new information, assimilate it, and apply it to commercial or policy ends (Cohen et al., 1990).

The control variables, X_{it}, capture additional structural and economic determinants such as energy use, trade openness, and disposable income inequality measured by the Gini Coefficient. The model includes country-fixed effects (α_i), time-fixed effects (δ_t) and the error term ε_{it} captures unobserved factors affecting emissions. While fixed effects estimation is robust for controlling unobservable heterogeneity in macro cross-country panels, concerns about endogeneity may still arise. For instance, countries experiencing rapid economic growth (i.e., increases in GDP per capita over time) and rising emissions might simultaneously increase education and R&D investment, making the direction of causality unclear. Moreover, unobserved institutional factors could simultaneously drive both educational expansion and emissions regulation.

While the model includes several potentially correlated variables, such as GDP per capita, R&D expenditures, and their interaction terms, these are included by design to capture nonlinearities and theoretically justified interactions. Multicollinearity is an expected feature of such models, but it does not bias coefficient estimates; rather, it may inflate standard errors. To assess this concern, variance inflation factors (VIFs) were calculated using a pooled OLS version of the baseline fixed effects model. The results, reported in Appendix A.2, indicate that multicollinearity is within acceptable bounds and does not materially affect inference.

To address potential endogeneity concerns, the analysis is complemented by a DiD design, presented in Section 5. This approach exploits the quasi-experimental setting of the EU 2020 Strategy, which introduced coordinated policies promoting education, innovation, and emissions reduction across member states (European Commission, 2010). By comparing treated EU countries with a control group of non-EU advanced economies, and examining pre- and post-policy trends, the DiD framework offers additional evidence to validate the main findings. In this setting, endogeneity is addressed by leveraging plausibly exogenous variation in the timing and implementation of EU-wide climate and innovation policies. If additional concerns about omitted variable bias remain, an IV approach is explored in the Appendix B.

3.2 Data

The dataset covers a balanced panel of 91 countries over a 25-year period from 1995 to 2019.[1] The dependent variable, CO_2 emissions per capita in metric tons, is sourced from the Our World in Data database (Ritchie et al., 2023). Income inequality data, measured by the disposable Gini coefficient, is obtained from the Standardized World Income Inequality Database (SWIID) (Solt, 2020). Additional variables, including GDP per capita (constant 2015 US$), tertiary education enrollment (gross %), R&D expenditures, energy use (kg of oil equivalent per capita), and trade openness, come from the World Bank's World Development Indicators (WDI). The variable R&D is defined as the gross domestic expenditure on research and development (public and private) as a percentage of GDP, covering business, government, higher education, and private non-profits. Countries are classified as high-, middle-, or low-income economies following the World Bank's income classification. Table A.3 in the Appendix classifies all countries in the analysis by income levels. Additionally, the Appendix presents summary statistics and a correlation matrix in Tables A.1 and A.2.

CO_2 emissions per capita vary across countries, reflecting differences in economic structures and energy consumption patterns. These differences are also appreciated in table 1 that presents summary statistics by income classification. As expected, CO_2 emissions per capita are significantly higher in high-income countries compared to middle- and low-income economies. This aligns with greater industrialization and energy consumption in wealthier nations, driven by manufacturing, transportation, and energy-intensive industries. GDP per capita also exhibits stark differences, with high-income countries outpacing middle- and low-income economies, underscoring productivity gaps, technological disparities, and differences

[1] The focus is on the period 1995–2019 because macro-level indicators are not consistently available across countries beyond 2019. This ensures comparability and avoids introducing selection bias due to incomplete or irregular post-2019 reporting in cross-country panel data.

Table 1: Summary Statistics by Income Level

	N	Mean	St.Dev.	Min	Max
Log CO_2 p.c.					
High-Income	1496	2.20	0.63	0.29	5.90
Middle-Income	1393	0.98	0.87	-1.45	3.39
Low-Income	1696	-0.85	1.19	-3.83	2.61
Log GDP p.c.					
High-Income	1496	10.24	0.65	8.25	11.63
Middle-Income	1384	8.56	0.65	6.81	10.14
Low-Income	1635	7.11	0.76	5.12	10.05
Log Tertiary Ed.					
High-Income	1167	3.84	0.65	1.23	4.78
Middle-Income	896	3.39	0.75	-1.55	5.12
Low-Income	970	2.00	1.27	-2.44	4.45
Log R&D					
High-Income	931	0.20	0.97	-3.48	1.74
Middle-Income	570	-1.11	0.85	-3.77	0.89
Low-Income	313	-1.61	1.08	-5.21	0.18
Log Energy Use					
High-Income	1084	8.30	0.61	6.44	10.00
Middle-Income	867	7.08	0.70	4.96	9.44
Low-Income	791	6.12	0.74	2.27	8.48
Log Trade					
High-Income	1362	4.43	0.59	2.62	6.08
Middle-Income	1265	4.33	0.46	2.72	5.40
Low-Income	1362	4.06	0.53	0.91	5.85
Income Inequality					
High-Income	1260	31.82	5.96	20.90	50.80
Middle-Income	1140	40.88	8.34	20.40	65.20
Low-Income	1173	42.26	5.61	24.40	54.80

Note: The construction of this dataset and the definitions of the variables are discussed in section 3.

in capital accumulation. While middle-income countries show notable income growth, they remain well below the income levels of high-income nations.

R&D investment is another key differentiator across income groups. High-income countries allocate significantly more resources to research and innovation, fostering technological advancements and high-value industries. Middle-income countries are increasing R&D spending but still lag in absolute investment and intensity relative to GDP. Low-income countries invest the least in R&D, constrained by limited funding, fewer research institutions, and weaker incentives for private-sector innovation. These patterns underscore the role of human capital and innovation capacity in shaping economic and environmental trajectories.

Figure 1 provides a descriptive overview of the relationship between GDP per capita and CO_2 emissions per capita. The scatterplot, with a lowess fit, shows a non-linear association

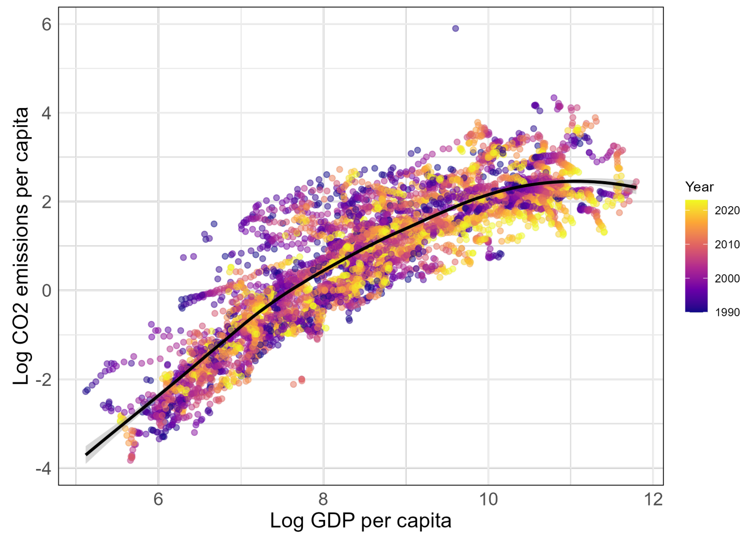

Figure 1: Relationship between GDP per capita and CO_2 emissions per capita (1995-2019). Note: Each point represents a country-year observation (colored by year). A lowess smoothing curve highlights the non-linear pattern consistent with EKC dynamics.

consistent with EKC dynamics: emissions increase at low and middle income levels, but flatten and eventually decline at higher income levels. For completeness, Appendix Figures A.1a and A.1b present the evolution of Pearson correlation coefficients over time for the full sample and by income groups, respectively.

4 Results

Table 2 presents the regression results examining the relationship between income levels, tertiary education, R&D expenditures, and CO_2 emissions per capita. In column (1), the coefficient for the log of GDP per capita is positive and statistically significant, while its squared term is negative and highly significant. This confirms the EKC hypothesis, suggesting that CO_2 emissions initially rise with income levels but decline beyond a certain income threshold. This is consistent with the large body of EKC evidence (e.g., Grossman and Krueger (1995); Stern (2018)), which similarly finds an inverted-U relationship between income and emissions.

Column (2) introduces tertiary education enrollment. The coefficient is positive and significant, while its squared term is negative and significant. These results indicate a nonlinear relationship: initially, higher tertiary education enrollment is associated with increased CO_2 emissions, likely due to industrial expansion and knowledge-driven economic activity. However, as education levels rise further, emissions decline, suggesting that human capital fosters environmental awareness and supports green innovation. This finding is consistent with evidence that education moderates the EKC, facilitating the shift toward cleaner technologies and reduced emissions (Balaguer and Cantavella, 2018). Column (3) incorporates R&D expenditures and their squared term, revealing also a nonlinear effect on emissions. The negative linear coefficient suggests that R&D generally reduces emissions by 4.9%, and the negative squared term implies that the decarbonization effect accelerates at higher levels of investment. These results align with findings that the effects of energy R&D on environmental performance are nonlinear (Popp, 2019).

Column (4) introduces the interaction term between tertiary education and R&D, which changes the interpretation of the main effects. The coefficient on R&D alone now reflects its effect when education is zero (a hypothetical baseline), while the interaction term captures how the effect of R&D varies with education levels. In this specification, the standalone R&D coefficient turns positive, but the interaction term is negative and highly significant.

Taken together, the combined effect at observed levels of education is negative, confirming that higher education strengthens the emissions-reducing role of R&D. This finding is consistent with the concept of absorptive capacity (Cohen et al., 1990), which emphasizes the role of human capital in enabling economies to internalize and apply new knowledge. These results extend this idea by providing systematic evidence that education conditions whether R&D translates into emissions-reducing innovation.

Quantitatively, the results indicate that R&D alone reduces carbon emissions by 4.9%, as shown in column 3, while the interaction with tertiary education leads to an amplified reduction of 6.4%. This 1.5 percentage point increase represents a 30.6% stronger decarbonization effect, underscoring the role of human capital in maximizing the environmental impact of

Table 2: Impact of Education and R&D on CO_2 Emissions

	(1)	(2)	(3)	(4)
Log GDP p.c	2.523***	1.797***	1.324***	1.176***
	(0.090)	(0.100)	(0.143)	(0.145)
Log GDP p.c Sq.	-0.142***	-0.098***	-0.071***	-0.062***
	(0.005)	(0.006)	(0.009)	(0.009)
Log Tertiary Enrollment		0.213***	0.172***	0.090*
		(0.020)	(0.049)	(0.051)
Log Tertiary Enrollment Sq.		-0.034***	-0.032***	-0.026***
		(0.004)	(0.007)	(0.007)
Log R&D Exp.			-0.049***	0.204***
			(0.017)	(0.053)
Log R&D Exp. Sq.			-0.010**	0.003
			(0.005)	(0.005)
Absorptive Capacity				-0.064***
				(0.013)
Log Energy Use	0.766***	0.861***	0.976***	0.955***
	(0.023)	(0.023)	(0.031)	(0.031)
Log Trade	0.083***	-0.006	-0.037*	-0.022
	(0.016)	(0.016)	(0.021)	(0.021)
Income Inequality	-0.002	-0.005***	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,471	1,793	984	984
Adjusted R^2	0.56	0.70	0.69	0.70

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Column (1) includes only income level variables, column (2) adds education, column (3) introduces R&D, and column (4) examines the interaction between education and R&D.

innovation. The interaction effect implies that without a sufficiently skilled workforce, the full potential of R&D in reducing emissions may remain unrealized.

Across all models, energy use remains a strong positive predictor of CO_2 emissions. Trade openness has a small and marginally significant negative effect, suggesting that higher trade integration may be associated with efficiency improvements or technology diffusion that lowers emissions. Income inequality, measured by the Gini coefficient, exhibits a small but statistically significant negative effect in some models, potentially reflecting redistributive policies or structural economic shifts linked to lower emissions.

To assess whether these findings depend on the specific proxies chosen for human capital and R&D, I re-estimated the models using alternative measures: upper-secondary and post-secondary educational attainment, as well as researchers in R&D per million people as a proxy for R&D inputs. The results, reported in Appendix Table C.1, confirm the robustness of the absorptive capacity effect, which remains negative and statistically significant across all specifications. This suggests that the finding is not an artifact of a particular proxy choice: whether absorptive capacity is measured via tertiary enrollment, upper-secondary or post-secondary attainment, or combined with alternative R&D input proxies, the moderating effect of human capital on the decarbonization impact of R&D holds consistently.

To address concerns about omitted-variable bias, I extend the baseline specification with additional controls in three groups, reported in the Appendix, section D. First, I add variables for the energy mix (renewables share, fossil share, fossil and renewable consumption levels, coal-based electricity; Table D.1). Second, I incorporate industrial structure and energy imports (sectoral employment shares, energy import dependence; Table D.2). Third, I add demographic controls (log population, urban share, population growth, labor force participation; Table D.3). I also present a "full set" specification combining one proxy per theme (Table D.4). Additionally, it includes net foreign direct investment (FDI) as it captures cross-border capital flows that can bring technology transfer, innovation spillovers, and exposure to foreign production practices. Across all specifications, the absorptive capacity effect remains negative and statistically significant, while the additional variables behave as expected. This provides reassurance that the main findings are robust to alternative specifications.

To address concerns about both potential reverse causality and delayed effects, I re-estimated the preferred specification using one- and two-period lagged values of education, R&D, and absorptive capacity. This approach allows for the possibility that decarbonization drivers operate with a delay due to structural, technological, or behavioral factors, while also mitigating simultaneity concerns. The results, presented in Table E.1 in the Appendix, remain highly consistent with the contemporaneous model. In all cases, the absorptive capacity effect continues to be negative and statistically significant. This robustness check provides reassurance that the main findings are not driven by simultaneity and that they persist when allowing for delayed effects.

4.1 Heterogeneous Effects by Income Level

Given the wide variation in institutional quality, innovation capacity, and economic structure across countries, this research explores whether the relationship between absorptive capacity and emissions differs by income group. Table 3 presents regression results estimated separately for high-, middle-, and low-income countries, highlighting key differences in the relationship between economic development, education, R&D, and CO_2 emissions. The EKC hypothesis holds for high- and middle-income countries, where emissions initially rise with GDP but decline beyond a threshold. High-income countries reach this turning point earlier, likely due to advanced regulations and cleaner technologies. In contrast, middle-income nations require higher GDP levels to experience emissions reductions, suggesting structural constraints in their energy transitions. For low-income countries, GDP has no significant nonlinear effect, implying that income growth alone is insufficient to drive emissions reductions.

Tertiary education impacts emissions differently across income groups. In high-income countries, education shows similar non-linear behavior discussed previously. In middle-income countries, tertiary education has a negative effect on emissions, indicating that factors such as improved energy efficiency, technological spillovers, or policy shifts contribute to decarbonization as education levels rise. In low-income countries, education's effect remains weak, indicating that education alone may not yet play a decisive role in shaping emissions trajectories in less developed economies.

The relationship between R&D expenditures and carbon emissions varies significantly by income level, reflecting differences in innovation capacity and the ability to translate technological advancements into environmental benefits. In high-income countries, R&D investment is associated with higher emissions, as indicated by the positive and significant coefficients for R&D expenditures and the squared term. However, the negative and statistically signifi-

Table 3: Impact of Education and R&D on CO_2 Emissions by Income Level

	High Income (1)	Middle Income (2)	Low Income (3)
Log GDP p.c	1.250***	2.417***	0.971*
	(0.370)	(0.393)	(0.529)
Log GDP p.c Sq.	-0.065***	-0.139***	-0.052
	(0.019)	(0.024)	(0.034)
Log Tertiary Enrollment	0.321**	-0.335**	0.125
	(0.135)	(0.161)	(0.081)
Log Tertiary Enrollment Sq.	-0.061***	0.031	-0.019
	(0.018)	(0.022)	(0.017)
Log R&D Exp.	0.250**	0.443***	-0.085
	(0.106)	(0.152)	(0.104)
Log R&D Exp. Sq.	0.017*	0.002	-0.033*
	(0.009)	(0.019)	(0.017)
Absorptive Capacity	-0.062**	-0.139***	-0.037
	(0.026)	(0.033)	(0.032)
Observations	488	296	145
Adjusted R^2	0.70	0.77	0.68

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Columns (1), (2), and (3) correspond to high-income, middle-income, and low-income countries, respectively. Control variables include the log of energy use, trade, and income inequality.

cant interaction between R&D and tertiary education indicates that the emissions-increasing effect of R&D is moderated in economies with a more skilled workforce. This interaction reduces by 6.2% carbon emissions per capita. This implies that education plays a crucial role in redirecting R&D toward green innovation. In other words, without sufficient human capital, R&D alone may not be enough to drive decarbonization in high-income economies.

R&D expenditures in middle-income economies exhibit a stronger effect. The coefficient on R&D is larger, but also the interaction term with tertiary education. The interaction effect reduces carbon emissions per capita by 14%, more than double the effect found in high-income countries. This suggests that middle-income countries are in a phase where investments in knowledge and technological innovation are particularly effective at reducing emissions, likely because these economies are undergoing structural transitions toward cleaner production methods. In low-income countries, neither R&D expenditures nor their interaction with tertiary education significantly influences emissions reductions. The coefficient for R&D is negative but not statistically significant, while the squared term suggests that any potential benefits from R&D may only materialize at higher levels of investment. This suggests that, in lower-income settings, constraints such as limited technology transfer mechanisms or insufficient absorptive capacity may prevent R&D investments from translating into effective emissions reductions.

4.2 Quantile Regression

In addition to OLS, I employ Quantile Regression (QR) following Koenker and Bassett (1978). QR is particularly well-suited for this setting because the effect of education and R&D on emissions may not be constant across the distribution of the outcome. For instance, high-emission economies may respond differently to policy or absorptive capacity than low-emission economies. By estimating conditional quantiles of the emissions distribution, QR allows me to assess heterogeneity in the effects of education and innovation, which OLS cannot capture as it only recovers the conditional mean. This distinction is important in the context of environmental policy, where distributional impacts matter for both efficiency and equity considerations Koenker and Hallock (2001); Koenker (2005). For the QR estimates, I use the standard Koenker–Bassett estimator with standard errors obtained via bootstrapping with 500 replications, which is the recommended approach for inference in QR models.

While the estimates presented in this section are not intended to imply causal relationships, the quantile regression results provide useful descriptive insights into how the association between education, R&D, and carbon emissions varies across the emissions distribution. Table 4 explores the heterogeneous effects of education and R&D on carbon emissions across different levels of emissions. It reports the estimates for the 25th, 50th, 75th, and 90th percentiles of the emissions distribution. The estimates for log GDP per capita are positive and significant across all quantiles, indicating that income growth is associated with higher emissions. The squared term is negative and significant, confirming the EKC hypothesis. Similar results are confirmed also for education. The coefficients for R&D expenditure indicate that investments in R&D contribute to emissions reductions. The squared term is also negative, confirming that higher levels of R&D investment accelerate emissions reductions.

The interaction term between tertiary education and R&D expenditure is negative and significant at the 25th, 50th, and 75th percentiles but not at the 90th percentile. This suggests that education enhances the emissions-reducing effect of R&D, particularly in low- to mid-high-emission economies. The magnitude of the interaction effect is largest at the median, where a one percent increase in both education and R&D leads to an additional 14.5% reduction in emissions. At the 25th and 75th percentiles, the effect is 9.4% and 12.4%, respectively. For the highest-emission countries (90th percentile), however, the interaction is not significant. This could be due to structural factors that make decarbonization particularly difficult in these economies. Many high-emission countries have a large share of industries such as steel, cement, and chemicals, which rely on carbon-intensive processes that are difficult to replace even with technological advancements.

Table 4: Quantile Regression Results

	Q25	Q50	Q75	Q90
Log GDP p.c	1.069***	0.631***	0.648***	0.642***
	(0.192)	(0.160)	(0.134)	(0.139)
Log GDP p.c Sq.	-0.050***	-0.027***	-0.030***	-0.034***
	(0.011)	(0.010)	(0.008)	(0.009)
Log Tertiary Enrollment	0.187**	0.051	0.180***	0.226***
	(0.085)	(0.031)	(0.026)	(0.078)
Log Tertiary Enrollment Sq.	-0.028**	-0.018***	-0.033***	-0.031***
	(0.012)	(0.005)	(0.005)	(0.011)
Log R&D Exp.	-0.028	-0.071***	-0.041**	-0.045**
	(0.021)	(0.020)	(0.017)	(0.018)
Log R&D Exp. Sq.	-0.010**	-0.025***	-0.020***	-0.029***
	(0.004)	(0.005)	(0.003)	(0.005)
Absorptive Capacity	-0.094**	-0.145***	-0.124***	-0.023
	(0.038)	(0.031)	(0.020)	(0.042)
Observations	984	984	984	984

Note: Bootstrap standard errors (500 replications) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Column Q25 estimates the 25th percentile, Q50 the median, Q75 the 75th percentile, and Q90 the 90th percentile effects of education and R&D on emissions. Additional control variables such as trade openness, energy use, income inequality, and the constant term are omitted for brevity. All models include country and year fixed effects.

5 Robustness Check

To assess the robustness of the main findings, this section implements an additional identification strategy. A DiD design addresses potential endogeneity concerns and strengthens the causal interpretation of the results.

The European Union (EU) has long been at the forefront of climate policy, implementing ambitious frameworks to reduce carbon emissions while fostering economic growth. In 2010, the EU introduced the Europe 2020 Strategy, a comprehensive plan designed to promote smart, sustainable, and inclusive growth (European Commission, 2010). One of the key components of this strategy was the EU 2020 Climate and Energy Package, which set legally binding targets for all member states. These targets aimed to reduce greenhouse gas (GHG) emissions by 20% compared to 1990 levels, increase the share of renewable energy in total final energy consumption to 20%, and improve energy efficiency by 20%.

Beyond direct regulatory mandates, the EU 2020 Strategy placed significant emphasis on education and innovation as key enablers of long-term decarbonization. Recognizing that achieving emissions reductions required structural economic transformations, the EU complemented its climate targets with policies designed to stimulate technological progress, human capital formation, and industrial transition. The Innovation Union initiative, launched under the Europe 2020 framework, sought to strengthen the role of R&D in fostering sustainable economic growth. The policy aimed to increase public and private R&D investment to at least 3% of GDP, enhance the capacity of higher education institutions to support technological advancements, and promote university-industry collaboration to accelerate the commercialization of clean energy technologies.

This study evaluates whether education enhances the emissions-reducing effects of R&D investment, testing the hypothesis that a highly educated workforce strengthens the role of innovation in decarbonization. A DiD approach within a Two-Way Fixed Effects framework is used, comparing emissions trends between EU member states (treated group) and advanced non-EU economies (control group).

$$\log(\text{CO}_{2it}) = \beta_1(\text{Post}_t \times \text{Treated}_i) + \beta_2 X_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (2)$$

where $\log(\text{CO}_{2it})$ represents per capita carbon emissions, α_i are country fixed effects and δ_t are year fixed effects. The main effects of Treated (time-invariant) and Post (time-specific) are absorbed by these fixed effects and therefore not separately estimated. The coefficient of interest is β_1, which captures the DiD effect of the EU 2020 policy. The model controls for GDP per capita, tertiary education enrollment, R&D expenditures (including squared terms), their interaction, energy use, trade, and income inequality.

Table 5: Difference-in-Differences Estimation of EU 2020 Policy Impact

	(1)	(2)
Post × Treated	-0.15***	-0.06***
	(0.06)	(0.02)
Post-Treated Absorptive Capacity	0.00	
	(0.01)	
L2.Post-Treated Absorptive Capacity		-0.01***
		(0.00)
Log GDP p.c	0.84*	1.21**
	(0.47)	(0.60)
Log GDP p.c Sq.	-0.05*	-0.06*
	(0.03)	(0.03)
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	236	191
Adjusted R^2	0.87	0.92

Note: Country-clustered (Arellano) standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Both specifications include country and year fixed effects. As a result, the main effects of Treated and Post are absorbed by the fixed effects and not reported. The coefficient on Post × Treated is the DiD estimator of the EU 2020 policy. Control variables include log enrollment in tertiary education, log R&D, log R&D squared, log energy use, trade, and income inequality.

Table 5 presents the results, showing a significant reduction in emissions for treated countries. The negative and significant coefficient for the Post × Treated interaction in column (1) indicates that the EU 2020 policy led to an immediate 15% reduction in CO_2 emissions among EU member states. However, as seen in column (2), this effect moderates to a 6% reduction in the longer term when accounting for a two-period lag.

The impact of education and R&D on emissions reduction emerges with a delay. This term suggests that in countries with higher levels of tertiary education and R&D investment, emissions decline an additional 1 percentage point, bringing the total long-term policy effect to 7% in these economies, similar to the results found previously. This suggests that innovation and human capital play a growing role over time, likely through technology adoption and structural adjustments. The results for GDP per capita and its squared term align with the EKC, indicating that emissions initially rise with income before declining at higher income levels.

The delayed role of absorptive capacity is consistent with the view that human capital conditions whether R&D translates into productivity-enhancing or emissions-reducing innovations (Cohen et al., 1990; Popp, 2010), while the persistence of the inverted-U pattern confirms that the EKC relationship is robust to policy-induced structural breaks, in line with cross-country evidence from Dinda and Coondoo (2006); Vollebergh et al. (2009).

I also estimated the model using only country fixed effects, which allows the Post dummy to be estimated explicitly. The results are nearly identical to those reported in Table 5, with the coefficient on the interaction Post $\times$ Treated remaining identical in magnitude and significance. This confirms that the causal effect is robust to alternative specifications. I prefer the Difference-in-Differences specification with country and year effects reported here, as it flexibly accounts for time-invariant differences across countries and common shocks over time.

6 How Does Absorptive Capacity Affect Emissions?

To deepen the interpretation of the main results, this section examines the channels through which absorptive capacity contributes to decarbonization. I first test whether absorptive capacity reduces emissions through the development of green inventions. The results are presented in Table 6. Column (1) shows that absorptive capacity has a positive and significant effect on the share of environment-related inventions. However, Column (2) indicates that newly developed green inventions have no significant effect on CO_2 emissions. As a result, Column (3) confirms that this channel does not mediate the relationship between absorptive capacity and emissions.

Several factors may explain this disconnect. First, many green inventions remain in early stages, such as patents, and face commercialization and adoption hurdles. Second, time lags in scaling and regulatory approval delay their environmental impact. Third, weak market incentives or insufficient policy support can limit firm adoption. Lastly, established high-carbon technologies may crowd out new solutions. These results align with prior evidence that the diffusion of climate mitigation technologies lags behind invention (Probst et al., 2021). These findings suggest that while the absorptive capacity expands the frontier of green innovation, their environmental benefits might depend on complementary policies that ensure the adoption and scaling of these technologies.

Table 6: Mediation Analysis: Development of Inventions

	Dependent Variable:		
	Dev. Inventions	Log CO_2 p.c.	
	(1)	(2)	(3)
Development Inventions		-0.00	-0.00
		(0.00)	(0.00)
Absorptive Capacity	0.43***		-0.08***
	(0.14)		(0.01)
Observations	869	1,763	869
Adjusted R^2	0.10	0.70	0.74

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on the development of green inventions. Model (2) estimates the effect of green inventions on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

Next, in Table 7, I examine whether absorptive capacity reduces emissions through the diffusion of green inventions. Column (1) shows that absorptive capacity has a positive and significant effect on the diffusion of environment-related inventions, suggesting that education strengthens a country's ability to absorb, adapt, and disseminate green technologies, reflected in increased patent citations, licensing, and international collaboration. Column (2) indicates that greater diffusion significantly reduces CO_2 emissions, underscoring the environmental gains associated with the broader uptake of green technologies. Finally, Column (3) confirms that absorptive capacity indirectly lowers emissions through diffusion. These results reinforce the idea that green invention development alone is insufficient; diffusion must be prioritized to fully realize the potential of environmental technologies. This is consistent with evidence that the diffusion of clean technologies across borders, through patent citations and licensing, plays a more critical role in decarbonization than invention alone (Verdolini and Galeotti, 2011; Dechezleprêtre et al., 2014).

Table 7: Mediation Analysis: Diffusion of Inventions

	Dependent Variable:		
	Diff. Inventions	Log CO_2 p.c.	
	(1)	(2)	(3)
Diffusion Inventions		-0.002***	-0.002**
		(0.00)	(0.00)
Absorptive Capacity	1.36***		-0.06***
	(0.48)		(0.01)
Observations	852	1,659	852
Adjusted R^2	0.26	0.73	0.77

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on Diffusion Innovation. Model (2) estimates the effect of Diffusion Innovation on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

I then turn to the diffusion of green technologies. Column (1) of Table 8 shows that absorptive capacity has a positive and significant effect on technology diffusion, suggesting that education enhances a country's ability to integrate green technologies into production and energy systems. Column (2) reveals that technology diffusion significantly reduces CO_2 emissions, and Column (3) confirms that absorptive capacity indirectly lowers emissions through this channel.

Unlike invention diffusion, which emphasizes knowledge sharing, technology diffusion directly impacts emissions by enabling the replacement of high-carbon production methods with low-carbon alternatives. These findings underscore that innovation alone is not enough and that education and supportive policy environments are critical to accelerating the large-scale adoption of green technologies and realizing their environmental benefits. This echoes the directed technical change literature, which finds that the environmental benefits of innovation depend on the large-scale adoption of low-carbon technologies in production systems (Acemoglu et al., 2012; Aghion et al., 2016).

Table 8: Mediation Analysis: Diffusion of Technology

	Dependent Variable:		
	Diff. Technology	Log CO_2 p.c.	
	(1)	(2)	(3)
Diffusion Technology		-0.00**	-0.00***
		(0.00)	(0.00)
Absorptive Capacity	1.99**		-0.06***
	(0.92)		(0.01)
Observations	852	1,659	852
Adjusted R^2	0.07	0.73	0.77

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on Diffusion Technology. Model (2) estimates the effect of Diffusion Technology on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

The results in Table 9 suggest that absorptive capacity contributes to stronger environmental regulation. Column (1) shows a positive association with the Environmental Policy Stringency Index (EPSI), indicating that countries with higher education and R&D levels are more likely to adopt stringent policies. Column (2) confirms that stricter environmental policies reduce CO_2 emissions. Column (3), which includes both direct and mediated effects, indicates that part of the absorptive capacity's impact on emissions operates through regulatory pathways. While technology and skills are essential, their full impact depends on regulatory frameworks that guide behavior and enforce compliance. These findings complement evidence that stronger innovation systems and human capital support the implementation of stringent environmental policies (Noailly, 2012; Fankhauser and Jotzo, 2018; Botta and Koźluk, 2014).

Table 9: Mediation Analysis: Environmental Policy Stringency Index

	Dependent Variable:		
	EPSI	Log CO_2 p.c.	
	(1)	(2)	(3)
EPSI		-0.04***	-0.04***
		(0.00)	(0.01)
Absorptive Capacity	0.83***		-0.06**
	(0.21)		(0.03)
Observations	495	916	495
Adjusted R^2	0.69	0.83	0.82

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on the EPSI. Model (2) estimates the effect of EPSI on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

Table 10 indicates that absorptive capacity is associated with lower carbon intensity of GDP (Column 1), pointing to improvements in energy efficiency. Column (2) shows that higher carbon intensity is strongly linked to greater per capita emissions, and Column (3) suggests that part of the effect of absorptive capacity on emissions operates through this channel. Overall, the results are consistent with the view that more educated and innovative economies are better able to reduce emissions by improving the efficiency of energy use. This is consistent with studies showing that absorptive capacity fosters energy efficiency improvements, thereby reducing carbon intensity (Lanzi et al., 2011).

Table 11 shows that absorptive capacity is positively associated with green job creation, as shown in Column 1. However, Column 2 shows that green employment has no significant effect on emissions, nor does it mediate the overall relationship, as shown in Column 3.

Table 10: Mediation Analysis: Carbon Intensity

	Dependent Variable:		
	Carbon Int. GDP	Log CO_2 p.c.	
	(1)	(2)	(3)
Carbon Int. GDP		0.28***	0.12***
		(0.01)	(0.02)
Absorptive Capacity	-0.13***		-0.05***
	(0.02)		(0.01)
Observations	978	2451	978
Adjusted R^2	0.61	0.62	0.72

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on Carbon Intensity (Carbon Int. GDP). Model (2) estimates the effect of Carbon Intensity on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

These results suggest that while stronger education and innovation systems generate more jobs in sustainability-related sectors, employment shifts alone do not directly reduce emissions without complementary technological or policy changes. One limitation is the smaller and less consistent sample of green employment data, which may affect robustness. This resonates with recent work emphasizing that green employment growth must be coupled with complementary technological and regulatory changes to translate into measurable emissions reductions (Secundo et al., 2020; Khanra et al., 2022).

To enforce temporal ordering and reduce concerns of reverse causality, education and R&D are lagged by one period, while mechanisms (e.g., diffusion of inventions, carbon intensity, EPSI, etc.) and emissions are measured contemporaneously. This ensures that absorptive capacity precedes the mediating channel, which in turn contemporaneously affects emissions. The results, shown in the Appendix H, remain consistent with the contemporaneous specification: diffusion and EPSI continue to play a significant mediating role, carbon intensity remains a strong channel, while technology diffusion and green jobs do not show robust effects. These findings confirm that the mediating role of absorptive capacity is not driven by simultaneity or omitted variable bias, but reflects a robust pathway linking

Table 11: Mediation Analysis: Green Jobs

	Dependent Variable:		
	Green Jobs	Log CO_2 p.c.	
	(1)	(2)	(3)
Log Green Jobs		-0.02	-0.02
		(0.03)	(0.05)
Absorptive Capacity	1.02***		0.09
	(0.26)		(0.11)
Observations	92	111	92
Adjusted R^2	0.49	0.82	0.77

Note: Driscoll–Kraay robust standard errors in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the effect of absorptive capacity on Green Jobs. Model (2) estimates the effect of Green Jobs on CO_2 emissions. Model (3) includes both the direct and mediated effects. All models control for log GDP per capita, education, R&D (and their squared terms), trade, energy use, and income inequality. All models include country and year fixed effects, but are omitted for brevity. Coefficients for control variables are omitted for clarity.

education and R&D to environmental outcomes.

7 Discussion and Conclusions

Technological innovation is central to decarbonization, but its impact depends on the conditions under which it operates. This study shows that absorptive capacity, defined as the combination of education and R&D, amplifies the effectiveness of green innovation in reducing CO_2 emissions. In other words, innovation must be embedded within a skilled and adaptive society to yield higher environmental returns. The clear policy implication is that governments cannot rely on technological progress alone; they must invest in human capital, education systems, and technical skills to unlock their full potential. These initial findings speak directly to the study's central objective of assessing whether human capital enhances the decarbonization impact of innovation.

The results confirm a non-linear relationship between income, education, and emissions. While R&D alone reduces emissions by 4.9%, its effect grows to 6.4% when combined with a strong knowledge base, highlighting a 30% larger decarbonization impact. This interaction is particularly strong in middle-income economies, where innovation uptake is more dynamic. The Difference-in-Differences analysis further supports these findings. It shows that the EU 2020 policy led to an immediate 15% reduction in CO_2 emissions among treated countries, which moderated to 6% in the longer term. Importantly, in countries with stronger absorptive capacity, those with higher levels of tertiary education and R&D, emissions fell an additional 1 percentage point, bringing the total long-term reduction to 7%. This pattern suggests that the benefits of climate policy deepen over time in knowledge-intensive economies, where education and innovation foster structural change and support the adoption of cleaner technologies. The findings provide consistent empirical support for the hypothesis that absorptive capacity conditions the effectiveness of both innovation and climate policy. These results emphasize that the same climate policy can deliver very different outcomes depending on a country's absorptive capacity. Countries with weak education and R&D systems may implement ambitious policies yet obtain limited emissions reductions, highlighting the need for climate finance and capacity-building mechanisms that target institutional and human capital constraints.

To unpack the channels driving this relationship, the analysis explores five potential mechanisms. First, green invention development alone does not reduce emissions, highlighting that innovation must move beyond the patent stage to widespread adoption. In contrast, the diffusion of inventions and technologies significantly lowers emissions. Second, absorptive capacity enhances regulatory effectiveness: countries with strong human capital and R&D implement more stringent environmental policies, which in turn reduce emissions. Third, efficiency gains are a key driver; lower carbon intensity reflects improved production methods rather than reduced output. Fourth, green job creation is positively associated with absorptive capacity but does not directly drive emissions reductions, suggesting employment shifts alone are insufficient without technology deployment. These channels reinforce the conceptual expectation that absorptive capacity operates through innovation uptake, regulatory strength, and efficiency improvements, thereby supporting the study's mechanism-based research objectives. These mechanisms point to a simple message: absorptive capacity transforms potential into realized impact. For policymakers, this means that accelerating diffusion, strengthening regulatory capacity, and improving energy efficiency should be treated as complementary pillars of national decarbonization strategies.

These findings reinforce the importance of integrated strategies that align education, innovation, and policy. Building on this, the results yield differentiated policy implications across country groups. For advanced economies, where absorptive capacity is already relatively high, the key challenge lies in aligning existing R&D investments with decarbonization goals. This can be achieved by coupling innovation policies with strong carbon pricing, targeted subsidies for clean technologies, and mission-oriented programs that direct technological change toward low-carbon outcomes. For emerging and developing economies, the results suggest that increasing R&D spending alone may be insufficient without parallel investments in human capital and institutional quality. Policies that expand access to higher education, strengthen technical training, and improve governance structures are essential for translating innovation into measurable environmental benefits. In this context, international cooperation and technology transfer can also play a complementary role in accelerating the diffusion of low-carbon technologies. Together, these group-specific strategies highlight that while innovation is a necessary engine of decarbonization, its effectiveness ultimately depends on the absorptive capacity of the societies where it is deployed. More broadly, the findings imply that unequal levels of absorptive capacity may widen differences in the pace of the low-carbon transition across countries, making capacity-building a global climate priority. Looking ahead, climate strategies should incorporate absorptive capacity as a core design principle rather than a background condition. Integrating human capital development, which enables the uptake of innovation and institutional change, into decarbonization planning can significantly accelerate emissions reductions and prevent countries from falling behind in the global transition.

While this study offers new insights, several limitations remain. Measurement inconsistencies in some indicators, such as green employment, and the potential for omitted variable bias must be acknowledged. In addition, the analysis is based on country-level data and does not capture within-country heterogeneity or firm-level dynamics. Future research could explore how absorptive capacity affects emissions at subnational or sectoral levels, and examine the equity implications of innovation-driven transitions, particularly the challenges faced by lower-skilled workers. Reskilling and workforce adaptation policies will be crucial to ensure that the green transition is both effective and inclusive.

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Appendix

A Appendix: Additional Empirical Information

Table A.1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Log CO_2 p.c	578	2.27	0.38	1.24	3.06
Log GDP p.c.	578	10.39	0.48	8.46	11.10
Log GDP p.c. Sq.	578	108.11	9.65	71.62	123.11
Log Tertiary Enrollment	477	4.13	0.36	2.66	4.79
Log Tertiary Enrollment Sq.	477	17.17	2.80	7.06	22.90
Log R&D Exp.	426	0.72	0.45	-0.62	1.60
Log R&D Exp. Sq.	426	0.71	0.53	0.00	2.55
Education $\times$ R&D	354	2.95	2.08	-2.54	7.35
Log Energy Use	442	8.38	0.33	7.68	9.04
Log Trade	573	4.19	0.52	2.76	5.26
Income Inequality	523	29.38	3.81	20.90	42.70

Note: Summary statistics include key variables used in the regression analysis.

Table A.2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log CO_2 p.c.	1.00	0.11	-0.01	0.06	0.03	0.67	-0.27	0.22
(2) Log GDP p.c.	0.11	1.00	0.51	0.69	0.69	0.56	-0.05	-0.05
(3) Log Tertiary Enrollment	-0.01	0.51	1.00	0.51	0.55	0.33	0.19	0.21
(4) Log R&D Exp.	0.06	0.69	0.51	1.00	1.00	0.55	-0.04	-0.20
(5) Education $\times$ R&D	0.03	0.69	0.55	1.00	1.00	0.62	0.08	-0.26
(6) Log Energy Use	0.67	0.56	0.33	0.55	0.62	1.00	-0.02	-0.00
(7) Log Trade	-0.27	-0.05	0.19	-0.04	0.08	-0.02	1.00	-0.53
(8) Income Inequality	0.22	-0.05	0.21	-0.20	-0.26	-0.00	-0.53	1.00

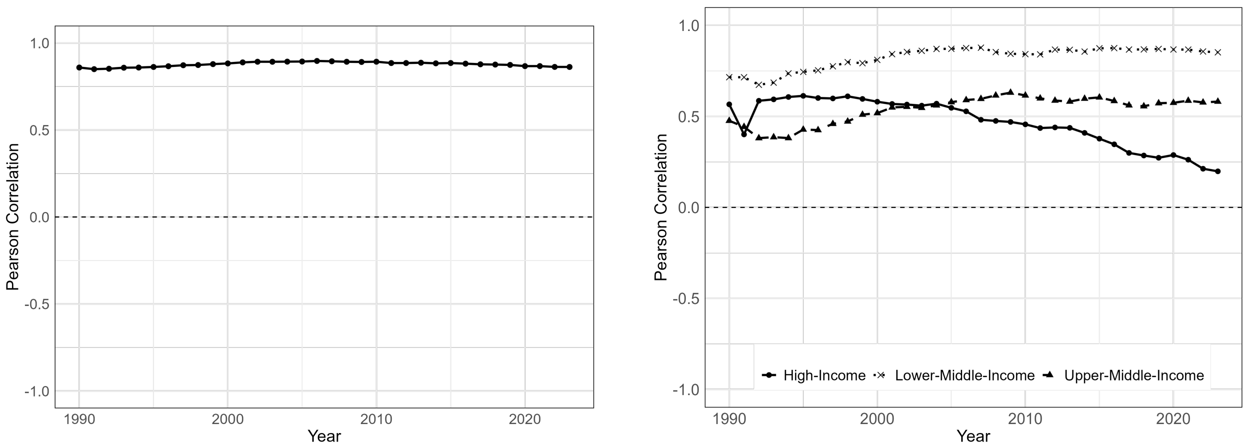
Note: The table presents the correlation coefficients between key variables in the analysis. All values are rounded to two decimal places. Squared terms have been excluded for clarity.

Table A.3: Low, Middle, and High-Income Countries

Low-Income		Middle-Income		High-Income	
Country	**ISO Code**	**Country**	**ISO Code**	**Country**	**ISO Code**
Armenia	ARM	Argentina	ARG	Austria	AUT
Bosnia	BIH	Azerbaijan	AZE	Belgium	BEL
Bulgaria	BGR	Bahrain	BHR	Canada	CAN
Ghana	GHA	Belarus	BLR	Switzerland	CHE
Honduras	HND	Brazil	BRA	Chile	CHL
India	IND	China	CHN	Germany	DEU
Senegal	SEN	Colombia	COL	Spain	ESP
El Salvador	SLV	Costa Rica	CRI	Finland	FIN
Sudan	SDN	Ecuador	ECU	France	FRA
Cambodia	KHM	Georgia	GEO	United Kingdom	GBR
Morocco	MAR	Greece	GRC	Hungary	HUN
Mozambique	MOZ	Indonesia	IDN	Ireland	IRL
Tanzania	TZA	Jamaica	JAM	Israel	ISR
Ukraine	UKR	Jordan	JOR	Italy	ITA
		Kazakhstan	KAZ	Japan	JPN
		Malaysia	MYS	South Korea	KOR
		Mexico	MEX	Luxembourg	LUX
		Moldova	MDA	Netherlands	NLD
		Montenegro	MNE	Norway	NOR
		North Macedonia	MKD	Portugal	PRT
		Paraguay	PRY	Sweden	SWE
		Peru	PER	United States	USA
		Philippines	PHL		
		Poland	POL		
		Romania	ROU		
		Slovenia	SVN		
		South Africa	ZAF		
		Thailand	THA		
		Tunisia	TUN		
		Uruguay	URY		
		Uzbekistan	UZB		

Note: This table categorizes countries into low-income, middle-income, and high-income groups based on World Bank criteria.

A.1 Descriptive Plots



(a) Full sample

(b) By income groups

Figure A.1: Pearson correlation between GDP per capita and CO_2 emissions per capita

Note: Figures A.1a and A.1b show that the strength of the GDP p.c.–CO_2 p.c. relationship varies both over time and across country income groups. These descriptive patterns are consistent with the argument that absorptive capacity conditions the translation of growth into environmental outcomes.

A.2 Diagnostic Checks

Table A.4 reports generalized variance inflation factors (GVIFs) from the main model 4 of Table 2. While the log of GDP per capita and its squared term show high VIF values (expected due to their mathematical relationship), the $\text{GVIF}^{1/(2Df)}$ values for key variables of interest such as education, R&D, and their interaction, remain below 3. This confirms that multicollinearity is not a major concern for the interpretation of the core coefficients.

To assess the sensitivity of results to functional form, a version of the model excluding the squared terms was estimated. This substantially reduced GVIF values across variables, confirming that multicollinearity was largely driven by these polynomial terms. However, since these squared terms are theoretically motivated (e.g., EKC, nonlinear absorptive capacity), they were retained in the final specification. Core results for the education–R&D interaction remained stable, further supporting this modeling choice.

Table A.4: Generalized Variance Inflation Factors (GVIF) for FE Model

Variable	**GVIF**	**Df**	**$\text{GVIF}^{1/(2\cdot Df)}$**
Log GDP p.c	318.32	1	17.84
Log GDP p.c Sq.	314.18	1	17.73
Log Tertiary Enrollment	381.13	3	2.69
Log Tertiary Enrollment Sq.	49.52	1	7.04
Log R&D Expenditure	381.13	3	2.69
Log R&D Expenditure Sq.	4.34	1	2.08
Log Energy Use	4.69	1	2.17
Log Trade	1.20	1	1.10
Income Inequality	2.21	1	1.49

Note: GVIF = Generalized Variance Inflation Factor. $\text{GVIF}^{1/(2\cdot \text{Df})}$ provides a comparable measure of multicollinearity for predictors with more than one degree of freedom, such as interaction or polynomial terms. Values above 10 (or $\text{GVIF}^{1/(2Df)}$ above 2.5) may suggest notable multicollinearity, though theoretical justifications and robustness checks mitigate concern.

B Appendix: Instrumental Variables Analysis

If additional concerns about omitted variable bias remain, an instrumental variables (IV) approach is employed. The main endogenous variable of interest is tertiary education enrollment, which may be influenced by unobserved country-level factors that also affect CO_2 emissions. Moreover, the analysis includes the term form Absorptive Capacity. Since this term inherits the endogeneity of education, it must also be instrumented. The instrument used for tertiary education is the duration of compulsory schooling laws, which proxy for long-term structural investments in human capital. These laws shape educational attainment over time but are plausibly exogenous to short-term fluctuations in CO_2 emissions. The IV estimation proceeds in two first-stage regressions, followed by a second-stage regression.

The first-stage regressions are given by:

$$\log(\text{Educ}_{it}) = \pi_0 + \pi_1 \text{Compulsory}_{it} + \pi_2 X_{it} + \alpha_i + \delta_t + u_{it}, \tag{B.1}$$

$$\text{Absorptive Capacity}_{it} = \rho_0 + \rho_1(\text{Compulsory}_{it} \times \log(\text{R\&D}_{it})) + \rho_2 X_{it} + \alpha_i + \delta_t + \nu_{it}, \tag{B.2}$$

where X_{it} denotes the full set of time-varying controls, α_i and δ_t are country and year fixed effects. The second-stage equation is:

$$\log(\text{CO}_{2it}) = \beta_1 \log(\widehat{\text{Educ}}_{it}) + \beta_2 \log(\text{R\&D}_{it}) + \beta_3 \widehat{\text{Absorptive Capacity}}_{it} + \beta_4 X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{B.3}$$

The first-stage results in columns (1) and (2) of Table B.1 confirm that compulsory schooling significantly predicts tertiary education and its interaction with R&D. The second-stage results show that the interaction term remains statistically significant and negative, suggesting that human capital enhances the effectiveness of innovation in reducing emissions. Instrument strength tests indicate that the instrument is valid for the interaction term, even if weaker for education alone.

Table B.1: Instrumental Variables Regression

	First Stage		Second Stage
	(1)	(2)	(3)
Compulsory Education	0.04***		
	(0.01)		
Comp. Education × Log R&D		0.05***	
		(0.01)	
Log Tertiary Enrollment			-0.88
			(0.61)
Absorptive Capacity			-0.77***
			(0.20)
Log R&D Expenditure	0.08**	3.41***	3.11***
	(0.03)	(0.09)	(0.83)
Log R&D Expenditure Sq.	-0.01	0.16***	0.15**
	(0.01)	(0.01)	(0.05)
Observations	877	877	867
Adjusted R^2	0.55	0.96	0.79
F-statistic	121.65***	2186.73***	392.00***
Weak IV Test (Tertiary)			1.93
Weak IV Test (Interaction)			15.79***

Notes: Standard errors are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1) estimates the first-stage relationship between compulsory education and tertiary enrollment, Model (2) estimates the first-stage regression for the interaction term, and Model (3) estimates the second-stage IV regression for CO_2 emissions. Additional variables included are GDP per capita, GDP per capita squared, energy use, trade and income inequality.

C Appendix: Alternative for Main Variables

Table C.1: Regression Results: Additional Proxy Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP p.c	1.176***	1.148***	0.919***	0.111	0.204	-0.411
	(0.145)	(0.281)	(0.321)	(0.184)	(0.481)	(0.514)
Log GDP p.c Sq.	-0.062***	-0.058***	-0.042**	0.000	-0.003	0.032
	(0.009)	(0.016)	(0.019)	(0.010)	(0.026)	(0.027)
Log Tertiary Enrollment	0.090*			0.400***		
	(0.051)			(0.056)		
Log Tertiary Enrollment Sq.	-0.026***			-0.044***		
	(0.007)			(0.012)		
Log Upper-Secondary Att.		0.056			0.362**	
		(0.229)			(0.165)	
Log Upper-Secondary Att. Sq.		-0.026			-0.022	
		(0.032)			(0.039)	
Log Post-Secondary Att.			-0.331*			0.036
			(0.194)			(0.119)
Log Post-Secondary Att. Sq.			0.018			0.082**
			(0.030)			(0.037)
Log R&D Expenditure	0.204***	0.144	0.225**			
	(0.053)	(0.121)	(0.104)			
Log R&D Expenditure Sq.	0.003	-0.012*	0.004			
	(0.005)	(0.007)	(0.014)			
Log Researchers in R&D				0.216***	0.326***	0.347***
				(0.046)	(0.089)	(0.087)
Log Researchers in R&D Sq.				-0.013***	-0.015***	-0.004
				(0.005)	(0.005)	(0.008)
Absorptive Capacity	-0.064***					
	(0.013)					
Absorptive Capacity P1		-0.050*				
		(0.029)				
Absorptive Capacity P2			-0.072**			
			(0.031)			
Absorptive Capacity P3				-0.025*		
				(0.013)		
Absorptive Capacity P4					-0.052*	
					(0.027)	
Absorptive Capacity P5						-0.111***
						(0.027)
Observations	984	569	377	769	498	348
Adjusted R^2	0.702	0.664	0.666	0.750	0.647	0.657

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Absorptive Capacity is defined as the interaction between education and R&D. In column (1), tertiary enrollment and R&D expenditure are used. Columns (2)–(6) replace these with alternative proxies (e.g., upper-secondary attainment, post-secondary attainment, researchers in R&D), so that Absorptive Capacity P1–P5 reflect different education–R&D interactions. Control variables are omitted for brevity.

D Appendix: Additional Control Variables

D.1 Energy Mix Controls

In Table D.1, we extend the baseline model by including variables that capture the composition of the energy mix. Specifically, we account for the share of renewables in total final energy consumption, the share of fossil fuels in total energy use, electricity production from coal, and the levels of fossil and renewable energy consumption.

Table D.1: Regression Results I: Controlling for Energy Mix

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP p.c	1.176***	0.999***	1.318***	0.923***	0.811***	1.131***
	(0.145)	(0.145)	(0.147)	(0.123)	(0.133)	(0.142)
Log GDP p.c Sq.	-0.062***	-0.051***	-0.070***	-0.049***	-0.041***	-0.058***
	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)	(0.009)
Log Tertiary Enrollment	0.090*	0.003	0.070	-0.035	-0.072	0.089*
	(0.051)	(0.053)	(0.051)	(0.044)	(0.048)	(0.051)
Log Tertiary Enrollment Sq.	-0.026***	-0.014*	-0.023***	0.003	0.004	-0.026***
	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
Log R&D Exp.	0.204***	0.197***	0.243***	0.142***	0.136***	0.181***
	(0.053)	(0.052)	(0.054)	(0.045)	(0.048)	(0.053)
Log R&D Exp. Sq.	0.003	0.001	0.006	0.005	-0.001	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Energy Use	0.955***	0.891***	1.074***	0.838***	0.834***	0.923***
	(0.031)	(0.032)	(0.041)	(0.027)	(0.029)	(0.031)
Log Trade	-0.022	-0.039*	-0.004	-0.004	0.017	-0.013
	(0.021)	(0.021)	(0.021)	(0.018)	(0.019)	(0.021)
Income Inequality	-0.001	-0.000	-0.001	-0.003	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Renewables Share		-3.163***				
		(0.552)				
Fossil Energy Share			3.005***			
			(0.674)			
Fossil Energy Level				0.014***		
				(0.001)		
Renewable Energy Level					-0.012***	
					(0.001)	
Coal-Based Electricity						0.004***
						(0.001)
Absorptive Capacity	-0.064***	-0.062***	-0.072***	-0.041***	-0.042***	-0.056***
	(0.013)	(0.013)	(0.013)	(0.011)	(0.012)	(0.013)
Observations	984	984	984	984	984	984
Adjusted R^2	0.702	0.713	0.709	0.787	0.759	0.712

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Columns (1)–(6) progressively add energy related variables.

D.2 Industrial Structure and Energy Controls

Table D.2 extends the baseline specification by incorporating measures of employment structure and energy dependence. Specifically, I add the shares of employment in agriculture, industry, and services, which capture differences in sectoral composition that influence energy demand and emissions intensity. In addition, I include total natural resource rents (% of GDP) and net energy imports as a share of total energy use.

Table D.2: Regression Results II: Controlling for Industrial Structure and Energy

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP p.c	1.176***	1.128***	0.818***	1.120***	0.930***	1.102***
	(0.145)	(0.148)	(0.146)	(0.143)	(0.133)	(0.145)
Log GDP p.c Sq.	-0.062***	-0.060***	-0.041***	-0.055***	-0.049***	-0.057***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Log Tertiary Enrollment	0.090*	0.090*	0.072	0.081	0.113**	0.101**
	(0.051)	(0.051)	(0.050)	(0.051)	(0.049)	(0.051)
Log Tertiary Enrollment Sq.	-0.026***	-0.027***	-0.017**	-0.017**	-0.028***	-0.028***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log R&D Exp.	0.204***	0.203***	0.216***	0.212***	0.029	0.185***
	(0.053)	(0.053)	(0.052)	(0.053)	(0.051)	(0.053)
Log R&D Exp. Sq.	0.003	0.003	0.008	0.007	-0.010*	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Energy Use	0.955***	0.952***	0.850***	0.905***	1.039***	0.942***
	(0.031)	(0.031)	(0.032)	(0.032)	(0.030)	(0.031)
Log Trade	-0.022	-0.023	-0.007	-0.013	0.025	-0.036*
	(0.021)	(0.021)	(0.020)	(0.021)	(0.019)	(0.021)
Income Inequality	-0.001	-0.001	-0.001	0.000	-0.007***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employment in Agriculture		-0.002				
		(0.002)				
Employment in Industry			0.013***			
			(0.002)			
Employment in Services				-0.008***		
				(0.001)		
Energy Imports					-0.001***	
					(0.000)	
Natural Resource Rents (% GDP)						0.005***
						(0.001)
Absorptive Capacity	-0.064***	-0.064***	-0.059***	-0.061***	-0.024**	-0.058***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
Observations	984	984	984	984	934	984
Adjusted R^2	0.702	0.703	0.723	0.712	0.769	0.706

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Columns (1)–(6) progressively add employment structure, energy imports, and natural resource rents.

D.3 Demographic and Population Controls

Table D.3 augments the baseline with demographic controls to capture scale and compositional forces behind emissions. I add the natural log of total population, the share of people living in urban areas, population growth, computed as the first difference of log population (country-specific Δ log population), and the labor force participation rate for ages 15–64.

Table D.3: Regression Results III: Controlling for Demographic and Population Factors

	(1)	(2)	(3)	(4)	(5)
Log GDP p.c	1.176***	1.174***	1.180***	1.198***	1.162***
	(0.145)	(0.146)	(0.145)	(0.144)	(0.151)
Log GDP p.c Sq.	-0.062***	-0.061***	-0.062***	-0.064***	-0.061***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log Tertiary Enrollment	0.090*	0.092*	0.093*	0.091*	0.089*
	(0.051)	(0.054)	(0.052)	(0.051)	(0.052)
Log Tertiary Enrollment Sq.	-0.026***	-0.026***	-0.026***	-0.025***	-0.026***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Log R&D Exp.	0.204***	0.204***	0.205***	0.211***	0.204***
	(0.053)	(0.053)	(0.054)	(0.053)	(0.054)
Log R&D Exp. Sq.	0.003	0.003	0.003	0.004	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Energy Use	0.955***	0.954***	0.956***	0.958***	0.954***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Log Trade	-0.022	-0.023	-0.022	-0.019	-0.022
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Income Inequality	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log Population		-0.008			
		(0.058)			
Urban Population			-0.001		
			(0.002)		
Population Growth				1.924***	
				(0.682)	
Labor Force (15–64)					-0.001
					(0.002)
Absorptive Capacity	-0.064***	-0.064***	-0.064***	-0.064***	-0.064***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	984	984	984	984	984
Adjusted R^2	0.702	0.702	0.702	0.705	0.702

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Columns (1)–(5) progressively add population and demographic controls.

D.4 Full Set of Additional Controls

Table D.4: Regression Results IV: Full Set

	(1)	(2)
Log GDP p.c	1.176***	0.324**
	(0.145)	(0.162)
Log GDP p.c Sq.	-0.062***	-0.013
	(0.009)	(0.009)
Log Tertiary Enrollment	0.090*	-0.096*
	(0.051)	(0.050)
Log Tertiary Enrollment Sq.	-0.026***	0.003
	(0.007)	(0.007)
Log R&D Exp.	0.204***	0.223***
	(0.053)	(0.053)
Log R&D Exp. Sq.	0.003	0.011**
	(0.005)	(0.005)
Log Energy Use	0.955***	0.752***
	(0.031)	(0.033)
Log Trade	-0.022	-0.039*
	(0.021)	(0.021)
Income Inequality	-0.001	-0.001
	(0.002)	(0.002)
Renewables Share		-4.632***
		(0.639)
Employment in Industry		0.015***
		(0.002)
Urban Population		-0.000
		(0.001)
Natural Resource Rents		-0.001
		(0.002)
Foreign Direct Investment		-0.00004
		(0.0003)
Absorptive Capacity	-0.064***	-0.052***
	(0.013)	(0.013)
Observations	984	921
Adjusted R^2	0.702	0.751

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. All specifications include country and year fixed effects, but omitted for clarity. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is log CO_2 per capita. Columns (2) include all additional controls.

E Appendix: Delayed Effects

Table E.1: Impact of Education and R&D on CO_2 Emissions (Robustness with Lags)

	Main	Lagged (1-year)	Lagged (2-year)
Log GDP p.c	1.176***	1.220***	1.240***
	(0.145)	(0.400)	(0.464)
Log GDP p.c Sq.	-0.062***	-0.064***	-0.064**
	(0.009)	(0.023)	(0.026)
Log Tertiary Enrollment	0.090*	0.056	0.055
	(0.051)	(0.121)	(0.124)
Log Tertiary Enrollment Sq.	-0.026***	-0.022	-0.021
	(0.007)	(0.017)	(0.018)
Log R&D Exp.	0.204***	0.196	0.169
	(0.053)	(0.139)	(0.146)
Log R&D Exp. Sq.	0.003	0.004	0.003
	(0.005)	(0.011)	(0.013)
Log Energy Use	0.955***	0.969***	0.977***
	(0.031)	(0.107)	(0.117)
Log Trade	-0.022	-0.021	-0.020
	(0.021)	(0.040)	(0.044)
Income Inequality	-0.001	-0.0004	0.0009
	(0.002)	(0.005)	(0.005)
Absorptive Capacity	-0.064***	-0.061**	-0.056*
	(0.013)	(0.030)	(0.032)
Observations	984	919	859
Adjusted R^2	0.70	0.99	0.99

Note: Driscoll–Kraay robust standard errors in parentheses. Results are robust to clustering by country. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The first column reports the contemporaneous specification. The second and third columns re-estimate the model using one- and two-period lagged values of education, R&D, and absorptive capacity. Other controls remain contemporaneous. The negative and significant absorptive capacity effect persists, confirming robustness to reverse causality concerns.

F Appendix: Difference in Differences

F.1 Average Carbon Emissions over Time

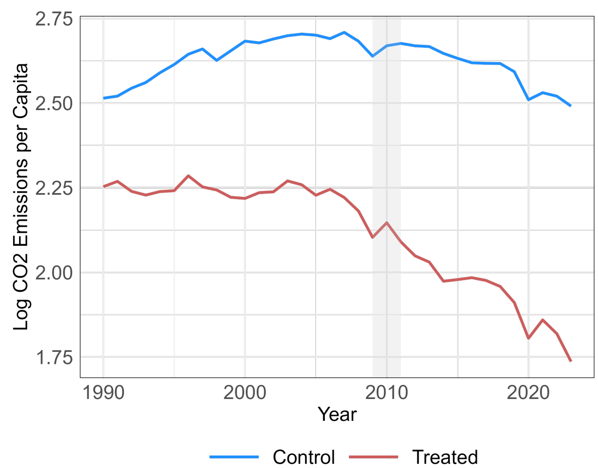


Figure F.1: Average CO_2 Emissions Over Time

F.2 List of Countries: DiD

Table F.1: Countries in the DiD Analysis

Treated		**Control**	
Country	**ISO Code**	**Country**	**ISO Code**
Germany	DEU	USA	USA
France	FRA	Canada	CAN
Italy	ITA	Japan	JPN
Spain	ESP	South Korea	KOR
Netherlands	NLD	Australia	AUS
Belgium	BEL		
Austria	AUT		
Sweden	SWE		
Finland	FIN		
Denmark	DNK		
Poland	POL		
Czech Republic	CZE		

Note: This table lists countries used in the DiD analysis by treated and control countries.

G Appendix: Additional Information - Mechanisms

Table G.1: Definitions of Green Patent Mechanisms and Related Indicators

Mechanism	Definition
Development Inventions	Measures the creation of new green technologies through domestic research efforts. This indicator is calculated as the number of environment-related inventions (based on OECD ENV-TECH classification) as a share of all domestic inventions. Only higher-value inventions, those with a patent family size of 2 or more (filed in at least two jurisdictions), are included. Source: OECD Environment Database, Patents – Technology Development, Botta and Koźluk (2014)
Diffusion Inventions	Indicates the international dissemination of green inventions. Measured as the percentage of environment-related patent applications filed in a jurisdiction relative to all applications worldwide over a 4-year window (year T and the previous 3 years). This reflects the extent to which inventors seek international protection for their inventions. Based on ENV-TECH classification, and includes high-value patents (family size ≥ 2). Source: OECD Environment Database, Patents – Technology Diffusion.
Diffusion Technology	Assesses the domestic uptake of foreign-origin green technologies. This is proxied by the number or share of green patent applications filed in a jurisdiction that originate from foreign inventors, or via citation/linkage to foreign inventions. It captures technology absorption, not just creation, and is calculated using patent data across environmental domains as defined in ENV-TECH. Source: OECD Environment Database, Patents – Technology Diffusion.
EPSI	Measured by the OECD Environmental Policy Stringency Index, which quantifies the strictness of environmental policies across countries. Stringency is defined as the degree to which policies impose an explicit or implicit cost on polluting or environmentally harmful behavior. The index ranges from 0 (least stringent) to 6 (most stringent) and is based on 13 environmental policy instruments related to climate and air pollution. It covers 40 countries from 1990 to 2020. Source: OECD data.
Carbon Int. GDP	Measures the carbon intensity of GDP, expressed as kilograms of CO_2 equivalent (kg CO_2e) per constant 2015 US dollar of GDP. A lower carbon intensity indicates improved environmental efficiency in economic activities, reducing reliance on carbon-intensive energy sources. Source: World Bank Data.
Green Jobs	Employment in the production of environmental goods and services, measured in full-time equivalent (FTE) jobs. FTE is defined as the total hours worked divided by the average annual working hours in a full-time job. This reflects the labor market's transition toward sustainability-focused industries such as renewable energy, pollution control, and energy efficiency. Source: Eurostat.

H Mechanisms with Lags

Table H.1: Mediation Analysis: Development Innovation (Lag)

	Dependent Variable:		
	Dev. Innovation	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	0.50***		-0.07***
	(0.11)		(0.01)
Dev. Innovation (t)		-0.00	-0.01
		(0.00)	(0.00)
Observations	814	1,763	814
Adjusted R^2	0.96	0.99	0.99

Note: Driscoll–Kraay robust standard errors (bandwidth $L = 2$) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): Development Innovation regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on Development Innovation. Model (3): CO_2 emissions regressed on Development Innovation and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.

Table H.2: Mediation Analysis: Diffusion of Innovation (Lag)

	Dependent Variable:		
	Diff. Innovation	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	1.29*		-0.04***
	(0.56)		(0.01)
Diff. Innovation (t)		-0.00***	-0.01***
		(0.00)	(0.00)
Observations	793	1,659	793
Adjusted R^2	0.90	0.99	0.996

Note: Driscoll–Kraay robust standard errors (bandwidth $L = 2$) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): Diffusion of Innovation regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on Diffusion of Innovation. Model (3): CO_2 emissions regressed on Diffusion of Innovation and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.

Table H.3: Mediation Analysis: Technology Diffusion (Lag)

	Dependent Variable:		
	Tech. Diffusion	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	-1.20		-0.05***
	(3.24)		(0.01)
Tech. Diffusion (t)		-0.00	-0.00
		(0.00)	(0.00)
Observations	793	1,659	793
Adjusted R^2	0.69	0.99	0.996

Note: Driscoll–Kraay robust standard errors (bandwidth $L = 2$) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): Technology Diffusion regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on Technology Diffusion. Model (3): CO_2 emissions regressed on Technology Diffusion and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.

Table H.4: Mediation Analysis: EPSI (Lag)

	Dependent Variable:		
	EPSI	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	0.43*		-0.03
	(0.16)		(0.03)
EPSI (t)		-0.02***	-0.01*
		(0.00)	(0.01)
Observations	461	916	461
Adjusted R^2	0.92	0.99	0.99

Note: Driscoll–Kraay robust standard errors (bandwidth $L = 2$) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): EPSI regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on EPSI. Model (3): CO_2 emissions regressed on EPSI and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.

Table H.5: Mediation Analysis: Carbon Intensity (Lag)

	Dependent Variable:		
	Carbon Intensity	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	-0.14***		-0.04*
	(0.03)		(0.02)
Carbon Intensity (t)		0.29***	0.12***
		(0.04)	(0.03)
Observations	913	2,451	913
Adjusted R^2	0.97	0.99	0.99

Note: Driscoll–Kraay robust standard errors (bandwidth $L = 2$) in parentheses. Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): Carbon Intensity regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on Carbon Intensity. Model (3): CO_2 emissions regressed on Carbon Intensity and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.

Table H.6: Mediation Analysis: Green Jobs (Lag)

	Dependent Variable:		
	Green Jobs	Log CO_2 p.c.	
	(1)	(2)	(3)
Absorptive Capacity (t–1)	0.19		0.08
	(0.37)		(0.07)
Green Jobs (t)		0.01	0.02
		(0.05)	(0.03)
Observations	90	111	90
Adjusted R^2	1.00	1.00	1.00

Note: Driscoll–Kraay robust standard errors in parentheses. Bandwidth $L = 1$ for Models (1) and (3), $L = 2$ for Model (2). Significance levels are: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Model (1): Green Jobs regressed on lagged absorptive capacity (interaction of tertiary education and R&D). Model (2): CO_2 emissions regressed on Green Jobs. Model (3): CO_2 emissions regressed on Green Jobs and lagged absorptive capacity. All models include country and year fixed effects and control for log GDP per capita (and square), energy use, trade, and income inequality. Coefficients for control variables and fixed effects are omitted for clarity.