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Inclusive Innovation and Green Growth in Emerging and Developing Economies

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Abstract

Faced with the challenge of balancing economic transformation and environmental preservation, this study examines the role of national innovation capacity in green growth across 30 emerging and developing economies over the 2011–2022 period. Green growth is assessed through GDP carbon intensity, while national innovation capacity is measured by the Global Innovation Index (GII). The analysis is based on a dynamic panel model estimated using the System GMM method, supplemented by Difference GMM estimates, which allow for the potential endogeneity of innovation. The results highlight strong persistence in carbon intensity and suggest that overall innovation capacity does not have a sufficiently robust relationship with green growth in the sample studied. In contrast, gross fixed capital formation is associated with a reduction in carbon intensity in the main Difference GMM estimates. These results underscore that the contribution of innovation to green growth depends on the context in which innovation capabilities are developed and mobilized and does not automatically result from a general improvement in national innovation capacity.

1. Introduction

The transition to greener growth is a major challenge for emerging and developing economies, where productive transformation is often associated with increasing resource and energy consumption. In this context, innovation is generally viewed as a potential driver of economic and environmental transformation. The endogenous growth models of Romer (1990) and Aghion and Howitt (1992) establish the role of technological progress in growth, while Jaffe, Newell, and Stavins (2002) show that its environmental consequences depend on economic incentives and the conditions under which technologies are developed and adopted. Innovation can thus improve resource efficiency and promote lower-carbon technologies, but it can also boost productivity, investment, and energy demand. Its effect on green growth is therefore, at first glance, ambiguous. This ambiguity raises an important question regarding how to measure innovation. WIPO's Global Innovation Index (GII) provides a multidimensional measure of a country's innovation capacity, covering institutions, human capital and research, infrastructure, market and business sophistication, as well as knowledge and technology outputs. It therefore measures a general capacity for innovation, which should not be confused with green innovation directly aimed at environmental goals. This distinction is important because an economy can strengthen its general capacity for innovation without necessarily directing that capacity toward technologies that reduce emissions. The available empirical results do not yet allow for a clear resolution of this issue. Weber, Falchi, and Chassagnon-Haned (2025) directly examine the link between the GII and CO_2 emissions in 229 countries over 2013–2020 and find a negative relationship between innovation and per capita CO_2 emissions. However, a significant portion of recent research focuses specifically on green innovation. Deng et al. (2024), using data from 33 developed and 42 developing economies over 2000–2019, show that green technological innovation reduces carbon intensity in both groups. Uzar (2024) also finds that green innovation technologies have a positive effect in seven emerging economies, while Shan and Shao (2024) show that green innovation reduces carbon intensity in 30 Chinese provinces. These results underscore the importance of environmentally oriented

innovation, but they do not allow us to conclude that overall innovation capacity, as measured by the GII, necessarily produces the same effect. This distinction becomes particularly relevant in emerging and developing economies, which exhibit significant heterogeneity in terms of technological level, productive structure, infrastructure, and energy consumption. In these economies, innovation can simultaneously generate efficiency gains and support the expansion of production. Efficiency and scale effects can thus reinforce or offset one another depending on the national context. This possibility is supported by the findings of Hardi et al. (2025), who highlight a negative relationship between the GII and carbon intensity in 35 advanced economies over 2011–2022. The literature therefore provides insights into advanced economies and the effects of green innovation, but findings regarding overall innovation capacity in emerging and developing economies remain less well documented. A second gap concerns the econometric dimension of this relationship. Carbon intensity exhibits significant inertia due to the persistence of production structures, installed capital, and energy infrastructure. At the same time, innovation may be endogenous to the environmental trajectory: economies facing environmental constraints may increase their technological investments. A static analysis may therefore lead to a biased estimate of the relationship between innovation and green growth. Incorporating the lagged dependent variable and addressing the potential endogeneity of the GII are therefore key steps toward more accurately identifying this relationship. In this context, this study examines to what extent national innovation capacity, as measured by the GII, is associated with green growth in emerging and developing economies when the persistence of carbon intensity and the potential endogeneity of innovation are taken into account. We use a balanced panel of 30 emerging and developing economies over the period 2011–2022, comprising 360 observations. Green growth is captured through GDP carbon intensity, while gross fixed capital formation, labor, and energy consumption are included as control variables. The empirical strategy is based on the System GMM, supplemented by the Difference GMM, with particular attention paid to the endogeneity of the GII, serial autocorrelation, and instrument validity. This study makes three contributions to the literature. First, it directly examines the relationship between general innovation capacity and green growth, distinguishing this dimension from green innovation, which dominates part of the recent literature. Second, it shifts the analysis to a set of emerging and developing economies, whereas studies directly focused on the GII tend to focus on global samples or advanced economies. Third, it explicitly incorporates the persistence of carbon intensity and the potential endogeneity of GII into a dynamic panel framework. This approach thus makes it possible to assess whether the association between innovation and green growth remains robust when the main sources of bias related to dynamics and endogeneity are taken into account.

The remainder of the article is organized as follows. Section 2 presents the literature review and research hypotheses. Section 3 describes the data, variables, and methodology. Section 4 presents the empirical results and robustness tests. Section 5 discusses the results in light of the existing literature. Finally, Section 6 concludes the study and presents its main implications, limitations, and avenues for future research.

2. Literature Review and Hypothesis Development

2.1. Innovation and Carbon Intensity

Innovation is an important mechanism capable of altering the relationship between economic activity and environmental pressure. Within the framework of endogenous growth theory, Romer (1990) and Aghion and Howitt (1992) emphasize that the accumulation of knowledge and technological progress are fundamental drivers of productivity and growth. Applied to environmental issues, this perspective suggests that technological progress can improve resource efficiency, reduce the energy required for production, and facilitate the adoption of less polluting technologies. Popp (2002) shows, in particular, that technological innovation can contribute to the development of technologies that reduce the costs associated with limiting emissions, while Jaffe et al. (2002) emphasize the importance of economic and environmental incentives in steering innovation toward cleaner technologies.

However, the environmental impact of innovation is not necessarily clear-cut. Innovation can simultaneously increase productivity, stimulate investment, and develop new economic activities, which may in turn increase energy demand and environmental pressures. The net effect thus depends on the direction of innovation, its actual adoption, and the structural characteristics of the economies in which it is developed. This distinction is particularly important when a general indicator of innovation is used, as an aggregate measure of national innovation capacity does not allow for a direct distinction between innovations geared toward environmental efficiency and those primarily intended to increase production. Empirical studies confirm this heterogeneity. Deng et al. (2024), using a sample of 33 developed economies and 42 developing economies over the period 2000–2019, show that green technological innovation significantly reduces carbon emissions intensity in both groups of countries, with a more pronounced effect in developing economies. However, this result pertains specifically to green technological innovation and cannot be directly equated with the effect of a general indicator of national innovation. Similar results emerge in studies focused on China. Shan and Shao (2024), using a panel of 30 Chinese provinces, find a significant negative effect of green innovation on carbon emission intensity and show that the development of big data can strengthen this relationship. Another study covering 284 Chinese cities between 2011 and 2020 also highlights a reducing effect of green innovation on carbon intensity, while emphasizing the importance of industrial structure modernization and regional differences. These results suggest that the environmental impact of innovation depends not only on its existence but also on the ability of economies to translate innovation into gains in productive and environmental efficiency. This heterogeneity of effects is also evident in emerging economies. Uzar (2024), in a study of seven major emerging economies over the period 1990–2018, shows that green innovation technologies help reduce the ecological footprint, while economic growth and energy consumption exert increased environmental pressure. This coexistence of opposing effects suggests that innovation can improve environmental performance without this relationship being necessarily automatic or uniform. A study particularly relevant to the present work is that of Hardi et al. (2025), who directly examine the relationship between the Global Innovation Index and GDP carbon intensity in 35 advanced economies over the period 2011–2022. Using FMOLS and DOLS estimators, among others, the authors highlight a long-term negative relationship between the GII and carbon intensity. Their

quantile regressions also indicate that the strength of this relationship varies depending on the level of carbon intensity, while the Dumitrescu–Hurlin causality test reveals a bidirectional causality between the two variables. This study therefore serves as a direct reference for the use of the GII, but its sample consists exclusively of advanced economies, and its approach relies primarily on long-term relationships rather than on a dynamic panel model that explicitly addresses persistence and potential endogeneity. The literature thus leads us to distinguish between two dimensions. On the one hand, studies on green innovation generally find a positive effect on environmental performance. On the other hand, findings regarding general innovation may depend more on the economic context, the structure of production, and the ability of economies to translate innovation into environmental gains. This distinction is particularly relevant for emerging and developing economies, which are characterized by significant heterogeneity in levels of development, energy structures, and technological capabilities. In this context, this study does not assume that general innovation necessarily leads to a reduction in carbon intensity. It empirically tests whether higher national innovation capacity, as measured by the GII, is associated with different levels of carbon intensity after accounting for the dynamics of carbon intensity, capital accumulation, the labor factor, and energy consumption.

H1 : Higher national innovation capacity, as measured by the Global Innovation Index, is associated with a significant variation in carbon intensity in emerging and developing economies.

2.2. Capital Accumulation and Carbon Intensity

Capital accumulation is another potential determinant of carbon intensity. Gross fixed capital formation (GFCF) reflects investments in infrastructure, machinery, equipment, and other fixed assets that support economic activity. Its environmental impact, however, can operate through opposing mechanisms. On the one hand, increased capital formation can boost productive capacity, industrialization, and demand for resources and energy. In emerging economies, a significant portion of investment may still be directed toward infrastructure, industrial equipment, and relatively energy-intensive activities. In such cases, capital accumulation can exert additional pressure on carbon intensity. On the other hand, investment is a key driver of the modernization of productive capital. The replacement of equipment can improve energy efficiency, incorporate more advanced technologies, and reduce the amount of energy required to produce a unit of wealth. Södersten et al. (2018) thus show that the environmental consequences of capital formation depend heavily on the structure of investments and the level of development. Less developed economies, in particular, devote a significant portion of their investments to infrastructure and physical capital, whereas more advanced economies direct a greater share of their capital accumulation toward digital technologies, software, and services. The findings from developing economies confirm this ambiguity. Studies focusing on India over the period 1971–2021 show that the relationship between gross fixed capital formation and carbon emissions varies depending on the period under consideration and the context of economic liberalization. In particular, the effect becomes positive and significant after liberalization, underscoring the importance of the productive structure in which investments are made. This heterogeneity is also evident in emerging economies. Esposito and Tedeschi (2025), in their study of the BICS economies—Brazil, India, China, and South Africa—over the period

1990–2022, highlight significant differences across countries in the interactions between capital accumulation, energy intensity, and greenhouse gas emissions. These results suggest that the same level of investment can have different environmental implications depending on the structural and energy characteristics of the economy. Thus, capital accumulation can simultaneously have an effect of expanding production and an effect of technological modernization. The former may increase environmental pressure, while the latter may reduce the resource and energy intensity required for production. This ambiguity justifies the inclusion of GFCF as a control variable without imposing a single sign a priori.

H2 : Gross fixed capital formation is significantly associated with carbon intensity in emerging and developing economies.

2.3. Labor Factor and Carbon Intensity

The labor factor is also a potential determinant of carbon intensity, as changes in labor force size influence productive capacity, economic activity, and, indirectly, energy demand. In emerging and developing economies, an increase in the labor force may accompany industrialization and the expansion of production. However, it can also enhance productive capacity when labor is accompanied by improvements in human capital, productivity, and technology adoption. Empirical results are mixed. Salahuddin et al. (2023), using a panel of 173 countries over the period 1996–2020, show that the relationship between labor force participation and environmental performance varies by income level. Increased labor force participation is associated with improvements in certain environmental indicators in low-income countries, whereas the effect may differ in upper-middle-income economies. These results suggest that the impact of the labor factor depends on the economic context and level of development. Conversely, Shahbaz et al. (2015), in an analysis of the determinants of the carbon footprint in several African countries, show that the share of the working-age population may be positively associated with CO_2 emissions in middle-income economies. In these economies, an increase in the labor factor may accompany the expansion of energy-intensive industrial and productive activities. These results suggest that the labor factor does not necessarily have a uniform environmental impact. When an increase in the labor force accompanies industrialization based on high-carbon technologies and energy sources, it can contribute to increased environmental pressure. Conversely, when labor is associated with improvements in human capital, higher-productivity activities, and more efficient technologies, its effect may be different. The labor force is therefore included in the model to account for differences in productive capacity among the countries in the sample, without imposing any specific sign a priori.

H3 : The labor force is significantly associated with carbon intensity in emerging and developing economies.

2.4. Energy Consumption and Carbon Intensity

Energy consumption is one of the factors most directly linked to environmental performance. In emerging and developing economies, economic expansion is generally accompanied by an increase in energy demand in industry, transportation, construction, and urban activities. However, the

environmental impact of this consumption also depends on the composition of the energy mix and the efficiency of the technologies used. Empirical studies show, in particular, that the structure of the energy supply plays a decisive role. Deng et al. (2024), drawing on data from 33 developed and 42 developing economies, demonstrate that renewable energy consumption significantly reduces carbon intensity, with a particularly pronounced effect in developing economies. This finding underscores that increases in energy consumption cannot be interpreted independently of the source of the energy used. Uzar (2024), in a study of seven major emerging economies, also shows that energy consumption contributes to an increase in the ecological footprint, while green innovation has a mitigating effect. This coexistence underscores the importance of energy efficiency and the composition of the energy mix in determining environmental performance. The findings for African economies point in the same direction. Shahbaz et al. (2015) show that energy intensity is a positive and significant determinant of CO_2 emissions in low- and middle-income African countries. The significance of this relationship can be explained in particular by the heavy reliance of many economies on fossil fuels and by the energy needs associated with industrialization. Energy consumption is therefore included in the model as a key control variable. Its inclusion helps prevent attributing variations in carbon intensity to the GII that might in fact be linked to differences in energy consumption across economies.

H4 : Higher energy consumption is significantly associated with higher carbon intensity in emerging and developing economies.

2.5. Literature Review and Study Framework

The reviewed literature highlights several interdependent determinants of carbon intensity. Innovation can help improve productive and environmental efficiency, but its effect depends on its direction, diffusion, and the structural characteristics of economies. Capital accumulation can simultaneously increase productive capacity and promote the modernization of equipment. The labor factor may be associated with increased environmental pressure when it accompanies energy-intensive industrialization, but its effect may differ when the workforce benefits from higher levels of human and technological capital. Finally, energy consumption remains closely linked to environmental performance, particularly when the energy system relies heavily on fossil fuels. A key limitation of the literature concerns the distinction between general innovation and green innovation. A significant portion of empirical studies on the environment use specific indicators such as green patents, environmental R&D spending, or green technologies. These measures make it possible to directly identify certain innovations aimed at reducing environmental pressures. However, they do not necessarily capture the full range of a country’s capabilities to produce, absorb, disseminate, and utilize knowledge and technologies. The Global Innovation Index offers a different perspective by assessing a country’s overall capacity for innovation across several dimensions—institutional, human, infrastructural, commercial, technological, and creative. However, this multidimensional coverage also presents a potential limitation : a high GII score does not necessarily mean that the resulting innovation is geared toward reducing emissions or improving energy efficiency. A second limitation concerns the context of the countries studied. Hardi et al. (2025) provide a reference particularly relevant to this research by simultaneously

using the GII and carbon intensity. Their analysis, however, focuses on 35 advanced economies and highlights a long-term negative relationship between the two variables. This relationship cannot be automatically applied to emerging and developing economies. These economies exhibit varying levels of industrialization, human capital, infrastructure, energy consumption, and technological absorption capacity. The sample selected for this study specifically allows us to examine this relationship within a different structural context. A third limitation concerns the dynamic dimension and potential endogeneity. Some of the existing research is based on static or long-term relationships and does not necessarily take into account the high persistence of carbon intensity. However, infrastructure, industrial equipment, energy systems, and production technologies are gradually changing. Current carbon intensity may therefore depend heavily on its previous level. Furthermore, the relationship between innovation and environmental performance may be affected by reverse causality: changes in the production system and environmental constraints may themselves influence innovation capabilities.

This study seeks to address these limitations by examining the relationship between the GII and carbon intensity in a balanced panel of 30 emerging and developing economies over the period 2011–2022. Unlike static approaches, this study explicitly accounts for the dynamics of carbon intensity through its lagged value and uses GMM estimators to address the potential endogeneity of the GII. The robustness of the results is then examined using various System GMM and Difference GMM specifications. The objective, therefore, is not to assume that innovation necessarily reduces carbon intensity, but to determine whether this relationship remains statistically significant when the persistence of carbon intensity, the heterogeneity of economies, and the potential endogeneity of innovation are taken into account.

The four empirical hypotheses are thus formulated as follows:

H1 : Higher national innovation capacity, as measured by the Global Innovation Index, is associated with a significant variation in carbon intensity in emerging and developing economies.

H2 : Gross fixed capital formation is significantly associated with carbon intensity in emerging and developing economies.

H3 : The labor force is significantly associated with carbon intensity in emerging and developing economies.

H4 : Higher energy consumption is significantly associated with higher carbon intensity in emerging and developing economies.

3. Methodology

3.1. Data and Sample Selection

The empirical analysis is based on a balanced panel of 30 emerging and developing economies, observed annually over the period 2011–2022, for a total of 360 country-year observations. The sample includes the following countries : China, India, Indonesia, Malaysia, the Philippines, Thailand, Vietnam, Bangladesh, Pakistan, Brazil, Mexico, Argentina, Chile, Colombia, Peru, Costa Rica, Ecuador, Poland, Hungary, Romania, Bulgaria, Türkiye, South Africa, Egypt, Morocco, Tunisia, Algeria, Kenya, Saudi Arabia, and Iran. The sample's composition spans several regions, including Asia, Latin America, emerging Europe, Africa, and the Middle East. This diversity allows for the consideration of significant differences among economies in terms of innovation capacity, industrial development, capital accumulation, and energy consumption. It thus provides an appropriate framework for examining the relationship between innovation and carbon intensity in heterogeneous economic and structural contexts. The 2011–2022 period was selected based on the availability and continuity of the data required for all model variables, particularly those related to the Global Innovation Index (GII). The final selection of countries is based on the availability of observations for all variables considered over the entire period, allowing for the construction of a balanced panel and avoiding observation losses due to missing data. Data on national innovation capacity are obtained from the Global Innovation Index (GII), published by the World Intellectual Property Organization (WIPO). Data on macroeconomic variables come primarily from the World Bank's World Development Indicators (WDI).

3.2. Variables and Measurement

3.2.1. Dependent Variable : Carbon Intensity

The dependent variable is GDP carbon intensity (CI), used as an indicator of the carbon footprint associated with economic output. According to Hardi et al. (2025), carbon intensity represents the amount of carbon dioxide emitted per unit of gross domestic product. It is calculated as the ratio of CO_2 emissions to real GDP :

$$CI_{i} = CO_{2i} / GDP_{i}$$

where CO_{2i} represents the carbon dioxide emissions of country i in year t, while GDP_{i} denotes its real gross domestic product. The value of this indicator lies in the fact that it simultaneously accounts for economic output and the associated carbon footprint. Unlike total emissions, which depend heavily on the size of an economy, carbon intensity measures the emissions associated with a unit of wealth produced. A decrease in CI thus corresponds to a shift toward less carbon-intensive production.

3.2.2. Main Explanatory Variable : Global Innovation Index

The main explanatory variable is the Global Innovation Index (GII), published annually by the World Intellectual Property Organization (WIPO). The GII is used as a measure of national innovation capabilities because it offers broader, multidimensional coverage than a single indicator such as research and development spending or the number of patents. In this study, the GII is used directly as published by WIPO and is not recalculated from the sample data. It is a composite index based on several dimensions of national innovation systems. According to WIPO's methodology, it is based in

particular on dimensions related to institutions, human capital and research, infrastructure, the sophistication of markets and firms, as well as the production of knowledge, technologies, and creativity. The GII thus provides a comprehensive measure of the overall innovation capabilities of the economies under study. Its use provides insight into the national environment in which innovation activities are developed, disseminated, and exploited.

3.2.3. Gross Fixed Capital Formation

Gross fixed capital formation (GFCF) is introduced as the first control variable. It allows for the accumulation of physical capital and changes in productive capacity. Capital formation can influence carbon intensity through the replacement of equipment and infrastructure. When new investments incorporate more efficient technologies, they can facilitate the modernization of the production system and reduce the amount of energy and emissions required for production. Conversely, when investment is concentrated in high-carbon sectors, its environmental impact may differ. The inclusion of GFCF thus makes it possible to distinguish the effect associated with innovation capacity from that resulting from capital accumulation.

3.2.4. Labor Force

The labor force (LF) is the second control variable. It represents the human resources available to participate in economic and productive activities. Its inclusion allows us to account for differences in size and productive capacity among the economies in the sample. The labor force may also play a role in the processes of learning, technology absorption, and technology diffusion. LF is therefore included to control for the productive and human dimensions that may be associated with the observed differences in carbon intensity among economies.

3.2.5. Energy Consumption

Energy consumption (EC) is the third control variable. Its inclusion is important because energy use is one of the main channels linking economic activity to carbon emissions. High energy consumption may be associated with higher carbon intensity when the energy system remains heavily dependent on fossil fuels. Controlling for EC thus allows us to account for the energy dimension in the analysis of the relationship between innovation and carbon intensity.

3.3. Stationarity Analysis

Before estimating the dynamic models, the stationarity of the variables is examined using several unit-root tests adapted for panel data. The analysis employs the Levin, Lin, and Chu (LLC) test, the Im, Pesaran, and Shin (IPS) test, and the Fisher-ADF test. The use of multiple tests allows us to account for differences in the assumptions regarding the homogeneity and heterogeneity of the series dynamics. For lnCI, the results obtained at the level are mixed : the LLC test rejects the unit root hypothesis, while the IPS and Fisher-ADF tests do not reject it. At the first difference, the various tests strongly reject the unit root hypothesis. These results indicate that the carbon intensity series is integrated of order one at most, without allowing us to assert uniform stationarity at the level according to all the tests. This finding

justifies the use of a dynamic approach based on difference transformations and endogenous instruments.

3.4. Specification of the Empirical Model

The basic static model can be represented as follows:

$$\ln CI_{i,t} = \alpha + \beta_1 GII_{i,t} + \beta_2 GFCF_{i,t} + \beta_3 \ln LF_{i,t} + \beta_4 \ln EC_{i,t} + \mu_i + \varepsilon_{i,t}$$

where i represents the country and t represents the year. However, carbon intensity likely has a strong persistent component. Energy systems, infrastructure, production technologies, and industrial equipment do not change overnight. The current level of carbon intensity may therefore depend on its past level. To account for this dynamic, the empirical model is specified as follows:

$$\ln CI_{i,t} = \alpha + \rho \ln CI_{i,t-1} + \beta_1 GII_{i,t} + \beta_2 GFCF_{i,t} + \beta_3 \ln LF_{i,t} + \beta_4 \ln EC_{i,t} + \mu_i + \varepsilon_{i,t}$$

where $\ln CI_{i,t-1}$ represents the lagged dependent variable and measures the temporal persistence of carbon intensity. GII is the main explanatory variable, while GFCF, lnLF, and lnEC are the control variables. μ_i represents the unobserved country-specific effects, and $\varepsilon_{i,t}$ denotes the idiosyncratic error term. The presence of the lagged dependent variable introduces a potential source of endogeneity and makes conventional panel estimators susceptible to dynamic bias. Furthermore, the relationship between innovation and carbon intensity may also be affected by potential reverse causality. These characteristics justify the use of dynamic GMM estimators.

3.5. Estimation Strategy : System GMM and Difference GMM

Dynamic analysis relies primarily on GMM estimators developed for dynamic panels with a short time dimension. The System GMM, proposed by Arellano and Bover (1995) and Blundell and Bond (1998), combines first-difference equations and level equations. This approach allows for the use of endogenous instruments constructed from lagged values of potentially endogenous variables. In this study, the use of the GMM is motivated primarily by the presence of the lagged dependent variable and by the possibility of endogeneity in the GII. Indeed, national innovation capacities can influence the characteristics of the production system, and conversely, economic and environmental transformations can affect innovation capacities. The System GMM is first used to examine the dynamic relationship and provide an initial test of the stability of the coefficient associated with the GII. However, the over-identification diagnostics obtained for the System GMM specifications do not allow this estimate to be considered a definitive econometric validation. In particular, Hansen’s tests lead to the rejection of the null hypothesis of global validity of the instruments at conventional thresholds in both specifications examined. For this reason, the analysis focuses specifically on the Difference GMM, which excludes level equations and relies solely on first-difference equations. A key specification treats the GII as potentially endogenous and uses its second- and third-order lags as endogenous instruments. This strategy allows

us to verify whether the absence of a statistically significant effect of the GII persists when its potential endogeneity is explicitly accounted for.

3.6. Instrumentation Strategy

The instrumentation strategy is defined in a parsimonious manner to limit the risk of instrument proliferation. In the central dynamic specification, the lagged dependent variable and the GII are treated as potentially endogenous variables and instrumented using their own second- and third-order lags. The instruments are constructed using the “collapse” option, in accordance with Roodman’s (2009) recommendation, to limit the number of instruments generated by the GMM procedure. In the central Difference GMM specification, GFCF, lnLF, and lnEC are introduced as Type IV instruments. The instrument matrix thus includes the internal GMM instruments associated with the lagged dependent variable and the GII, supplemented by the IV instruments corresponding to the control variables. This strategy results in a parsimonious instrument matrix. In the core specification, the model uses 7 instruments for 30 groups, meaning the number of instruments is significantly lower than the number of groups. This restriction aims to reduce the risk that an excessive number of instruments will weaken the power of the over-identification tests.

3.7. Validity Tests and Diagnostics

Several diagnostics are used to assess the quality of the dynamic estimates. The Arellano–Bond autocorrelation tests are used to examine the presence of serial correlation in the differenced residuals. First-order autocorrelation, AR (1), is generally expected after taking differences and does not, on its own, invalidate the model. However, the absence of second-order autocorrelation, AR (2), is an important condition for the validity of lagged instruments. The overall validity of the over-identification constraints is examined using the Hansen and Sargan tests. The null hypothesis of these tests corresponds to the joint validity of the instruments. The Difference-in-Hansen test is also used in the System GMM specifications to examine the validity of specific subsets of instruments, particularly those associated with level equations. The results are interpreted in conjunction with the number of instruments and the number of groups. In the System GMM specifications, the absence of AR (2) is consistent with the chosen dynamic structure, but the Hansen tests indicate weak over-identification conditions. These results suggest that the System GMM should be interpreted with caution and that particular importance should be placed on the Difference GMM specification. In the central Difference GMM specification, the AR (2) test is not significant ($p = 0.180$), while the Hansen test does not reject the null hypothesis of global validity of the instruments ($p = 0.165$). The limited number of instruments also reinforces the parsimony of this specification.

3.8. Robustness Analysis

The robustness of the results is assessed using several dynamic specifications. First, the model is estimated using System GMM with different instrument windows for the lagged dependent variable. Second, the model is re-estimated using Difference GMM to examine the stability of the results when the level equations of the System GMM are excluded. One Difference GMM specification initially treats the

GII as exogenous, while a more rigorous specification explicitly treats the GII as endogenous and uses its second- and third-order lags as internal instruments. The latter constitutes the central robustness specification, as it allows for potential reverse causality between innovation and carbon intensity. The comparison of the different estimates focuses primarily on the stability of the sign, magnitude, and significance of the coefficient associated with the GII, as well as on the coefficients of the lagged dependent variable and the control variables. Particular attention is paid to the AR (2), Hansen, and Sargan diagnostics. The objective of this strategy is not to select an estimate based solely on the significance of the coefficients, but to verify whether the result regarding the GII remains stable when the assumptions regarding dynamics and endogeneity are modified. In particular, the convergence of the Difference GMM estimates shows that the GII coefficient remains statistically insignificant when its potential endogeneity is explicitly taken into account.

4. Empirical Results

This section presents the empirical results obtained for the 30 emerging economies studied over the 2011–2022 period. The analysis is conducted using a highly balanced panel of 360 country-year observations. The empirical strategy proceeds in several stages. We first present the descriptive statistics and the correlation and multicollinearity tests. The time-series properties of carbon intensity are then examined using unit root tests. A dynamic fixed-effects estimation is then used to assess the persistence of carbon intensity. Finally, System GMM and Difference GMM estimators are employed to account for the dynamics of the dependent variable and potential endogeneity issues. Particular attention is given to a Difference GMM specification in which the GII is treated as potentially endogenous.

4.1. Sample Structure and Descriptive Statistics

The sample consists of 30 emerging economies observed over the 2011–2022 period, representing 360 country-year observations. It exhibits significant heterogeneity in terms of economic development, innovation capacity, and technological transformation. More specifically, the sample includes both relatively advanced emerging economies—some of which closely resemble developed economies in terms of structural and technological characteristics—and emerging economies that remain at lower levels of development, technological infrastructure, and innovation capacity. This heterogeneous composition is important for interpreting the results. The environmental impact of innovation may indeed vary depending on the degree of technological maturity, the structure of production, energy efficiency, and the institutional capacity of the economies under consideration. Thus, the use of the Global Innovation Index (GII), which measures innovation in aggregate terms, can lead to different effects depending on whether innovation is primarily oriented toward technology- and environment-intensive activities or toward activities more closely associated with production expansion. The empirical analysis therefore accounts for this heterogeneity by using a dynamic panel structure and GMM estimators, which allow, in particular, for controlling for the high persistence of carbon intensity and potential endogeneity issues. Table 4.1 presents the descriptive statistics for the variables used in

the estimates. The differences observed between the minimum and maximum values confirm the existence of substantial variation among the economies in the sample, particularly for the GII and gross fixed capital formation.

Table 1
Descriptive statistics for the model variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
lnCI	360	-9.3038	0.9959	-11.6979	-7.0232
lnLF	360	17.0196	1.3053	14.5642	20.4763
lnEC	360	7.1399	0.7227	5.3000	8.9846
GII	360	34.6124	6.6976	16.7000	55.3000
GFCF	360	23.8574	6.6425	12.4460	44.0755

Note : lnCI, lnLF, and lnEC refer to the logarithms of carbon intensity, labor force, and energy consumption, respectively. GII refers to the Global Innovation Index, and GFCF refers to gross fixed capital formation.

Source : Authors' calculations based on data from the study.

The descriptive statistics reveal relatively significant heterogeneity among the economies studied, particularly with regard to innovation and capital accumulation. The GII ranges from 16.7 to 55.3, reflecting substantial differences in national innovation capacities. This dispersion is economically significant, as emerging economies have varying capacities in terms of research, technology adoption, infrastructure, and the institutional environment. The dispersion observed for energy consumption also reflects the diversity of the panel's production structures. Some economies are more oriented toward industrial and energy-intensive activities, while others have less energy-intensive production structures. This heterogeneity justifies the use of a dynamic panel approach that allows for simultaneous consideration of differences between countries and the persistence of carbon intensity over time.

4.2. Correlation and Multicollinearity

Before performing multivariate estimations, the correlations between the main explanatory variables and the dependent variable are examined. This step helps identify any strong linear relationships among the variables that could affect the accuracy of the estimated coefficients.

Table 2
Correlation Matrix and Variance Inflation Factors

Variable	lnCI	GII	GFCF	lnLF	lnEC
lnCI	1.000	-0.358***	0.257***	0.442***	-0.451***
GII	-0.358***	1.000	0.146**	0.006	0.581***
GFCF	0.257***	0.146**	1.000	0.425***	0.001
lnLF	0.442***	0.006	0.425***	1.000	-0.244***
lnEC	-0.451***	0.581***	0.001	-0.244***	1.000
VIF		1.58	1.25	1.34	1.66
Average VIF			1.46		
Note : ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.					

Source : Authors' calculations.

Source: Authors' calculations.

The correlation matrix indicates a negative association between the GII and carbon intensity (-0.358), suggesting that, at a descriptive level, economies with better innovation performance tend to have lower carbon intensity. However, this simple relationship should not be interpreted as a causal effect, as it does not account for the dynamics of carbon intensity or other economic determinants. The GII also shows a relatively high correlation with energy consumption (0.581). This association may reflect the fact that economies with greater technological capabilities are also those with higher levels of economic activity and energy consumption. The variance inflation factors range from 1.25 to 1.66, with an average of 1.46. These values do not suggest a significant problem of multicollinearity among the explanatory variables. The coefficients estimated in the multivariate models can therefore be interpreted without any indication of strong statistical redundancy among the explanatory variables.

4.3. Stationarity Tests

Given the time dimension of the panel data and the potential high persistence of carbon intensity, unit root tests are conducted prior to the dynamic estimations. Three complementary approaches are used: Levin–Lin–Chu (LLC), Im–Pesaran–Shin (IPS), and Fisher tests based on ADF statistics.

Table 3
Unit root tests for carbon intensity

Test	lnCI – Niveau	ΔlnCI – First difference
Levin–Lin–Chu	-2.2553 (0.0121)	-9.5856 (0.0000)
Im–Pesaran–Shin	2.2282 (0.9871)	-6.0276 (0.0000)
Fisher-ADF – χ^2 inverse	47.1548 (0.8862)	191.8281 (0.0000)
Fisher-ADF – Z inverse	2.8799 (0.9980)	-7.7070 (0.0000)
Fisher-ADF – Logit	2.8470 (0.9975)	-8.9140 (0.0000)
Fisher-ADF – χ^2 Modified	-1.1726 (0.8795)	12.0342 (0.0000)
Note : Statistics are reported with p-values in parentheses. The tests are specified with a constant, no time trend, and a lag.		

Source : Authors' calculations.

The level results are mixed. The LLC test rejects the null hypothesis of a unit root for lnCI (p = 0.0121), whereas the IPS test and the various versions of the Fisher-ADF test do not reject it. The stationarity of carbon intensity at the level can therefore not be considered uniformly established. In contrast, the three approaches converge after first differentiation. The p-values are all equal to 0.000, indicating that ΔlnCI is stationary. This convergence provides strong evidence in favor of the stationarity of changes in carbon intensity. From an economic perspective, this dynamic is consistent with the structural nature of carbon intensity. Energy infrastructure, industrial equipment, and production technologies are characterized by a certain degree of inertia, such that levels of carbon intensity can remain persistent while their annual variations are more stable. These results reinforce the relevance of a dynamic approach to studying the determinants of carbon intensity.

4.4. Persistence of Carbon Intensity

Before proceeding with the GMM estimates, the persistence of carbon intensity is examined using a dynamic fixed-effects model. The lagged term for carbon intensity is included to assess the extent to which past environmental performance influences current performance.

Table 4
Estimates of Carbon Intensity Persistence

Variables	Fixed Effects	Fixed Effects Country + Year
L.lnCI	0.9213*** (0.0213)	0.8640*** (0.0290)
Fixed Effects Country	Oui	Oui
Fixed Effects Year	Non	Oui
Observations	330	330
Country	30	30
R^2 within / R^2	0.8617	0.9979
Note : The standard errors in the second model are cluster-corrected at the country level. *** indicates significance at the 1% level.		

Source : Authors' calculations.

The coefficient for lagged carbon intensity is positive and highly significant in both estimates. It reaches 0.9213 in the fixed-effects model and 0.8640 when time effects are also included. These results indicate strong persistence in carbon intensity. This persistence means that current environmental performance remains strongly linked to past trajectories. Economies generally cannot rapidly change their carbon intensity due to the lifespan of infrastructure, existing productive capital, the technologies used, and sectoral specialization. The transition to a lower-carbon economy thus appears to be a gradual process requiring the renewal of capital and technological and energy transformations. The high persistence observed also provides an econometric justification for the use of dynamic GMM models in the remainder of the analysis.

4.5. System GMM Estimates

The presence of a lagged dependent variable and the possibility of endogeneity among innovation, investment, and environmental performance justify the use of a System GMM estimation. The models are estimated in two stages with robust standard errors and a limited number of instruments obtained using the collapse option.

Table 5
System GMM Estimates

Variables	System GMM (lag 2–3)	System GMM (lag 2)
lnCI	1.1142*** (0.0643)	1.0933*** (0.0726)
GII	0.0016 (0.0018)	0.0000 (0.0019)
GFCF	-0.0049 (0.0033)	-0.0045 (0.0033)
lnLF	-0.0271* (0.0136)	-0.0166 (0.0135)
lnEC	0.0456 (0.0341)	0.0465 (0.0369)
Constant	1.2263* (0.6223)	0.8902 (0.6700)
Observations	330	330
Countries	30	30
Instruments	8	7
AR(1), p-value	0.000	0.000
AR(2), p-value	0.160	0.118
Hansen, p-value	0.027	0.019

Note: Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The estimates are obtained using a two-stage System GMM with instruments reduced by collapse.

Source: authors' calculations.

The coefficient of L.lnCI is positive and highly significant in both specifications. Its value greater than one 1.1142 and 1.0933, respectively indicates strong inertia in carbon intensity but also calls for caution in interpreting this dynamic specification. The coefficient of GII is positive in both models but statistically insignificant. It is equal to 0.0016 in the first specification (p = 0.392) and virtually zero in the second (p = 0.997). The System GMM therefore provides no statistical evidence of an effect of the general level of innovation on carbon intensity. From an economic perspective, this result can be explained by the broad nature of the GII. This indicator measures an economy's general innovation capabilities and does not necessarily distinguish between innovations intended to reduce energy consumption or emissions. An economy can therefore increase its innovation capabilities while simultaneously developing energy-intensive industrial, manufacturing, or technological activities. The coefficient for GFCF is negative but not significant in both specifications. Thus, in the System GMM, capital formation does not have a statistically significant effect on carbon intensity. Labor has a negative coefficient that is significant at the 10% level in the first specification, but this result disappears when the instrument window is narrowed. It should therefore be interpreted with caution. Finally, energy consumption has a positive but non-significant coefficient. The lack of significance may reflect, in particular, differences among

economies regarding the composition of their energy mix and the efficiency with which energy is converted into economic activity. The AR(2) tests are not significant in either model (p = 0.160 and p = 0.118), which provides no evidence of second-order autocorrelation. However, the Hansen tests are significant (p = 0.027 and p = 0.019). The over-identification restrictions are therefore rejected at conventional significance levels, which suggests that the System GMM should be interpreted with caution rather than considered a definitive econometric validation.

4.6. Robustness Analysis: Difference GMM and Treatment of GII Endogeneity

To verify whether the results depend on the choice of the GMM system, Difference GMM estimates are calculated. Three specifications are considered: the first with lags 2–3, the second with only the second lag, and the third in which the GII is treated as potentially endogenous.

Table 6
Difference GMM Estimates and Robustness

Variables	Difference GMM (lag 2–3)	Difference GMM (lag 2)	Difference between GMM and endogenous GII
L.lnCI	1.0430*** (0.0962)	0.9874*** (0.0897)	0.9795*** (0.0643)
GII	0.0012 (0.0014)	0.0004 (0.0015)	0.0042 (0.0051)
GFCF	-0.0094** (0.0044)	-0.0086** (0.0040)	-0.0102** (0.0040)
lnLF	-0.3534 (0.2722)	-0.3886 (0.2314)	-0.3954 (0.2391)
lnEC	-0.0270 (0.1219)	-0.0368 (0.1122)	-0.0404 (0.1153)
Observations	300	300	300
Countries	30	30	30
Instruments	6	5	7
AR(1), p-value	0.000	0.000	0.000
AR(2), p-value	0.140	0.111	0.180
Hansen, p-value	0.092	—	0.165

Note: Robust standard errors are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The third specification treats GII and L.lnCI as potentially endogenous variables and uses their 2–3 lags as instruments. The second specification is exactly identified; therefore, the Hansen test is not available.

Source: Authors' calculations.

The three Difference GMM specifications confirm the strong persistence of carbon intensity. The coefficient of the lagged term is 1.0430, 0.9874, and 0.9795, respectively, and remains highly significant.

The result obtained when the GII is treated as potentially endogenous is particularly interesting, since the coefficient of the lagged carbon intensity approaches unity. The result regarding the GII is remarkably stable in terms of significance. The coefficient is positive in all three specifications, but none provides statistical evidence of a significant effect: p = 0.399, p = 0.811, and p = 0.415, respectively. Explicitly accounting for the potential endogeneity of the GII therefore does not alter the overall conclusion. This result suggests that general innovation, as measured by the GII, does not automatically translate into improved carbon performance. From an economic perspective, innovations can operate simultaneously through multiple channels. They can improve process efficiency and reduce resource use, but they can also stimulate production, investment, and energy demand. The net effect therefore depends on the nature of the innovations and the productive and energy structure of each economy.

This interpretation is consistent with the literature, which distinguishes between general innovation and innovation explicitly focused on the environment. Weber, Falchi, and Chassagnon-Haned (2025), drawing on a global panel of 229 countries from 2013 to 2020, highlight a negative relationship between innovation and CO_2 emissions, while emphasizing that innovation alone is not sufficient to ensure a sustainable environmental trajectory. Conversely, Deng et al. (2024), analyzing 33 developed and 42 developing economies over the period 2000–2019, show that green technological innovation reduces carbon intensity, with a particularly pronounced effect in developing economies. These differences suggest that the environmental orientation of innovation may be a determining factor. GFCF, on the other hand, shows a more stable result. Its coefficient is negative and significant in all three Difference GMM specifications, with values ranging from − 0.0086 to -0.0102. This relationship suggests that capital accumulation may help reduce carbon intensity when equipment replacement is accompanied by improvements in productivity or energy efficiency. This interpretation should nevertheless be treated with caution, as GFCF does not allow for a direct distinction between green investments and conventional investments.

Labor and energy consumption have negative coefficients in all three models, but these are not statistically significant. These results therefore do not allow us to establish a robust effect of these variables on carbon intensity within the scope of this study.

4.7. Robustness of the Selected Specification

Among the estimated dynamic specifications, the Difference GMM with potentially endogenous GII constitutes the central robustness specification. This estimate yields a GII coefficient of 0.0042, but it remains insignificant (p = 0.415). It also confirms the negative and significant effect of GFCF and the high persistence of carbon intensity. The econometric diagnostics are also more favorable in this specification The AR(2) test is not significant (p = 0.180), providing no evidence of second-order serial autocorrelation. The Hansen test is not rejected (p = 0.165), providing no evidence against over-identification constraints. Furthermore, the model uses only seven instruments for 30 groups, thereby limiting the risk of instrument proliferation. In contrast, the Hansen tests for the two System GMM specifications are significant (p = 0.027 and p = 0.019). The System GMM is therefore retained as a supplementary estimate, but it is not considered the primary validation specification.

4.8. Economic Summary of the Results

One of the main findings of the analysis concerns the absence of a statistically significant effect of the Global Innovation Index (GII) on carbon intensity across the various dynamic specifications. This result remains stable when the GII is treated as exogenous in the Difference GMM and when it is considered potentially endogenous in the central robustness specification. In the latter specification, the GII coefficient is positive but statistically insignificant (0.0042; $p = 0.415$). The results therefore do not allow us to establish a direct and robust effect of aggregate innovation on carbon intensity in the sample studied. This lack of statistical significance can be interpreted, in particular, in light of the sample's high heterogeneity. The sample comprises emerging economies with varying levels of development and technological maturity: some have innovation capabilities relatively close to those observed in developed economies, while others are still characterized by less advanced technological infrastructure, productive capacities, and innovation systems. In such a group, the same level of aggregate innovation can produce different environmental effects depending on the productive structure, the energy mix, technological efficiency, and the ability of institutions to steer innovation toward lower-carbon activities. A second factor relates to the nature of the GII itself. The GII measures an economy's overall capacity for innovation and does not necessarily distinguish between innovations intended to improve environmental performance and those likely to increase productivity, output, or energy consumption. Thus, an increase in the GII does not automatically imply an increase in green innovation. The environmental impact of innovation may depend on its composition and sectoral focus. This finding contrasts with certain international studies that identify a reduction in emissions resulting from innovation. For example, Weber, Falchi, and Chassagnon-Haned (2025), using a sample of 229 countries from 2013 to 2020, highlight a negative relationship between innovation as measured by the GII and per capita CO_2 emissions. Conversely, Yu et al. (2022), analyzing 52 countries, show that innovation can also increase environmental pressures when financial conditions do not allow this innovation to be accompanied by improvements in environmental efficiency. Similarly, Deng et al. (2024) show that it is specifically green technological innovation that helps reduce carbon intensity in both developed and developing economies.

These differences suggest that the absence of a significant effect of the GII in the present study does not necessarily mean that innovation is unimportant for the environmental transition. Rather, it indicates that general innovation does not automatically translate into improved carbon efficiency. In such a heterogeneous sample of emerging economies, the environmental benefits of innovation may depend on its nature, its focus on green technologies, and the economic and institutional environment in which it is implemented. Furthermore, the high persistence of carbon intensity is the most stable result among the estimates. In the Difference GMM specification chosen as the core robustness test, the lagged coefficient for carbon intensity is 0.9795 ($p < 0.001$), indicating strong inertia in carbon performance. This persistence means that past characteristics of the productive and energy structure continue to strongly influence current environmental performance. The transition to a lower-carbon economy thus appears to be a gradual process rather than an immediate adjustment.

Finally, gross fixed capital formation has a negative and statistically significant coefficient in the main specification (-0.0102; p = 0.016). This result indicates that an increase in investment is associated with a decrease in carbon intensity, all else being equal. This relationship may be consistent with the renewal of productive capital and improved equipment efficiency, but this interpretation should be viewed with caution, as the data used do not allow for a direct distinction between conventional and green investments.

5. Discussion of the Results

5.1. Innovation and Carbon Intensity

The main finding of this study concerns the relationship between innovation—measured by the Global Innovation Index (GII)—and carbon intensity. Unlike some studies that identify a significant effect of innovation on environmental performance, the estimates obtained in this research do not reveal a statistically significant effect of the GII on carbon intensity. In the System GMM model, the GII coefficient is 0.00158 (p = 0.392) with a lag window of two to three periods and becomes virtually zero in the specification using only the second lag (0.000008; p = 0.997). The same result is observed in the Difference GMM: the coefficient is 0.00120 (p = 0.399) when the GII is treated as exogenous and 0.00420 (p = 0.415) when it is considered potentially endogenous. Thus, the change in estimation method and the explicit treatment of GII endogeneity do not alter the main conclusion : the direct effect of the overall level of innovation on carbon intensity is not statistically significant in the sample studied. This result must first be interpreted in light of the sample's composition. The study covers 30 emerging economies with widely varying levels of development, technological capabilities, and productive transformation. The sample therefore does not consist of homogeneous economies. Some emerging economies have relatively well-developed innovation systems and technological characteristics that bring them closer to those of advanced economies, while others remain characterized by more limited innovation capabilities, less developed technological infrastructure, and a productive structure that is more dependent on traditional industrial and energy activities. This heterogeneity can lead to different environmental effects resulting from the same improvement in the GII. From an economic perspective, an increase in the GII represents an overall improvement in innovation capacity, but does not necessarily mean that the innovations developed are directly aimed at reducing emissions. Innovation can improve productivity, process quality, digitization, or business organization, while simultaneously fueling the expansion of production and energy demand. In some emerging economies, the efficiency gains generated by innovation may thus be partially offset by the expansion of economic activity, increased infrastructure, and greater energy use. The lack of statistical significance of the GII may therefore reflect the coexistence of these opposing mechanisms rather than a general lack of contribution by innovation to the environmental transition. This interpretation is consistent with the findings of Yu et al. (2022), who studied 52 countries over the period 1990–2014. The authors initially find a positive and significant effect of innovation on CO_2 emissions, suggesting that innovation can increase environmental pressure. However, their analysis also shows that this effect becomes less detrimental when the level of financial

development is sufficiently high. In particular, the authors identify thresholds for private credit growth and market capitalization beyond which innovation is associated with an improvement in environmental quality. Their findings thus show that the environmental impact of innovation depends on the economic and financial context in which it is implemented. Conversely, Weber, Falchi, and Chassagnon-Haned (2025), using a panel of 229 countries from 2013 to 2020 and drawing directly on the GII, identify a robust negative relationship between the level of innovation and per capita CO_2 emissions. Their findings hold even after controlling for the level of development and other determinants of emissions. The authors emphasize, however, that innovation—even when it improves environmental performance—is not sufficient on its own to ensure a sustainable level of emissions, and they highlight the growing importance of green innovations or eco-innovations. The difference between this finding and that obtained in the present study can be explained by several factors. First, the study by Weber et al. covers a much broader set of countries and includes economies at very different levels of development, whereas the present study focuses on emerging economies. Second, the present analysis uses a dynamic panel structure that places particular emphasis on the persistence of carbon intensity and potential endogeneity issues. Third, although both studies use the GII, the composition of the economies under observation and the structure of their energy and production systems may lead to different effects. The distinction between general innovation and green innovation also appears to be essential. Deng et al. (2024) analyze 33 developed countries and 42 developing countries over the 2000–2019 period and show that green technological innovation helps reduce carbon intensity. Their study focuses specifically on the green dimension of innovation, which distinguishes it from an aggregate indicator such as the GII. Similarly, Uzar (2024), in a study focusing on seven major emerging economies, shows that green innovation technologies reduce the ecological footprint, while economic growth and energy consumption increase environmental pressure. These results provide a better understanding of the non-significance of the GII found here. The GII measures general innovation capacity and aggregates innovations whose environmental impacts may vary. An economy can therefore improve its level of innovation without this improvement necessarily being focused on clean technologies, energy efficiency, or the decarbonization of production. In a sample composed of heterogeneous emerging economies—some of which are close to advanced economies and others still undergoing industrial transformation—these opposing effects may cancel each other out at the aggregate level. The result should therefore not be interpreted as indicating that innovation is unimportant for the environmental transition. Rather, it suggests that innovation in general does not automatically lead to an improvement in carbon intensity. The nature of innovation, its focus on green technologies, the energy structure, and the economic and financial conditions under which it is adopted can determine its environmental impact. This interpretation is particularly important in the context of emerging economies, where innovation can simultaneously support technological modernization and the expansion of productive capacities that are still relatively energy-intensive.

5.2. Persistence of Carbon Intensity

Beyond the GII coefficient, the most stable result from the estimates concerns the high persistence of carbon intensity. The coefficient for the lagged dependent variable is 0.9213 in the fixed-effects model

and 0.8640 when individual and time-specific fixed effects are included. In the GMM estimates, the coefficient remains high : 1.1142 and 1.0933 in the two System GMM specifications, 1.0430 in the standard Difference GMM, and 0.9795 in the Difference GMM specification in which the GII is treated as endogenous. This persistence indicates that carbon performance exhibits strong temporal inertia. Current levels of carbon intensity remain strongly linked to the productive, energy, and technological structures inherited from previous periods. From an economic perspective, an economy cannot therefore rapidly change its carbon intensity solely through a one-time increase in innovation or investment. Production equipment, energy infrastructure, the technologies used, and consumption patterns are relatively persistent determinants. The value close to unity obtained in the central Difference GMM specification reinforces this interpretation. It indicates that changes in carbon intensity occur gradually and that past characteristics continue to play an important role in the current situation. This result also justifies the use of a dynamic model rather than a static specification, since omitting this persistent component could lead to attributing to contemporary explanatory variables a portion of an effect that actually stems from the past trajectory of carbon intensity. This strong persistence also helps explain why the contemporary effect of the GII does not appear to be significant. When current levels of carbon intensity are strongly determined by past conditions, an improvement in innovation capacity may take several periods to translate into a measurable transformation in carbon performance.

5.3. Gross Fixed Capital Formation and Carbon Intensity

In contrast to the result obtained for the GII, gross fixed capital formation (GFCF) exhibits a negative and statistically significant coefficient in the Difference GMM estimates. The coefficient is -0.00937 ($p = 0.043$) when the GII is treated as exogenous and − 0.01015 ($p = 0.016$) when the GII is treated as endogenous. The sign and significance of GFCF are therefore relatively stable across the two Difference GMM specifications. From an economic perspective, this result indicates that an increase in capital accumulation is associated with a decrease in carbon intensity in the sample, once the dynamics of carbon intensity and the potential endogeneity of the GII are taken into account. One possible interpretation is that capital accumulation facilitates the renewal of productive equipment and the adoption of more efficient technologies. Investments in more modern equipment can make it possible to produce more with a relatively smaller amount of energy and emissions per unit of output. This interpretation should, however, be viewed with caution. GFCF is an aggregate indicator that does not allow for distinguishing between green investments and conventional investments. The negative coefficient obtained therefore does not mean that any form of investment necessarily reduces emissions. Rather, it may reflect, in the sample under consideration, a process of modernization of productive capital in which new equipment is relatively more efficient than existing capital. The significance of GFCF in the Difference GMM estimates—even though its coefficient is not statistically significant in the System GMM—should also be interpreted with caution. The Hansen tests for the System GMM are 0.027 and 0.019, respectively, which raises doubts about the overall validity of the over-identification restrictions in these two specifications. Conversely, the Difference GMM with endogenous GII yields a Hansen test value of 0.165 and an AR (2) test value of 0.180. The negative result for GFCF is

therefore primarily interpreted as a robust relationship within properly diagnosed Difference GMM specifications, rather than as a conclusion independent of any econometric sensitivity analysis.

5.4. Labor Force, Energy Consumption, and Carbon Intensity

The labor force and energy consumption do not have a statistically significant effect in the Difference GMM specification chosen as the baseline. The coefficient for the logarithm of the labor force is -0.3954 ($p = 0.109$), while that for the logarithm of energy consumption is -0.0404 ($p = 0.728$). Both coefficients are negative, but their lack of significance does not allow us to establish a systematic relationship with carbon intensity in the sample. For the labor force, the negative sign may be consistent with an improvement in labor productivity and a more efficient use of resources when the increase in the labor force is accompanied by skill accumulation and technological diffusion. However, the lack of significance indicates that this effect is not systematic enough to be considered a robust determinant of carbon intensity in the economies studied. This lack of effect may also reflect the significant differences in labor markets, productivity levels, and sectoral structures among the countries in the sample. Energy consumption also has a negative coefficient, but one that is largely insignificant. This result does not mean that energy is unimportant for environmental performance. Rather, he suggests that the total amount of energy consumed does not, on its own, adequately characterize carbon intensity. The environmental impact of energy depends, in particular, on how efficiently it is used and on its composition. An increase in energy consumption can occur simultaneously with an expansion of production and the modernization of equipment. Furthermore, two economies consuming comparable amounts of energy may have different carbon intensities depending on their energy mix. This interpretation is consistent with Uzar (2024), who shows, across seven emerging economies, that energy consumption contributes to increased environmental pressure, whereas green innovation technologies reduce it. It is also in line with Deng et al. (2024), whose analysis of developed and developing countries highlights the importance of distinguishing between energy consumption and green technologies when explaining emissions intensity. Thus, the non-significant coefficients obtained for the labor force and energy consumption should not be interpreted as indicating that these factors lack economic significance. Rather, they suggest that their aggregate effect is difficult to identify in a sample of highly heterogeneous emerging economies, particularly when past trends in carbon intensity are explicitly controlled for.

5.5. Summary

Taken as a whole, the results highlight three main characteristics of the relationship between innovation and carbon intensity in the economies studied. First, the GII does not have a statistically robust effect on carbon intensity. This conclusion holds when different instrument windows are used and when the GII is treated as potentially endogenous. Second, carbon intensity is highly persistent, indicating that current environmental performance depends largely on past trends. Third, gross fixed capital formation exhibits a significant negative relationship with carbon intensity in the Difference GMM specifications. A comparison with the literature shows that the finding regarding the GII does not necessarily contradict

previous research. Weber et al. (2025) find a negative relationship between the GII and CO_2 emissions in a large international sample, whereas Yu et al. (2022) show that innovation may initially increase environmental pressure before financial development mitigates this effect. For their part, Deng et al. (2024) and Uzar (2024) place greater emphasis on the role of specifically green innovation in enhancing green growth. The difference between these results can therefore be understood in terms of the composition of the sample and the nature of the innovation measured. In this study, the 30 emerging economies exhibit varying levels of development and technological maturity. Some are relatively close to advanced economies in terms of technology, while others remain in a phase of industrial transformation and accumulation of productive capacity. In this context, an increase in the GII may correspond to environmentally beneficial innovations in some countries, but to innovations more oriented toward productive expansion in others. These effects may then offset each other at the panel level. The results thus suggest distinguishing between general innovation capacity and decarbonization capacity. The GII is a relevant indicator of national innovation capacity, but it does not directly provide information on the proportion of innovations dedicated to clean technologies, energy efficiency, or emissions reduction. The results therefore suggest that the environmental impact of innovation depends less on its aggregate level than on its direction and the economic conditions under which it is implemented. Ultimately, the results indicate that innovation, on its own, is not an automatic mechanism for reducing carbon intensity in the emerging economies studied. The high persistence of carbon intensity shows that the environmental transition also depends on legacy production and energy structures. The negative relationship observed for gross fixed capital formation further suggests that the modernization of productive capital can play a role in reducing carbon intensity. The economic challenge therefore lies less in a general increase in innovation than in the ability of economies to direct their technological capabilities and investments toward more efficient and less carbon-intensive forms of production.

6. Conclusion

This study analyzes the relationship between national innovation capacity and carbon intensity across a panel of 30 emerging economies over the 2011–2022 period, taking into account the dynamics of carbon intensity and potential endogeneity issues. The econometric analysis, based on System GMM and Difference GMM estimates, shows that the Global Innovation Index (GII) has no statistically significant effect on carbon intensity across the various specifications considered. This result remains unchanged when the GII is treated as potentially endogenous, indicating that a general increase in innovation capacity does not automatically translate into a measurable improvement in carbon performance in the economies studied. From an economic perspective, this result underscores that general innovation capacity alone is not sufficient to guarantee a transition to a low-carbon economy. The economies under consideration exhibit varying levels of development, technological maturity, productive structure, and energy dependence. Some possess relatively advanced technological capabilities, while others remain engaged in processes of industrial transformation and the accumulation of productive capacities. In this context, innovations may be directed toward different objectives and produce heterogeneous environmental effects. The economic challenge, therefore, is not

merely to increase the overall level of innovation, but to steer it toward technologies, processes, and investments capable of sustainably improving resource efficiency and reducing carbon intensity. The results also highlight a high degree of persistence in carbon intensity. The high coefficient of the lagged dependent variable in the various estimates indicates that current environmental performance remains strongly linked to past trajectories. This persistence reflects the importance of existing production structures, infrastructure, technologies, and energy systems. It implies that the transformation of carbon intensity is a gradual process and that the effects of technological or production changes may take time before significantly altering the environmental trajectory. Gross fixed capital formation is also a key finding of the analysis. In the Difference GMM estimates, its coefficient is negative and statistically significant, suggesting that increased capital accumulation is associated with a reduction in carbon intensity in the sample. From an economic perspective, this relationship may be consistent with a process of renewal and modernization of productive capital, leading to a more efficient use of resources. However, since gross fixed capital formation is an aggregate indicator, it does not allow us to directly determine what portion of this investment corresponds to low-carbon equipment or infrastructure. The challenge, therefore, is not only the accumulation of capital, but also the quality, technology, and environmental orientation of the capital invested. The findings thus have several economic implications. For emerging economies, improvements in innovation capacity should be accompanied by a stronger focus on clean technologies, energy efficiency, and the modernization of production equipment. Similarly, investment policies can play an important role when they promote the renewal of capital toward more efficient and less carbon-intensive technologies. The environmental transition therefore does not depend on a single factor, but on the ability to transform technological progress and capital accumulation into sustainable improvements in productive and environmental efficiency. This study does, however, have certain limitations. First, the GII is an aggregate measure of innovation and does not allow for a precise distinction between green innovation and other forms of innovation. Second, despite the significant heterogeneity among the 30 economies studied, the sample size does not allow for an in-depth examination of the differences between groups of countries based on their level of development, productive structure, or energy mix. Third, gross fixed capital formation and energy consumption are also measured on an aggregate basis and do not allow for a precise identification of the technological or environmental composition of investments and energy sources. These limitations open up several avenues for future research. Future research could distinguish between general innovation and green innovation, examine economies separately based on their level of development or energy structure, and incorporate more precise measures of clean technologies, green investments, and energy efficiency. It would also be relevant to investigate whether the effect of innovation on carbon intensity depends on institutional quality, financial development, the energy mix, or trade openness. Ultimately, the results show that innovation is an important driver of economic transformation, but that its contribution to reducing carbon intensity is not automatic. In emerging economies, this contribution depends on how innovation capabilities and capital accumulation are effectively transformed into more efficient technologies, equipment, and production processes. A sustainable reduction in carbon intensity thus appears to be a gradual process, relying less on innovation alone than on its ability to support a structural transformation of the production system toward a more efficient and lower-carbon trajectory.

Declarations

A. Ethics statement

Not applicable.

B. Consent to participate

Not applicable.

C. Consent to publish

Not applicable.

D. Statement on Data Availability

The data used in this study are publicly available through the Global Innovation Index (GII) database of the World Intellectual Property Organization (WIPO) https://www.wipo.int/global_innovation_index/en/.

and the World Bank's World Development Indicators (WDI) database https://databank.worldbank.org/source/world-development-indicators

Author Contribution

Fayrouz Guesmi (FG) conducted the conceptualization, methodology, data collection and curation, formal analysis, investigation, and preparation of the original manuscript. Younes Boujelbene (YB) provided supervision, conceptual guidance, validation, and critical revision of the manuscript. Both authors read and approved the final version of the manuscript.

Data Availability

Data availability: The data used in this study are publicly available through the Global Innovation Index (GII) database of the World Intellectual Property Organization (WIPO) https://www.wipo.int/global_innovation_index/en/.and the World Bank's World Development Indicators (WDI) database https://databank.worldbank.org/source/world-development-indicators

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Figures

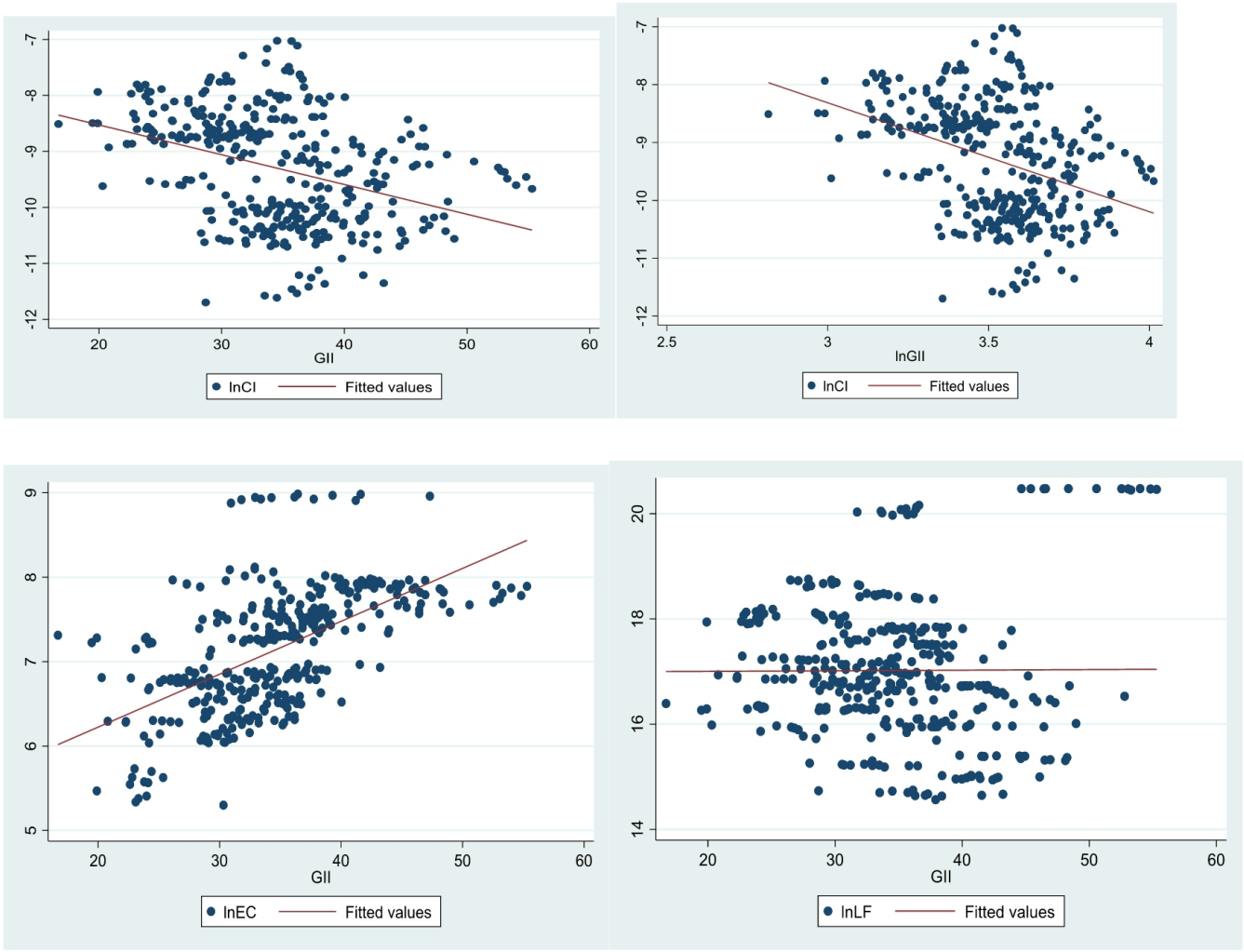


Figure 1

Relationship between Inclusive Innovation and Carbon Intensity in Emerging Economies (2011–2022)
Source: Authors' calculations.