

Towards a cleaner post-production agro-system with agricultural innovation: theoretical and empirical evidence on a global scale

Minh-Khoa Nguyen¹

Foreign Trade University, Vietnam

nguyenminhkhoea.nckh@gmail.com

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Abstract

Despite the agricultural post-production phase accounting for a substantial portion of the global agricultural emissions, empirical inquiry into its decarbonization remains sparse. This study addresses this critical research gap by examining the green transition of post-production processes, specifically evaluating the role of agricultural R&D expenditure as a catalyst for environmental remediation. Initially, this research develops a theoretical model grounded in the transitional stage, in which rational, profit-maximizing producers choose the optimal combination of “brown” (carbon-intensive) and “green” (low-carbon) inputs in the presence of agricultural innovation. Two regimes are identified: the *scale-up regime* (where innovation is complementary to carbon-intensive inputs, making the inputs complements), and the *substitution regime* (where innovation complements low-carbon inputs, allowing green resources to substitute carbon-intensive ones). Consequently, in the scale-up regime, agricultural R&D spending will increase the use of carbon-intensive inputs, resulting in an increase in emissions. In contrast, in the substitution regime, agricultural R&D introduces sustainability-inducing effects. With the global data covering 89 countries from 1990 – 2021, the empirical analysis has confirmed the theoretical model developed and revealed that the scale-up regime is dominating the global economy, as agricultural R&D spending actually leads to a rise in both CO₂ and CH₄ emissions resulting from the post-production activities. Hence, with both theoretical and empirical findings, this study fundamentally challenges the conventional view that efficiency can lead to sustainability. Instead, without appropriate management, the Jevons Paradox prevails, where innovation induces production expansion and worsens the environment.

Keywords: agricultural post-production; agricultural innovation; theoretical; empirical; global analysis; Jevon Paradox

JEL Codes: Q16; Q55; C02; C23

¹ Senior Student; Faculty of International Economics, Foreign Trade University, 91 Chua Lang Street, Lang Ward, Ha Noi, 100000, Vietnam

1. Introduction

Besides ensuring food security, the agricultural sector is also a fundamental engine of socio-economic development, from providing employment opportunities, promoting rural development, mitigating poverty, to fostering economic prosperity across countries worldwide (Christiaensen et al., 2006; Dethier & Effenberger, 2012; Loizou et al., 2019). Nevertheless, due to the direct link to natural resources and ecological systems, agriculture is also a significant cause of environmental issues (Umesha et al., 2018). Statistically, according to the UNEP's Emissions Gap Report 2025, the agricultural sector accounted for approximately 11% of global net greenhouse gases (GHG). Thus, there is a pressing call for the transition toward a low-carbon agricultural system, and low-carbon agriculture has also been regarded as the fundamental thrust in the progress towards green growth (Ji et al., 2024; Norse, 2012).

In response to the crucial need for food security and mitigating the environmental impacts of agricultural activities, innovation or research and development (R&D) initiatives have been of paramount importance to global economic development by: providing enhanced farm productivity, improving income and living standards of poor farmers, offering cheaper and more abundant food supply, reducing the reliance on natural resource stocks (Alston & Pardey, 2021). For instance, in Malawi – an underdeveloped agro-based economy, it was empirically found that the adoption of enhanced maize and storage technologies significantly increased maize output per unit area as well as mitigated risks (Mutenje et al., 2016). Similarly, agricultural innovation investments also boost food security among African countries by fostering productivity and nutrient-rich foods (Malec et al., 2024). Besides the productivity-inducing effects, agricultural innovation can also foster income-enhancing effects along with positive environmental effects (Konfo et al., 2024).

Nevertheless, there are also rising concerns regarding the unintentional negative effects or rebound effects of agricultural innovation (Alston & Pardey, 2021), in terms of the environment, human health, poverty, and other unintended consequences of agricultural production (Lusk & Norwood, 2011; Swinburn et al., 2019; Willett et al., 2019). For instance, while the investment in agricultural innovations can enhance the food security issue in Southern and Western Africa, it may exacerbate the shortage of food in Central Africa, revealing heterogeneous effects (Malec et al., 2024). Controversy also exists within the environmental effects of agriculture-based innovation, such that, while some agree on the benefits of agricultural R&D to the environment, contrasting views assert the opposite. For instance, while in Nepal, during the 1990–2018 period, Regmi et al. (2026) emphasized on the role of agricultural innovation in ensuring long-term environmental prosperity, evidence from Nigeria from 1981 to 2014 showed that agro-based innovation escalated the CO₂ emissions (Ali et al., 2021). Therefore, the existence of counteracting effects against the environmental quality of agricultural innovation has critically challenged the belief that “economic productivity” impedes “ecological degradation” (Grossman & Krueger, 1991; Kirikkaleli, 2023; Liang & Wang, 2023). Therefore, this controversy reveals a critical evidence gap, necessitating the need for further validation of whether agricultural innovation actually enables a low-carbon agro-system.

Additionally, existing studies only focus on sustainable agricultural production, such as how innovation mitigates carbon emissions stemming from agricultural production (Zhang, 2024), without looking at the broader agricultural system with the pre- and post-stage of production. Meanwhile, it was estimated that while the primary agricultural production accounted for around 7.1 billion tonnes of CO₂-equivalent emissions, the total emissions from the supply chain and post retail stage were also significant, with 5.1 billion tonnes (Crippa et al., 2021). Therefore, focusing on the main agricultural production stage only, without comprehensively taking other stages into consideration, can restrict the progress towards a

low-carbon agricultural system, demonstrating a critical knowledge gap where limited studies have been conducted on how agricultural innovation contributes to the sustainability of the comprehensive agricultural system.

Stemming from the mixed results on the environmental effects of innovations and the lack of research on the post-production of the agricultural system, this research empirically investigates how agricultural innovation contributes to a comprehensive sustainable agricultural system based on the global data from 1990 to 2023. Additionally, before the empirical investigation, this research also develops a theoretical model explaining how agricultural R&D investment.

The remainder of the research is structured as follows. The second section reviews existing literature for the formulation of the theoretical model. The third section outlines the methods for empirical investigation of the study. Next, the fourth section presents the results and discussion of research findings. Finally, the last section gives concluding remarks and implications.

2. Theoretical framework

Based on neoclassical assumptions of the Aggregation Principle and the Representative Agent Hypothesis, in this framework, the global agricultural sector is modeled as a representative producer whose profit-maximizing behavior reflects the aggregated equilibrium of individual firms operating under a common technological frontier. Hence, the theoretical foundation of this study is rooted in the neoclassical theory of the firm, where a representative agricultural producer seeks to maximize profit by optimizing input use and innovation investment.

Initially, we begin with the fundamental profit function (Π), where the firm balances total revenue against the total costs of its inputs (X) such that:

$$\Pi = P \cdot f(X) - \omega \cdot X$$

Where: P represents the market price of the output, $f(X)$ is the production function, and ω is the vector of input prices. Additionally, the production function $f(X)$ is strictly concave and twice-differentiable, representing diminishing marginal returns to all inputs.

As the current landscape of the modern agricultural system remains at transitional stages or the “hybrid” stage, which includes both carbon-intensive inputs/technologies and low-carbon inputs/technologies (Geels, 2002). Therefore, to practically reflect this hybrid transition, we extend the baseline model to differentiate between carbon-intensive inputs (x_C) – such as fossil-fuel-based machinery and chemical fertilizers, and low-carbon inputs (x_G), alongside agricultural innovation (R):

$$\max_{x_C, x_G, R} \Pi = P \cdot f(x_C, x_G, R) - \omega_C \cdot x_C - \omega_G \cdot x_G - rR$$

Where: ω_C and ω_G is the prices of carbon-intensive inputs (x_C) and low-carbon inputs (x_G), respectively, R represents the investment in agricultural R&D, while r is the unit cost of innovation. The firm’s objective is to choose the optimal combination of x_C, x_G, R that yields the highest net return.

On the other hand, total agricultural emissions (E) are modeled as a linear combination of the intensities of the chosen inputs with the assumption that total environmental impacts are highly sensitive to the firm’s input substitution behavior:

$$E = \epsilon_C \cdot x_C + \epsilon_G \cdot x_G \quad (1)$$

Where: ϵ_C and ϵ_G are the emission coefficients per unit of carbon-intensive and low-carbon inputs, respectively. Given that $\epsilon_C > \epsilon_G$ (as the emission of carbon-intensive inputs is higher than the emission of low-carbon inputs) and for simplicity, we assume that the emissions levels of green inputs are near zero ($\epsilon_G \approx 0$).

Regarding how innovation influences the emission levels of the agricultural activities, two primary pathways based on the second-order cross-partial derivatives of the production function are identified: (1) the scale-up regime and (2) the substitution regime.

Definition 1: *In the scale-up regime, innovation (R) is a technical complement to carbon-intensive inputs ($f_{x_C R} > 0$; $f_{x_G R} > 0$) and inputs themselves are technical complements ($f_{x_C x_G} > 0$). The latter is because when innovation supports the productivity of carbon-intensive inputs, a rational, profit-maximizing firm can not use green inputs as a substitute for “dirty” inputs; therefore, the green inputs can not substitute carbon-intensive inputs. In addition, while innovation is a technical complement to carbon-intensive inputs, it will still support the productivity of green inputs, but the magnitude is less than the productivity gains of “dirty” inputs ($f_{x_C R} > f_{x_G R}$). Mathematically:*

$$\begin{cases} \frac{\partial^2 f}{\partial x_C \partial R} = f_{x_C R} > 0 \\ \frac{\partial^2 f}{\partial x_G \partial R} = f_{x_G R} > 0 \\ f_{x_C R} > f_{x_G R} \end{cases}$$

Lemma 1: *If innovation (R) is a technical complement to carbon-intensive inputs ($f_{x_C R} > 0$) and the inputs themselves are technical complements ($f_{x_C x_G} > 0$), then the optimal demand for carbon inputs (x_C) increases with innovation. Specifically:*

$$\frac{\partial x_C^*}{\partial R} > 0$$

Proof: As the firm chooses the maximum combination (x_C, x_G) to maximize the profit: $\Pi = P \cdot f(x_C, x_G, R) - \omega_C \cdot x_C - \omega_G \cdot x_G - rR$. To find the optimal level, we set the first derivatives to zero (FOCs):

$$\begin{cases} \frac{\partial \Pi}{\partial x_C} = P \cdot f_{x_C} - \omega_C = 0 \\ \frac{\partial \Pi}{\partial x_G} = P \cdot f_{x_G} - \omega_G = 0 \end{cases} \quad (2)$$

To see how x_C and x_G change when innovation (R) changes, we take the total derivative of both FOCs with respect to R . This creates a system of equations:

$$\begin{cases} f_{x_C x_C} \frac{\partial x_C^*}{\partial R} + f_{x_C x_G} \frac{\partial x_G^*}{\partial R} + f_{x_C R} = 0 \\ f_{x_G x_C} \frac{\partial x_C^*}{\partial R} + f_{x_G x_G} \frac{\partial x_G^*}{\partial R} + f_{x_G R} = 0 \end{cases} \Leftrightarrow \begin{cases} f_{x_C x_C} \frac{\partial x_C^*}{\partial R} + f_{x_C x_G} \frac{\partial x_G^*}{\partial R} = -f_{x_C R} \\ f_{x_G x_C} \frac{\partial x_C^*}{\partial R} + f_{x_G x_G} \frac{\partial x_G^*}{\partial R} = -f_{x_G R} \end{cases}$$

By applying Cramer’s rule, we can represent this system in matrix form as $H \cdot X = B$ as follows:

$$\begin{bmatrix} f_{x_C x_C} & f_{x_C x_G} \\ f_{x_G x_C} & f_{x_G x_G} \end{bmatrix} \begin{bmatrix} \frac{\partial x_C^*}{\partial R} \\ \frac{\partial x_G^*}{\partial R} \end{bmatrix} = \begin{bmatrix} -f_{x_C R} \\ -f_{x_G R} \end{bmatrix}$$

To solve for $\frac{\partial x_C^*}{\partial R}$, the Cramer’s rule suggests replacing the first column of the Hessian matrix (H) with the vector on the right-hand side:

$$H_1 = \begin{bmatrix} -f_{x_C R} & f_{x_C x_G} \\ -f_{x_G R} & f_{x_G x_G} \end{bmatrix}$$

Then, the solution for $\frac{\partial x_C^*}{\partial R}$ is calculated by dividing the determinant of the new matrix ($|H_1|$) by the determinant of the original Hessian ($|H|$):

$$\frac{\partial x_C^*}{\partial R} = \frac{|H_1|}{|H|} = \frac{(-f_{x_{CR}} f_{x_G x_G}) - (-f_{x_{GR}} f_{x_C x_G})}{|H|} \quad (3)$$

Where: $f_{x_{CR}} f_{x_G x_G}$ represents the scale-up effects (innovation reinforces and increases the use of carbon-intensive inputs); $f_{x_{GR}} f_{x_C x_G}$ represents the substitution effects (innovation increases the use of low-carbon inputs, substituting carbon-intensive inputs).

Assumption 1: For the profit-maximizing equilibrium (x_C^*, x_G^*) to exist in the production function $f(x_C, x_G, R)$, the Hessian matrix (H) of the profit function must be negative definite. This condition necessitates that the determinant of the Hessian is strictly positive:

$$|H| = \begin{vmatrix} f_{x_C x_C} & f_{x_C x_G} \\ f_{x_G x_C} & f_{x_G x_G} \end{vmatrix} = (f_{x_C x_C} \cdot f_{x_G x_G}) - (f_{x_C x_G})^2 > 0$$

Assumption 2: We assume that the production function is strictly concave with respect to green inputs (x_G), such that the second-order partial derivative is strictly negative, specifically:

$$f_{x_G x_G} < 0$$

This assumption implies that while increasing green inputs may enhance total output, the rate of increase diminishes as the volume of these inputs rises, reflecting the law of diminishing returns, and ensuring that firms cannot achieve infinite growth simply by expanding a single input category.

Continue with Equation (3), combining with the assumption that $|H| > 0$ (**Assumption 1**) and $f_{x_G x_G} < 0$ (**Assumption 2**), as $f_{x_{CR}} > 0$ and $f_{x_C x_G} > 0$ (**Definition 1**), it is evident that $-f_{x_{CR}} f_{x_G x_G}$ (the scale-up effects) is positive while $-f_{x_{GR}} f_{x_C x_G}$ (the substitution effects) is negative, leading to the numerator $(-f_{x_{CR}} f_{x_G x_G}) - (-f_{x_{GR}} f_{x_C x_G})$ is strictly positive.

Thus, $\frac{\partial x_C^*}{\partial R} > 0$. Moreover, when evaluating the complete numerator, the net sign depends on which force is larger. Because the productivity gains of innovation heavily favor carbon-intensive inputs over green inputs ($f_{x_{CR}} > f_{x_{GR}}$), the positive scale-up effect mathematically dominates the subtracted substitution effect, ensuring the numerator remains strictly positive when innovation is a technical complement to carbon-intensive inputs ($f_{x_{CR}} > 0$; $f_{x_{GR}} > 0$).

Definition 2: In the substitution regime, innovation (R) is a technical complement to low-carbon inputs ($f_{x_{GR}} > 0$; $f_{x_{CR}} < 0$) and inputs themselves are technical complements ($f_{x_C x_G} < 0$). The latter is because when innovation supports the productivity of low-carbon inputs, a rational, profit-maximizing firm can use green inputs as a substitute for “dirty” inputs; therefore, the green inputs can substitute carbon-intensive inputs ($f_{x_C x_G} < 0$). In addition, different from the scale-up regime, when the innovation is complementary to low-carbon inputs, the carbon-intensive inputs can not benefit from this due to incompatibility; therefore, the marginal productivity of “dirty” inputs falls with innovation in this case. This misalignment helps ensure that technological progress actively incentivizes the removal of dirty inputs from the production process. Mathematically:

$$\begin{cases} \frac{\partial^2 f}{\partial x_G \partial R} = f_{x_{GR}} > 0 \\ \frac{\partial^2 f}{\partial x_C \partial R} = f_{x_{CR}} < 0 \end{cases}$$

Lemma 2: *If innovation (R) is a technical complement to green inputs ($f_{x_G R} > 0$; $f_{x_C R} < 0$) and the inputs themselves are technical substitutes ($f_{x_C x_G} < 0$), then the optimal demand for carbon inputs (x_C) decreases with innovation. Specifically:*

$$\frac{\partial x_C^*}{\partial R} < 0$$

Proof: Continue with Equation (3), combining with $|H| > 0$ (**Assumption 1**) and $f_{x_G x_G} < 0$ (**Assumption 2**), because $f_{x_G R} > 0$; $f_{x_C R} < 0$ and $f_{x_C x_G} < 0$ (**Lemma 2**), it is evident that $\frac{\partial x_C^*}{\partial R} < 0$.

Proposition: *Net effects of agricultural innovation (R) on the optimal levels of carbon-intensive inputs (x_C^*), and consequently on firm-level emissions, are non-monotonic and determined by the prevailing technical regime. The relationship is defined as follows:*

1. **The scale-up regime:** *If agricultural innovation and carbon-intensive inputs are technical complements, innovation leads to **positive** effects on emission levels ($\frac{\partial x_C^*}{\partial R} > 0$).*
2. **The substitution regime:** *If agricultural innovation facilitates technical substitution, it will lead to **negative** effects on emission levels ($\frac{\partial x_C^*}{\partial R} < 0$).*

Proof: Based on Equation (1), the total effect of innovation on agricultural CO₂ emissions (dE/dR) is determined by the weighted sum of these input shifts (applying the chain rule):

$$\frac{dE}{dR} = \epsilon_C \frac{\partial x_C^*}{\partial R} + \epsilon_G \frac{\partial x_G^*}{\partial R} \approx \epsilon_C \frac{\partial x_C^*}{\partial R} \quad (\epsilon_G \approx 0) \quad (4)$$

As $\epsilon_C > 0$, the sign of $\frac{dE}{dR}$ depends wholly on the sign of $\frac{\partial x_C^*}{\partial R}$, which can be heterogeneous as pointed out by **Lemma 1** and **Lemma 2**. A positive $\frac{dE}{dR}$ indicates the scale-up regime, where the efficiency gains from innovation are eclipsed by the expansion of carbon-intensive activities. Conversely, a negative result implies that innovation successfully facilitates a transition toward green inputs.

3. Methods

3.1 Empirical procedure

To empirically investigate the relationship between agricultural innovation and emissions from agricultural post-production activities (for empirical proof of the Proposition), the following research model is proposed:

$$Emission_{i,t,r} = \beta_0 + \beta_1 AgriInno_{i,t} + \sum \beta Controls_{i,t} + \varepsilon_{i,t}$$

Where: $Emission_{i,t,r}$ represents the emission levels from the agricultural post-production activity r of country i in year t ; $AgriInno_{i,t}$ indicates the levels of agricultural innovation (represented by the agricultural R&D spending of country i in year t ; $Controls_{i,t}$ is the set of control variables that captures the economic characteristics of countries; $\varepsilon_{i,t}$ is the error term.

3.2 Variables and data

For empirical analysis, this research employs the global dataset covering 89 countries from 1990 to 2021. The dataset for the empirical investigation of this study was merged from the data of FAOSTAT, Agricultural Science and Technology Indicators (ASTI), and the World Bank (WB). The transition from a micro-founded theoretical model to a macro-level empirical investigation is justified by the Aggregation Principle and the Representative Agent Hypothesis. Under these neoclassical assumptions, the global agricultural sector is modeled as a representative producer whose profit-maximizing behavior can reflect the

aggregated equilibrium of individual firms. The summary of variable description is presented in **Table 1**.

Dependent variable: According to the definitions and classifications provided by the Food and Agriculture Organization (FAO) of the United States, the post-production in the food system consists of four key stages, which are: processing, packaging, transporting, and retailing. Thus, in order to evaluate the role of agricultural innovation in influencing the emissions levels of the post-production phase in the agro-system, this research employs the CO₂ emissions and CH₄ emissions from the four post-production activities data provided by FAOSTAT.

Main explanatory variable: In order to measure agricultural innovations, this research uses the data on total agricultural R&D spending provided by ASTI as the core proxy. While there is a wide range of proxies for quantifying innovation, such as patent applications, R&D personnel, the use of R&D spending is one of the most popular among empirical studies (Jiang et al., 2024; Phuong & Thuy Anh, 2025; Tung & Hoang, 2024).

Control variables: In order to isolate the effects of agricultural R&D spending on emissions levels, the empirical model also includes control variables. To simulate the use of “brown” inputs (x_c), this study includes the energy consumption of nations (ENERGY) as a control variable. Next, to control for the size of the economy and the agricultural sector, which can significantly influence the emissions level, the Gross Domestic Product (GDP) and the agricultural value added (AGRI) of nations are also added. Moreover, to account for the scale and structural transformation of the agricultural market, population (POP) and urbanization – the number of urban population (URB) are also included in the empirical model. Theoretically, as the global population and urbanization expand, the aggregate demand for food or agricultural products rises, necessitating a proportional expansion in agricultural production (World Health Organization, 2023), and potentially influences the environmental impacts from the agro-system.

Table 1. Variables description

Variable	Description	Data source
C_PACK	Natural logarithm of national CO ₂ emissions from four key post-production activities in agriculture: processing, packaging, transporting, and retailing.	FAOSTAT
C_PROCE		
C_RETAIL		
C_TRANS		
M_PACK	Natural logarithm of national CH ₄ emissions from four key post-production activities in agriculture: processing, packaging, transporting, and retailing.	FAOSTAT
M_PROCE		
M_RETAIL		
M_TRANS		
R&D	Natural logarithm of national agricultural R&D spending.	ASTI
GDP	Natural logarithm of national GDP.	WB
POP	Natural logarithm of national population.	WB
URBAN	Natural logarithm of national urban population.	WB
ENERGY	Natural logarithm of national energy use.	WB
AGRI	Natural logarithm of national agricultural value added.	WB

Source: Authors' compilation.

Table 2 presents the descriptive statistics of variables included in the empirical research model. Overall, the maximum number of country-year observations is 2,850, while the minimum is 1,216, illustrating that there are missing observations in the dataset. In

addition, with the highest average value, the transportation stage appears to account for the majority of the CO₂ emissions, compared to the other three post-production stages. Meanwhile, regarding the CH₄ emissions, the emissions levels of post-production stages are relatively lower than the CO₂ emissions, revealing that unlike primary agricultural production (which mainly induces CH₄), post-production mainly induces CO₂ emissions. The standard deviation of all variables is relatively small due to the natural logarithm transformation, ensuring consistent statistical analysis.

Table 2. Descriptive statistics of variables

Variable	Obs	Mean	Std. dev.	Min	Max
C_PACK	1,536	3.0887	3.0663	-14.4004	13.6597
C_PROCE	1,216	4.7388	5.2814	-21.4823	48.1522
C_RETAIL	2,848	3.7634	2.7612	-18.1118	9.5309
C_TRANS	2,848	5.4243	1.9594	1.1133	10.2765
M_PACK	1,536	0.0592	0.1973	-0.0536	1.5428
M_PROCE	1,216	0.0918	0.2777	-0.2491	1.9622
M_RETAIL	2,848	0.0375	0.0866	-0.1302	0.7991
M_TRANS	2,848	0.1830	0.3367	0.0002	2.1132
R&D	2,848	3.3737	1.9831	-5.8257	9.9284
GDP	2,848	7.3889	1.2379	3.9365	10.0688
POP	2,848	15.9563	1.9376	10.6055	21.0698
URBAN	2,848	15.0523	1.9947	9.5407	20.0040
ENERGY	2,464	4.4120	0.7251	0.0517	7.1947
AGRI	2,848	21.2570	2.0130	15.6900	27.0336

Source: Authors' compilation.

3.3 Statistical analysis method

To estimate the baseline model parameters, this study employs the Fixed Effects (FE) estimator. The choice of the FE specification is justified by the Hausman specification test and the Breusch-Pagan LM test. Specifically, the Breusch-Pagan LM test strongly rejects the null hypothesis of no unobserved country-specific intercepts, confirming that a simple Pooled OLS estimation would yield biased and inefficient parameters. Concurrently, the Hausman specification test statistic systematically rejects this null hypothesis, demonstrating that a Random Effects (RE) specification suffers from inconsistency, confirming the suitability of the FE estimation. Consequently, the Fixed Effects estimator stands as the most rigorous and consistent static panel method, isolating the true structural impacts of agricultural innovation by controlling all time-invariant, nation-specific unobserved heterogeneity. The suitability of the FE model is preserved across all models.

4. Results and discussion

4.1 Main results

4.1.1 Agricultural innovation and carbon dioxide emissions from agriculture

Table 3. Estimation results with CO₂ emissions

	(1)	(2)	(3)	(4)
	C_PACK	C_PROC	C_RETAIL	C_TRANS
R&D (spending)	0.4974*** (0.062)	0.6861*** (0.195)	0.0531 (0.036)	0.0631*** (0.008)
GDP	0.5847*** (0.136)	-1.9980*** (0.325)	0.9972*** (0.095)	0.4195*** (0.021)
POP	-0.9256 (0.717)	-1.7161 (1.640)	1.4020*** (0.389)	0.9091*** (0.086)
URBAN	0.0043 (0.491)	4.4754*** (1.199)	1.0527*** (0.243)	0.1099** (0.054)
ENERGY	-0.1199 (0.217)	-5.0346*** (0.496)	-0.1427 (0.117)	0.2152*** (0.026)
AGRI	0.3581** (0.144)	0.0453 (0.324)	-0.4736*** (0.102)	-0.0815*** (0.023)
_cons	4.5571 (5.627)	-1.5767 (12.053)	-31.485*** (3.362)	-13.318*** (0.746)
<i>N</i>	1344	1056	2466	2466
R2	0.1614	0.1290	0.3108	0.6208

Note: Standard errors are presented in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Source: Authors' compilation.

Regarding the first indicator of a cleaner agricultural system – the carbon dioxide emissions (CO₂),

Table 3 presents the estimation results of how agricultural R&D spending influences the levels of emissions from four key post-production activities. In general, it is evident that the R&D spending for agriculture consistently illustrates positive effects on the emissions levels from food packaging ($\beta = 0.4974$; p-value < 0.01), food processing ($\beta = 0.6861$; p-value < 0.01), and food transportation ($\beta = 0.6861$; p-value < 0.01). Meanwhile, the effects on food retailing have statistical insignificance, even though positive ($\beta = 0.0531$; p-value > 0.1). Comparatively, the pollution-inducing effects of agricultural innovation are largest within food processing activities. Hence, this empirical evidence on a global scale has supported the existence of the scale-up regime, where current agricultural investments in innovation (R) is a technical complement to carbon-intensive inputs ($f_{x_C R} > 0$) and the inputs themselves are technical complements ($f_{x_C x_G} > 0$), then the optimal demand for carbon inputs (x_C) increases with innovation ($\frac{\partial x_C^*}{\partial R} > 0$), leading to higher emissions levels (**Lemma 1**). In terms of control variables, it is evident that the coefficients vary significantly across different post-production phases. This indicates that the drivers of emission levels are not uniform, but rather exhibit sector-specific heterogeneity stemming from the unique technical configurations as well as resource sensitivity and intensities inherent to each activity.

4.1.2 Agricultural innovation and methane emissions from agriculture

Table 4. Estimation results with CH₄ emissions

	(1)	(2)	(3)	(4)
	M_PACK	M_PROC	M_RETAIL	M_TRANS
R&D (spending)	0.0044 (0.003)	0.0273** (0.011)	0.0020 (0.001)	0.0264*** (0.003)
GDP	0.0550*** (0.007)	0.0169 (0.018)	0.0028 (0.004)	0.1116*** (0.008)
POP	0.1114*** (0.039)	-0.3139*** (0.090)	-0.0108 (0.014)	-0.0032 (0.031)
URBAN	-0.0118 (0.027)	0.3571*** (0.066)	0.0567*** (0.009)	0.0324* (0.019)
ENERGY	-0.0397*** (0.012)	-0.1219*** (0.027)	-0.0079* (0.004)	-0.0078 (0.009)
AGRI	-0.0550*** (0.008)	-0.0240 (0.018)	0.0106*** (0.004)	-0.0438*** (0.008)
_cons	-0.6287** (0.306)	0.4767 (0.662)	-0.8648*** (0.124)	-0.2036 (0.269)
N	1344	1056	2466	2466
R2	0.1302	0.1321	0.1853	0.2523

Note: Standard errors are presented in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Source: Authors' compilation.

As agriculture also accounts for the majority of global methane emissions (CH₄), this study also employs this as a proxy for agricultural sustainability. From **Table 4**, which presents the results of estimation, it is evident that pollution-inducing effects of agricultural innovation are preserved as with CO₂ emissions. More specifically, investing more in agricultural innovation contributes to higher levels of CH₄ emissions emitted from food processing ($\beta = 0.0273$; p-value < 0.01) and food transportation ($\beta = 0.0264$; p-value < 0.01). However, innovation has no significant influence on the CH₄ emissions from the food packaging ($\beta = 0.0044$; p-value > 0.1) and the food retailing phase ($\beta = 0.0020$; p-value > 0.1). Similarly, this also supports the scale-up regime and **Lemma 1**. The effects of control variables are also various across four post-production activities, consistent with the results for CO₂ emissions.

4.2 Robustness checks

4.2.1 Endogeneity analysis

In order to address potential endogeneity issues, this study also conducts robustness checks by estimating the model with Instrumental Variable – Two Stages Least Squares (IV-2SLS). More specifically, while agricultural R&D may decrease emissions, emissions levels may also drive innovative activities, as when a country experiences an increase in the levels of emissions, it can trigger the tightening of environmental policies, requiring governments, firms, or organizations to reallocate their budget toward sustainable technologies (Alston & Pardey, 2021). This reverse causality violates the orthogonality condition, causing the error term to correlate with the innovation proxy and biasing baseline coefficients. Moreover, as a country expands its economic capacity and the size of the agricultural sector, the fiscal space available for public and private agricultural innovation allocations also increases. Thus, IVs are required to ensure the reliability of the estimation.

This study instruments the endogenous variable, agricultural R&D spending, using first-order lagged variables of economic growth, agricultural production, and emission levels. Statistically, all tests for instruments, including the Kleibergen-Paap rk LM statistic, Cragg-

Donald Wald F statistic, and Hansen J statistic, are valid, confirming that the instruments are strong and suitable for the model. From **Table 5**, which presents the endogeneity analysis results, it is evident that even when adjusting for endogeneity, the effects of innovation on emissions of agricultural post-production emissions remain consistently positive. Therefore, the robustness and consistency of the empirical findings are further supported.

Table 5. Estimation results with endogeneity analysis

Dependent variable: Carbon dioxide emissions				
	(1) C_PACK	(2) C_PROC	(3) C_RETAIL	(4) C_TRANS
R&D (spending)	3.3752*** (0.881)	9.6909** (4.103)	2.7012*** (0.752)	1.2355*** (0.101)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1302	1023	2389	2389
<i>LM statistic</i>	12.613***	16.686***	19.503***	27.143***
<i>Wald F statistic</i>	196.52***	22.749***	241.44***	1510.5***
<i>Hansen J statistic</i>	4.154	3.036	3.186	3.357
Dependent variable: Methane emissions				
	(5) M_PACK	(6) M_PROC	(7) M_RETAIL	(8) M_TRANS
R&D (spending)	0.1150*** (0.037)	0.0916* (0.052)	0.0481*** (0.011)	0.1634*** (0.026)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1302	1023	2389	2389
<i>LM statistic</i>	12.613***	16.686***	19.503***	27.143***
<i>Wald F statistic</i>	135.46***	22.749***	241.44***	1510.5***
<i>Hansen J statistic</i>	3.263	2.633	4.664	6.029

Note: Standard errors are presented in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Source: Authors' compilation.

4.2.2 Alternative sustainability and innovation indicators

To ensure the structural integrity of our empirical findings, a robustness check is conducted by substituting the absolute measurement with an intensity-based measurement. First, the agricultural R&D intensity is defined as the total ratio of agricultural R&D spending to agricultural value added. Second, the emission intensity of post-production activities is also defined as the ratio of total emissions to agricultural value added.

From the estimation results with alternative proxies in

Table 6, it is evident that the emission-inducing effects of agricultural innovation remain consistent throughout both absolute and intensity-based measurement. Hence, the robustness of our empirical findings is confirmed, further supporting the prevalence of the scale-up regime.

Table 6. Estimation results with intensity-based measurement

	(1)	(2)	(3)	(4)
CO₂ intensity	C_PACK (intensity)	C_PROC (intensity)	C_RETAIL (intensity)	C_TRANS (intensity)
Agricultural R&D spending				
R&D (spending)	0.4974*** (0.062)	0.0330*** (0.009)	0.0026 (0.002)	0.0028*** (0.000)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1344	1056	2466	2466
<i>R²</i>	0.0699	0.1498	0.2832	0.4501
Agricultural R&D spending intensity				
R&D (intensity)	10.3757*** (1.307)	0.7208*** (0.195)	0.0374 (0.034)	0.0638*** (0.008)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1344	1056	2466	2466
<i>R²</i>	0.0689	0.1508	0.2828	0.4527
	(1)	(2)	(3)	(4)
CH₄ intensity	M_PACK (intensity)	M_PROC (intensity)	M_RETAIL (intensity)	M_TRANS (intensity)
Agricultural R&D spending				
R&D (spending)	0.0002 (0.000)	0.0012*** (0.000)	0.0001 (0.000)	0.0011*** (0.000)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1344	1056	2466	2466
<i>R²</i>	0.1295	0.1325	0.1797	0.2497
Agricultural R&D spending intensity				
R&D (intensity)	0.0018 (0.003)	0.0167* (0.009)	0.0002 (0.001)	0.0180*** (0.003)
<i>Controls</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
<i>N</i>	1344	1056	2466	2466
<i>R²</i>	0.1285	0.1291	0.1790	0.2397

Note: Standard errors are presented in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Source: Authors' compilation.

4.3 Discussion

While the role of agricultural innovation on the emissions levels of the primary agricultural production has been investigated (Ali et al., 2021; Regmi et al., 2026), empirical evidence on how R&D influences emissions from post-production phases remains limited. Meanwhile, practically, the post-production phases are also responsible for a significant level of emissions, making them one of the most important components of a cleaner agricultural system.

Initially, this study develops a theoretical model that is rooted in the neoclassical theory of the firm, where a representative agricultural producer seeks to maximize profit by optimizing input utilization and innovation investment. Similar to the primary agricultural production, the reliance of post-production processes on natural resources manifests as a resource-intensive transition from raw harvest to consumer-ready goods, primarily driven by a high demand for energy, water, and land. Theoretically and intentionally, agricultural innovation is capable of reducing the reliance on natural resources (Alston & Pardey, 2021). For instance, precision agricultural technologies (i.e., variable rate application, sensors, smart

sprayers, GPS guidance, remote sensing) reduce fertilizer, pesticide, water contamination, and fuel use as well as less carbon-intensive inputs, allowing the use of low-carbon ones (Ruder et al., 2026). Similarly, the application of drones in agricultural production can also boost productivity as well as efficiency (Chi et al., 2024).

However, whether innovation actually leads to lower emissions or environmental impacts remains a question, especially during the transitional phase. Specifically, during this phase, green technologies are incapable of replacing all carbon-intensive inputs but can only replace them partially, leading to a mixture of low-carbon inputs or carbon-intensive inputs. Thus, based on this practical assumption, the theoretical model of this study takes the coexistence of both types of inputs into account and analyzes how rational, profit-maximizing producers will choose the optimal mixture of inputs along with agricultural R&D spending. Accordingly, the relationship between emissions and agricultural innovation is analyzed.

Consequently, the theoretical model has identified two regimes: the *scale-up regime*, and the *substitution regime*. Accordingly, in the scale-up regime, innovation will promote the use of carbon-intensive inputs, leading to higher emissions levels. On the contrary, in the substitution regime, as using green inputs will be more compatible and productive, carbon-intensive inputs are replaced, leading to lower emissions. Hence, this theoretical evidence has challenged the notion that “economic productivity” fundamentally slows “ecological degradation” (Grossman & Krueger, 1991; Kirikkaleli, 2023; Liang & Wang, 2023), showing that this notion may fail during transitional phases where both “clean” and “dirty” resources coexist.

Empirically, evidence indicates support for the proposition of the theoretical model. Our empirical findings reveal a counterintuitive relationship: higher levels of agricultural innovation are systematically associated with an increase in post-production emissions. This outcome provides strong real-world validation for the scale-up regime formalized in our theoretical model. Therefore, emissions rise due to the increase in the use of carbon-intensive inputs. While there is a lack of literature on the effects of agricultural innovation on the post-production phase, these findings have additionally proven that R&D spending does not necessarily contribute to a cleaner agricultural system (Ali et al., 2021). Theoretically, this further illuminates the Jevon Paradox, which posits that efficiency gains from technological innovations can rebound or even backfire on sustainability goals (Alcott, 2005). This implies that “productivity” and “environmental quality” are currently in a zero-sum relationship: as long as innovation is complementary to the current carbon-intensive energy mix, every increment in agricultural productivity will further worsen ecological degradation.

Significantly, unlike conventional theoretical models, which consider dichotomous transitions towards green technology, the theoretical model of this study specifically accounts for the hybrid transitional phase in which carbon-intensive and green inputs have to coexist in the agricultural production process. Therefore, it has relaxed the assumption that producers do not have an alternative choice but to choose brown inputs over green ones. Consequently, this model challenges the view that technological progress always results in ecological gains. By endogenizing both types of technical change regimes, namely, the scale-up regime and the substitution regime, the present study provides a mathematical explanation for the expansion of carbon use through innovations in the market.

5. Implications and concluding remarks

However, these findings on the pollution-inducing role of agricultural R&D should not be interpreted as evidence against the development of technological innovation. Instead, this research necessitates stronger redirecting efforts and better innovation management practices. The empirical evidence suggests that market-driven R&D is drifting towards the dominant, high-carbon infrastructure as it offers the highest marginal productivity. Most importantly, it

is recommended that governments should decouple innovation from carbon-intensive inputs. Governments must transition public agricultural R&D funding criteria away from metrics focused purely on optimization of volume or processing speed. In terms of private R&D spending, financial subventions and national grants should be provided for projects that are sustainability-compatible. Second, reducing the marginal productivity of high-carbon inputs to incentivize producers to shift to green inputs is also necessary. Market-based intervention to forcibly reduce the complementarity between new technological innovation and carbon-intensive inputs can also be applied. For instance, higher taxes on carbon-intensive inputs and agricultural technological innovation that is environmentally indifferent. Similarly, the complementarity between new technological innovation and low-carbon inputs should also be improved, for instance, reducing costs with subsidies or co-investments. Overall, the most general and important principle recommended for governments in innovation management towards sustainability is that: beyond absolute productivity and efficiency, the assessment of an innovative technology must be based on its compatibility with types of inputs as well.

In conclusion, this study provides a critical theoretical and empirical interrogation of the nexus between agricultural R&D spending and environmental quality within the post-production sector. With these findings, this research has provided insights into sustainable agro-systems, while current literature mainly focuses on the primary agricultural production with little attention to the post-stages. Specifically, the findings of this study depart from the optimistic view that “economic productivity” can fundamentally mitigate “ecological degradation” (Grossman & Krueger, 1991; Kirikkaleli, 2023; Liang & Wang, 2023). Instead, during transitional phases where both “brown” and “green” resources both exist, efficiency gains may rebound and worsen the environment. By developing a theoretical model rooted in the neoclassical theory of firms, this study identifies two regimes: the *scale-up regime* (where innovation is complementary to carbon-intensive inputs, making low-carbon and carbon-intensive inputs complements), and the *substitution regime* (where innovation complements low-carbon inputs, allowing low-carbon inputs to substitute for carbon-intensive ones). With the global dataset covering 89 countries worldwide from 1990 – 2021, the empirical analysis has confirmed the theoretical model and reveals that agricultural R&D spending actually leads to environmental degradation with higher emissions levels (both CO₂ and CH₄). This demonstrates that the scale-up regime still remains predominant. However, these results do not imply that innovation should be halted; rather, they underscore the urgent need for redirecting the trajectory of technical change within the agricultural system.

Nevertheless, this study is not without limitations. For instance, while this study provides a comprehensive global analysis of post-production decarbonization, it is limited by its empirical reliance on CO₂ and CH₄ emission metrics. Future research can incorporate broader sustainability indicators, such as food loss and waste rates, packaging material composition, and supply chain resource efficiency.

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