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Determinants of pollutant emissions in the Spanish agri-food sector: The role of international trade

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Abstract: This study aims to analyse the key company-level variables influencing pollutant emissions in the Spanish agri-food sector and investigate the bidirectional relationship between international trade and environmental performance. Using panel data from 2007–2020, we employ discrete choice models to test causal relationships between business variables and environmental impact. Empirical findings show a negative correlation between internationalisation and polluting emissions from agri-food companies. Additionally, other factors, such as company age and size, also influence this index. These results provide valuable insights for economic decision-makers in the agri-food market, highlighting the implications of international trade and business variables on pollution levels.

Keywords: agriculture; binary and ordered logit models; internationalisation; microeconomic level; environmental emissions

The push for sustainable development emphasises the importance of prioritising production quality through efficient resource use and eco-friendly practices. Global market competition and international environmental regulations are driving exporting companies to improve their environmental performance (Cui and Qian 2017).

In recent decades, the number of studies on environmental performance determinants has increased considerably. As a result of the economic globalisation phenomenon, a line of research has emerged to determine whether internationalisation benefits or, on the contrary, harms the environment (Liu et al. 2018; Ali et al. 2020).

Intense global competition and stringent international environmental regulations are driving exporting companies to improve their environmental performance. However, the relationship between internationalisation and environmental performance is a relatively new and complex topic, particularly at the microeconomic level. While numerous studies have explored this relationship at the macro level, there is a significant gap in the literature regarding its implications for firms, especially within the agri-food sector (Sorroche-del-Rey et al. 2023).

In the case of agri-food, it must be acknowledged that this sector plays a fundamental role in the environment due to its direct relationship. Although the sustainable development of this sector has traditionally received scarce attention, a growing commitment to food safety and environmental sustainability in the food sector has been observed in recent years, both

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at the international level in general and in Europe specifically (Bellesi et al. 2005; Barth et al. 2017). The sustainable development goals of the United Nations (United Nations 2016) and the European Union Research and Innovation program 'Horizon 2020' (European Commission 2011), along with the recent reforms to the Common Agriculture Policy (CAP), emphasise research and innovation in sustainable agriculture with the aim of providing, among other results, food safety and the competitiveness of European agriculture in international markets. In this context, however, few analyses can be found that focus on either the impact of environmental efficiency on the international activity of agri-food companies or the interrelationship between environmental behaviour and internalisation at the microeconomic level (Forslid et al. 2018; Liu et al. 2021).

Therefore, the present study seeks to address these issues by:

(*i*) Obtaining evidence of the influence of exporting activities on pollutant emissions in the agri-food sector;

(*ii*) determining the variables and dimensions at the company level that are determinants of pollution;

(*iii*) analysing bidirectional relationship between level of emissions and international trade.

The present work is structured as follows. Section 2 reviews the relevant literature, outlines the research hypotheses, and describes the methodology followed and the data utilised for the empirical analysis. Section 3 presents and discusses the empirical results. Finally, Section 4 concludes the study and offers suggestions for future research directions.

MATERIAL AND METHODS

Literature review and research hypothesis

The impact of internationalisation on environmental performance in the agri-food sector remains a complex and under-researched area, especially at the microeconomic level (Sorroche-del-Rey et al. 2023). While numerous studies have explored this relationship in the manufacturing sector (Macchion et al. 2016, Forslid et al. 2018; Holladay and LaPlue 2021), the agri-food industry presents unique challenges and opportunities.

Some studies suggest that environmental protection strategies can actually benefit agri-food firms by increasing export intensity (Martin-Tapia et al. 2010). Participation in international markets can also positively influence environmental practices through learning-by-doing effects (Rodriguez-Rodriguez et al. 2012; Barbosa et al. 2022). These studies highlight the potential for a positive feedback loop, where environmental commitment leads to increased export opportunities and vice versa. However, other research finds negative correlations between agricultural exports and environmental performance, particularly in developing countries (Salari et al. 2021; Saghaian et al. 2022). These studies raise concerns about increased pollution due to greenhouse gas emissions associated with large-scale agricultural production for export.

This mixed evidence underscores the need for further research to understand the nuances of the relationship between internationalisation and environmental performance in the sector.

The impact of internationalisation on the environment has traditionally been analysed using the theory of comparative advantages and factor endowments. However, while some consider energy and environmental performance a source of comparative advantage in industries (La 2018), other studies maintain that improving efficiency has no influence and that countries lose comparative advantages due to strict environmental regulations (Managi and Karamera 2005).

In contrast to the traditional hypotheses mentioned, new trade theory emphasizes firm heterogeneity in explaining the relationship between productivity and exporting. In recent years, different perspectives have emerged. One perspective supports the self-selection theory, such as Roberts and Tybout (1997) and Forslid et al. (2018), suggest that high productivity drives internationalisation, as only the most productive firms can overcome market entry barriers. These firms, being more productive, are better positioned to adopt environmentally friendly practices. Conversely, other analyses argue that export experience itself leads firms to adopt better practices through learning by doing (Galdeano-Gómez 2010; Macchion et al. 2016). As firms gain experience in international markets, they acquire new knowledge and skills that can be applied to improve their environmental behaviour.

Other studies, such as Shapiro and Walker (2018) and Copeland et al. (2021), have found that more productive firms tend to be more environmentally efficient, as they can reduce input usage. This suggests a bidirectional relationship: not only can trade openness influence environmental performance, but also firms with stronger environmental commitments may gain a competitive advantage in an international markets.

Based on these theoretical perspectives, this study tests the following hypotheses:

H_1: Exporting firms have better environmental behaviour.

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H_2: Environmental performance enhances export market access.

Other key variables, such as firm age, size, financial performance, and inventory management, have been analysed in the literature to understand their influence on firm-level environmental efficiency. Firstly, recent literature has studied the age of the company. In general, new machines are more eco-efficient, and due to fixed costs, it is more likely that the processes and machinery of newer companies will be more innovative compared to those of older ones (Bu et al. 2011). Secondly, company size may influence the capacity to invest in eco-friendly technologies or procedures due to economies of scale and financial resources (Henriques and Sadorsky 1996; Pal et al. 2008; Martín-Tapia et al. 2010). Thirdly, strong financial performance can enable firms to invest in environmental initiatives and adopt sustainable practices (Aivazian et al. 2005; Nouman et al. 2022). Finally, efficient inventory management can reduce energy consumption and emissions by minimising waste and optimising supply chain operations. Therefore, this paper delves into the following hypothesis:

H_3: Younger firms are more likely to adopt eco-efficient technologies and practices.

H_4: Larger firms have a greater capacity to reduce their environmental impact.

H_5: Firms with strong financial performance are more likely to reduce their level of pollutant emissions.

H_6: Efficient inventory management can help reduce emissions levels.

By combining these hypotheses, this study aims to investigate the complex relationship between internationalisation and environmental impact in the agri-food sector, considering both firm-level characteristics and the potential for a bidirectional influence.

Sample and variables

This investigation combines two official databases at the company level. On the one hand, the Pollutant Release and Transfer Register database (PRTR – Spain) was used to extract information from business emissions. PRTR was established by Regulation (EC) 166/2006 E-PRTR, and in Spain, by Royal Decree 508/2007, of April 20, which controls the provision of information on emissions of the E-PRTR Regulation and Integrated Environmental Authorisations. On the other hand, the information related to economic-financial data was extracted from the Iberian Balance Sheet Analysis System (SABI in Spanish) – an online platform with the accounting data of more than 2.7 million Spanish companies.

The analysis was conducted on unbalanced panel data containing 915 observations for the period 2007–2020, compiled from 77 companies in the Spanish agri-food sector. The application of a panel data set allows the consistency and explanatory capacity of the regression analysis to be improved, to control for unobservable heterogeneity and to correct problems of endogeneity (Hsiao 2007).

The Environmental Impact Assessment (*EIA*) of this study, based on pollutant emissions levels, aligns with recent literature (Sorroche-del-Rey et al. 2023). Building on previous research (Horváthová 2012; Muhammad et al. 2016), we introduce an *EIA* indicator applicable at the sector, and company levels, that allows for comparative studies between members of the European Union. While this approach represents a partial view of environmental performance, this indicator is widely used in the literature (Fikru 2011; Sörme et al. 2016; Homroy and Slechten 2019; OECD 2023). For Spanish agrifood firms, this indicator is particularly relevant due to their strong export orientation to European markets (approximately 70% of exports), where these environmental regulations are paramount.

However, PRTR data has inherent limitations. Firstly, direct comparisons based on total emissions are challenging due to varying toxic potentials of different pollutants. Secondly, companies complying with emission limits may not report detailed data. To mitigate these issues, we propose a normalisation approach similar to Fikru (2011). Our EIA is a binary variable: 1 if a company exceeds legal emissions by more than 10%, and 0 otherwise.

Alternatively, we consider *EIA* as a discrete variable, ranging from 0 to 3, where higher values indicate greater environmental impact. This categorisation is based on the percentage of emission exceedance: 0 if the company exceeds pollutant emissions by less than 10%; 1 if exceeded by between 10 and 100 percent; 2 between 100 and 200 percent; and 3 by more than 200 percent.

Likewise, with the aim of homogenising the variable and eliminating the scale effect of production, we categorised the dependent variable based on the number of emissions exceeded for every EUR 1 000 sold (see Table 1).

To analyse the influence of exporting activity (EA) on *EIA*, a dummy variable is created which takes two values: 1 if the company exports, and 0 if not. With the aim of controlling heterogeneity at the company level, a set of company characteristics is also included in the analysis, along with other factors that various studies

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have considered relevant to environmental behaviour (see Table 1).

Table 2 displays the descriptive statistics and frequencies of the variables utilised in the estimation. Table 3 shows the descriptive statistics of the continuous variables before coding. No multicollinearity problems were detected (see Table 4).

Econometric approaches

Following the methodology of Walelign et al. (2016) and Ziegler (2019), binary logit and ordered logit models were utilised for the econometric analysis. As explained below, the parameters in the binary logit models can only be interpreted in relation to the highest *EIA* category in comparison with the three lowest categories. In contrast, the ordered logit model uses all information for the dependent variable. However, it is important to also apply the binary logit as a robustness control.

Therefore, in the initial stage of the analysis, *EIA* is considered to be a binary variable. Given its dichotomous nature, the logit regression is herein proposed as a binary probability model and is also widely adopted in business research (Wooldridge 2002; Cameron

Table 1. Description of variables

Dependent variables	Description	Dimension	Source
EIAd	environmental impact assessment: percentage of emissions exceeding the threshold	dummy variable: *EIAd* = 0; emissions < 10%; *EIAd* = 1; emissions ≥ 10%	PRTR-Spain
EIAo	–	Ordinal variable: *EIAo* = 0; emissions <= 10%; *EIAo* = 1; 10% < emissions <= 100%; *EIAo* = 2; 100% < emissions <= 200%; *EIAo* = 3; emissions > 200%	PRTR-Spain
EIAd/sales	environmental performance: emissions (kg) exceeded for every EUR 1 000 of sale	dummy variable: *EIAd*/sales = 0; kg emissions/ EUR 1 000 sales = 0; *EIAd*/sales 1; kg emissions/ EUR 1 000 sales > 0	PRTR-Spain
EIAo/sales	–	ordinal variable: *EIAd*/sales = 0; kg emissions/EUR 1 000 sales <= 0; *EIAd*/sales = 1; 0 < kg emissions/ EUR 1 000 sales <= 10; *EIAd*/sales = 2; 10 < kg emissions/ EUR 1 000 sales <= 150; *EIAd*/sales = 3; kg emissions/ EUR 1 000 sales > 150	PRTR-Spain
Independent variables	**Description**	**Dimension**	**Source**
EA	export activity	dummy variable: 1 = the company exports; 0 otherwise	SABI
Age	age of the company in years	ordinal variable: 0 = age 5; 1 = 5 < age 15; 2 = 15 < age 25; 3 = 25 < age 35; 4 = age > 35	SABI
Size	firm size measured in number of employees	ordinal variable: 0 = size 10; 1 = 10 < size 50; 2 = 50 < size 250; 3 = size > 250	SABI
ROA	return on assets	dummy variable: 1 = *ROA* > mean (4.47%); 0 otherwise	SABI
Debt	debt level	dummy variable: 1 = debt 60%; 0 otherwise	SABI
Liquidity	liquidity ratio	dummy variable: 1 = liquidity 1.5; 0 otherwise	SABI
Subsector	activity subsector according to the CENAE-2009 classification	categorical variable: 0 = Food industry; 1 = Agriculture, livestock, forestry, and fishery; 2 = Beverage manufacturing	SABI
Stock rotation	stock turnover ratio	dummy variable: 1 = stock > mean; 0 otherwise	SABI

EIA – Environmental impact assesment; EA – Exporting activity; ROA – Return on assets; PRTR – Polutant release and transfer register database; SABI – Iberian balance sheet analysis system

Source: Author's own elaboration

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Table 2. Summary and descriptive statistics

Variable	Frequency	Mean (Standard deviation)
$EIAd_0$	0.6275	0.62
$EIAd_1$	0.3725	(0.48)
$EIAo_0$	0.6275	
$EIAo_1$	0.0913	2.14
$EIAo_2$	0.0754	(1.22)
$EIAo_3$	0.2058	
$EIAd_0$/sales	0.6008	0.66
$EIAd_1$/sales	0.3992	(0.01)
$EIAo_0$/sales	0.6008	
$EIAo_1$/sales	0.2873	3.52
$EIAo_2$/sales	0.0846	(0.02)
$EIAo_3$/sales	0.0271	
EA_0	0.4379	0.56
EA_1	0.5621	(0.49)
Age_0	0.0383	
Age_1	0.1886	2.45
Age_2	0.3044	(1.16)
Age_3	0.2148	
Age_4	0.2540	
Size_0	0.2004	
Size_1	0.1983	1.67
Size_2	0.3237	(1.08)
Size_3	0.2776	
ROA_0	0.5325	0.46
ROA_1	0.4675	(0.49)
Debt_0	0.5140	0.48
Debt_1	0.4860	(0.50)
Liquidity_0	0.6535	0.34
Liquidity_1	0.3465	(0.47)
Subsector_0	0.5219	
Subsector_1	0.3735	0.58 (0.67)
Subsector_2	0.1046	
Stock rotation_0	0.8276	0.17
Stock rotation_1	0.1724	(0.37)

EIA – Environmental impact assesment
Source: Author's own elaboration

and Trivedi 2005). Due to the structure of the panel data, it was considered preferable to apply a random effects model. The logit model of random effects in terms of the probability of being environmentally efficient [$P(Y_{it})$=1] is defined as:

$$P[P(Y_{it}=1/x_{it},\alpha_i)]=F(\alpha_i+x_{it}\beta) \quad (1)$$

where: i – 1,2,3, ..., N; t – 2007–2020; α_i – normally distributed individual effect; β – vector of coefficients; F(.) – function of the accumulative distribution that supposedly follows a logistic distribution; x_{it} – vector associated with the independent variables, which in this study include variables related to the companies that can influence their *EIA*, and which were also detailed in the previous subsection.

In accord with the self-selection theory, environmental performance could show reverse causality with export activity. Therefore, with the aim to verify firm heterogeneity hypothesis, according to which exporting companies are more productive and have more experience in the sector, the following model is proposed as a robustness analysis:

$$\begin{aligned}&P[p(EA_{it}=1/x_{it},\alpha_i)]=\\&=F(\alpha_i+\beta_1 EIA_{it}+\beta_2 Age_{it}+\beta_3 ROA_{it})\end{aligned} \quad (2)$$

where: EA – export activity; i – 1,2,3, ..., N; t – 2007–2020; x_{it} – vector associated with the independent variables; α_i – normally distributed individual effect; *EIA* – Environmental Impact Assessment; *Age* – measures the antiquity of the companies; *ROA* – return on assets ratio; β – vector of coefficients; F(.) – function of the accumulative distribution that supposedly follows a logistic distribution (see Table 1 for detailed description of the variables).

In the second stage, four levels of *EIA* are distinguished (Table 1). In this case, the formulation of the ordered logit model (OLM) with random effects is the following (Crouchley 1995):

$$y_{it}=\beta_0+\beta' x_{it}+b_i' z_{it}+e_{it} \quad (3)$$

where: i – 1, 2, 3, ..., N; t – 2007–2020; b_i – vector of specific individual random effects; x_{it} –known design matrix; e_{it} – stochastic disturbance. The model is immediately simplified to a single random effect, $b_i'z_{it} = e_i$.

The structure of the ordered choice model with random effects is:

$$\begin{aligned}&y_{it}*=\beta' x_{it}+u_i+e_{it}\\&y_{it}=j.if\,\mu_{t-1}<y_{it}*<\mu_{it}\end{aligned} \quad (4)$$

where: e_{it}~f(.) with mean zero and variance $\pi^2/3$; μ_i~g(.) with zero mean and constant variance; σ^2 independently of e_{it}, for all t.

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Table 3. Descriptive statistics of continuous variables

Variable	Number of observations	Mean (standard deviation)	Min	Max
Age	1 071	28.77 (19.00)	0.000	110
Size	933	253.36 (504.24)	1.000	5 095
ROA	961	4.47 (0.62)	–354.000	341.370
Debt	961	60.40 (46.54)	0.263	1 253.500
Liquidity	961	2.04 (12.53)	0.013	379.412
Stock rotation	934	30.62 (90.10)	0.000	1 506.230

ROA – Return on assets
Source: Author's own elaboration

The probability of occurring outcome j given the independent variables in OLM can be defined as:

$$\begin{aligned} prob(Y_{it} = j / x_{it-1}) &= prob(c_{t-1} < Y_{it}* \leq c_t) \\ &= prob(c_{t-1} < \alpha_i + \beta x_{it-1} + \mu_{it} \leq c_t) \\ &= prob(c_{t-1} - \alpha_i - \beta x_{it-1} < \mu_{it} < c_t - \alpha_i - \beta x_{it-1}) \\ &= F(c_t - \alpha_i - \beta x_{it-1}) - F(c_{t-1} - \alpha_i - \beta x_{it-1}) \end{aligned} \tag{5}$$

where: Y_{it} – *EIA* level of the company; *i* at time *t*; $X_{it\text{-}1}$– lagged independent variable; α_i – individual effect; β–vector of coefficients ; μ_{it} – error term; c_t and c_{t-1} – thresholds defining the categories; *F*(.) – cumulative distribution function of μit.

It represents the *EIA* level of the company. This figure can acquire values, indicated in the previous subsection. The same set of independent variables utilised in the logit model was considered relevant to the OLM.

Similarly, the mixed logit model is also applied to solve the non-observable heterogeneity, as it relaxes the assumption of independent and identical distribution (Marcucci and Gatta 2012). The intuition behind

Table 4. Bivariate correlations between variables

Variables	*EIAo*	*EA*	*Age*	Size	Subsector	Debt	Liquidity	*ROA*	Stock rotation
EIAo	1.0000	–	–	–	–	–	–	–	–
EA	0.2519	1.0000	–	–	–	–	–	–	–
Age	–0.0572	0.1992	1.0000	–	–	–	–	–	–
Size	–0.1255	0.3196	0.3628	1.0000	–	–	–	–	–
Subsector	–0.1596	–0.2875	–0.0232	–0.0836	1.0000	–	–	–	–
Debt	0.0413	–0.1441	–0.2110	–0.4058	–0.0909	1.0000	–	–	–
Liquidity	–0.0166	0.0486	–0.0223	0.0515	0.0791	–0.3711	1.0000	–	–
ROA	–0.0311	0.0753	0.0986	0.1598	0.0019	–0.2233	0.1391	1.0000	–
Stock rotation	0.0285	–0.0267	–0.0984	–0.2368	0.0254	0.1036	–0.0587	0.0521	1.0000

EIA – Environmental impact assessment; EA – Exporting activities; *ROA* – Return on assets
Source: Author's own elaboration

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mixed logit can be summarised as follows: Assume, for simplicity, that there is only one parameter β. The logit probability is fixed for a given value of β. Furthermore, suppose that β itself is a random variable. Then, the logit probability will be a function of this random variable. Hence, the 'unconditional' probability of a certain alternative will be given by:

$$\int L(\beta) f_{\theta}(\beta) d\beta \tag{6}$$

where: $L(\beta)$ – logit probability given β; (β) – density of β given the parameter vector θ. That is, the mixed logit probability is the weighted average of the logit probabilities for all possible values of β, where weights are determined by the probability density function evaluated at each value of β. Thus, we are mixing different logit distributions via an underlying density (Uz et al. 2020).

We applied the estimation robust to solve the heteroskedasticity problem. The three models were compared utilising their interval of confidence, and the two information criteria were applied (AIC and BIC) to evaluate which model was preferable. Additionally, marginal effects are utilised with the aim of obtaining more detailed information about the behaviour of the variables, bearing in mind each level of *EIA*. The marginal effects are calculated to illustrate the impact of a unit change in the explanatory variable on the probability of the results of the different levels of *EIA*.

$$E_{x_{it}}^{P_i} = \frac{1}{n}\sum_{i=1}^{n}[P_i(x_{it}=1) - P_i(x_{it}=0)] \tag{7}$$

where: the average difference value of overall observations is calculated when the *j*-th explanatory variable changes from 0 to 1.

RESULTS AND DISCUSSION

Our empirical analysis provides strong support for Hypothesis 1, confirming a positive association between business internationalisation and environmental behaviour. Across all models, exporting activity is significantly and negatively correlated with pollutant emissions at the 1% level. Consistent with previous research, export orientation can stimulate resource efficiency and the adoption of eco-friendly practices.

Given the possible complementarity of the dependency among variables, the possible endogeneity between *EIA* and EA has also been considered. We carry out an additional estimation of the reverse causality between *EIA* and internationalisation (see Table 5) using the method of binary logit model. These results support Hypothesis 2, confirming a bidirectional relationship with a 99% confidence level. Therefore, this robustness analysis shows that in addition to the interrelation between these variables, the main results according to the theories presented are not affected.

Table 5. Regression results of the reverse causality – Binary logit with random effects, 2007–2020

Dependent variable	EA
Independent variables	
EIAd	−2.81*** (0.94)
Age_1	1.85* (1.00)
Age_2	4.58** (2.10)
Age_3	6.73** (3.35)
Age_4	9.69 (7.13)
ROA	0.77 (0.49)
Log likelihood	−138.98
Joint test of model	10.49*
AIC	201.24
BIC	244.79

***,**,* *P* < 0.001; < 0.05; < 0.1; number of observations – 915; standard errors in parenthesis; EA – Exporting activity; *EIA* – Environmental impact assessment; *ROA* – Return on assets; AIC – Akaike information criterion; BIC – Bayesian information criterion

Source: Author's own elaboration

The marginal estimated effects of the ordered logit model are shown below in Table 6.

Our analysis also reveals that firm age also significantly moderates the relationship with *EIA*. Companies older than 5 years have a negative environmental impact compared to younger companies. Table 6 confirms this trend, showing that all business categories with a history of more than 5 years in the sector are more likely to be classified as high impact. These results provide empirical support for Hypothesis 3.

Contrary to our expectations (Hypotheses 4), our findings indicate a positive relationship between firm size and EIA. Model 3 (Table 7) reveals that firms with

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Table 6. Average marginal effects from the estimated ordered logit model with random effects

Explanatory variables	*EIA*o = 0	*EIA*o = 1	*EIA*o = 2	*EIA*o = 3
EA	0.1824***	0.0061***	0.0376***	–0.1385***
Age_1	–0.2416***	0.0147***	0.0692***	0.1575***
Age_2	–0.2701***	0.0155**	0.0748***	0.1797***
Age_3	–0.2382***	0.0146**	0.0685***	0.1550***
Age_4	–0.2061***	0.0134*	0.0615**	0.1311***
Size_1	–0.1275***	0.0072***	0.0348***	0.0853***
Size_2	–0.1808**	0.0092	0.0461*	0.1254**
Size_3	–0.3603***	0.0123**	0.0702***	0.2778***
ROA	–0.0387	0.0013	0.0080	0.0294
Debt	–0.0611*	0.0020	0.0126*	0.0464*
Liquidity	0.0061	–0.0002	–0.0012	–0.0046
$\mathrm{Subsector}_1$	–0.1652*	0.0049*	0.0316**	0.1287
$\mathrm{Subsector}_2$	–0.0529	0.0021	0.0123	0.0383
Stock rotation	–0.0940***	0.0031*	0.0194**	0.0714***

***,**,* $P < 0.001$; < 0.05; < 0.1; number of observations – 915; standard errors in parenthesis; *EIA* – Environmental impact assessment; EA – Exporting activity; *ROA* – Return on assets

Source: Author´s own elaboration

more than 10 employees exhibit a detrimental impact on the environment. Table 6 further supports this observation, showing that large firms are significantly more likely to be categorised as high-polluting compared to micro-firms. This aligns with the expectation that increased scale often leads to higher emissions. To account for this scale effect, Models 4 to 6 analyse emissions per EUR 1 000 sold.

Additionally, while financial capacity does not appear to significantly influence environmental behaviour (Hypothesis 5), efficient inventory management plays a crucial role. Model 2 reveals a positive coefficient for the level of stock rotation, significant at the 5% level, suggesting that companies with higher stock rotation levels are more likely to exceed pollutant emission thresholds. This supports Hypothesis 6.

Firm heterogeneity plays a crucial role in understanding this relationship. As suggested by the learning-by-exporting theory, exporting companies may acquire new techniques and knowledge, leading to increased organic productivity. Furthermore, the growing demand for eco-friendly practices among consumers, especially large retailers, has elevated the importance of environmental quality certifications in the agri-food industry (Hatanaka et al. 2005). Improving environmental performance is a key factor in enhancing the competitive position of European agri-food companies in the global market (Schulze et al. 2008).

This analysis suggests that business heterogeneity within the industry can be explained endogenously. While traditional perspectives often focus on the impact of international trade on the environment, our findings highlight the reciprocal influence. Companies adopting cleaner technologies can gain a competitive advantage in international markets, leading to increased export activity. Conversely, better international market access can incentivise companies to adopt pollution abatement technologies.

Spanish food companies with international dealings may achieve better environmental performance due, in part, to the stringent eco-friendly practice standards of the European Union market (Gawron and Theuvsen 2009), where 67.4% of Spanish exports (in euros) and 52.7% of imports were destined in 2023 (Ministry of Agriculture, Fisheries and Food of Spain 2023). However, other factors such as government incentives or company-specific initiatives could also play a role.

Contrary to predictions, evidence obtained shows that participation in eco-friendly practices is not greater for more profitable companies or larger companies. In other terms, company capacity to reduce pollutant emissions is not dependent on economic resources, which could mean that other variables such as productivity and environmental regulations have greater influence. As for future investigations, it would be interesting to also ana-

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Table 7. Regression Results–Logit estimations, 2007–2020

Dependent variable	*EIAd*	*EIAo*	*EIAo*	*EIAd*/sales	*EIAo*/sales	*EIAo*/sales
Independent variables	model 1 binary logit with random effects	model 2 ordered logit with random effects	model 3 mixed ordered logit model	model 4 binary logit with random effects	model 5 ordered logit with random effects	model 6 mixed ordered logit model
EA	−3.04*** (0.76)	−1.97*** (0.70)	−1.51*** (0.17)	−3.10*** (0.73)	−2.05*** (0.63)	−1.39*** (0.18)
Age_1	3.19*** (1.20)	3.34*** (1.29)	1.83*** (0.76)	2.98*** (1.25)	1.77 (1.41)	1.69*** (0.66)
Age_2	3.72*** (1.25)	3.64*** (1.30)	2.35*** (0.75)	3.82*** (1.31)	2.23 (1.41)	2.29*** (0.65)
Age_3	3.18*** (1.32)	3.30*** (1.40)	2.04*** (0.76)	4.05*** (1.40)	2.45* (1.51)	2.01*** (0.67)
Age_4	2.80** (1.35)	2.96** (1.42)	2.26*** (0.75)	4.84*** (1.46)	3.11** (1.55)	2.39*** (0.65)
$Size_1$	1.82 (1.26)	1.76 (1.12)	1.13*** (0.27)	0.98 (1.01)	0.29 (0.48)	0.59** (0.27)
$Size_2$	2.61* (1.42)	2.37** (1.25)	1.92*** (0.29)	2.40** (1.11)	0.92 (0.60)	1.20*** (0.28)
$Size_3$	4.14*** (1.72)	4.24*** (1.67)	2.91*** (0.34)	4.34** (1.86)	2.53** (1.27)	2.05*** (0.33)
ROA	0.58 (0.44)	0.42 (0.26)	0.09 (0.17)	0.54 (0.49)	0.54* (0.33)	0.26* (0.16)
Debt	0.70 (0.51)	0.66* (0.38)	0.19 (0.18)	0.54 (0.49)	0.38 (0.34)	0.20 (0.15)
Liquidity	-0.07 (0.35)	0.06 (0.30)	0.02 (0.16)	0.17 (0.39)	0.17 (0.26)	-0.10 (0.15)
$Subsector_1$	1.30 (1.20)	1.75* (1.07)	1.28*** (0.22)	3.78*** (1.27)	2.58*** (0.95)	1.49*** (0.19)
$Subsector_2$	0.52 (1.11)	0.59 (1.07)	−0.28 (0.22)	0.16 (1.56)	0.15 (1.47)	0.49* (0.26)
Stock rotation	0.80 (0.60)	1.02** (0.42)	0.18 (0.19)	0.60 (0.61)	0.45 (0.52)	-0.05 (0.20)
Log likelihood	−331.11	−630.15	−824.35	−283.73	−500.71	−741.93
Joint test of model	47.03***	59.97***	155.11***	68.38***	41.86***	205.37***
AIC	694.23	1 296.31	1 682.71	599.4737	1 039.43	1 519.863
BIC	771.33	1 383.05	1 764.63	676.5764	1 130.99	1 606.604

***,**,* $P < 0.001$; < 0.05; < 0.1; number of observations – 915; standard errors in parenthesis; *EIA* – Environmental impact assessment; EA – Exporting activity; *ROA* – Return on assets; AIC – Akaike information criterion; BIC – Bayesian information criterion

Source: Authors own elaboration

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lyse other strategic characteristics of companies that might be influencing the level of pollutant emissions.

Other variables also influence greenhouse gas emissions. For example, younger companies may exhibit more environmentally friendly behaviour, supporting the hypothesis that newer companies are more aware of the balance between economic profitability and environmental performance (Piedra-Muñoz et al. 2016; Hao et al. 2021). Moreover, contrary to conventional wisdom, exporting experience itself may not be as critical as organisational learning derived from internationalisation (Aguilera-Caracuel 2012).

CONCLUSION

This study seeks to contribute to the analysis of the interrelationship between pollutant emissions and international trade at the microeconomic level, using Spanish agri-food companies as reference. In this regard, the results contribute new empirical evidence on the causal relationships between international trade and environmental impact.

The results indicate a negative and bidirectional relationship between pollutant emissions and international trade, suggesting that both variables influence each other. This challenges the traditional assumption of a unidirectional causal relationship from international trade to environmental performance.

Furthermore, firm-specific characteristics influence environmental behaviour. Our study shows that firm age and size are significant determinants of environmental impact, while economic-financial variables do not appear to be relevant in this context. Moreover, effective inventory management can play a crucial role in reducing pollutant emissions within the Spanish agri-food sector.

Notwithstanding, this study has several limitations that should be considered for future research. Firstly, the availability and scope of the data used may limit the comprehensiveness of our analysis. Expanding the dataset to include a broader range of environmental performance indicators would enable a more detailed assessment of companies' environmental impact. Ideally, developing efficiency indicators that encompass multiple dimensions and allow for the use of continuous variables would strengthen the analysis and provide a deeper understanding of these complex relationships. Secondly, exploring the heterogeneity of companies within the agri-food sector in greater detail would provide a more nuanced understanding of the factors influencing their environmental behaviour. Finally, further investigation into the causal relationships between environmental impact, exporting orientation, and other relevant variables is necessary to gain a more comprehensive understanding of the complex dynamics within this sector.

This study offers several contributions to the existing literature on the agri-food sector and has important policy implications. First, it expands the scope of research by examining the relationship between international trade and environmental impact, addressing a significant gap in the literature. Second, the study establishes connections between its findings and various theories on international trade, providing a more comprehensive understanding of the factors influencing firm environmental behaviour. Third, our analysis offers valuable insights for economic decision-makers in the agri-food market. The results highlight the importance of certain business variables, particularly for micro businesses and recently-formed companies, suggesting that they can gain a competitive advantage in international markets. Fourth, to improve the quality of research in this line of research, public databases should be expanded and improved to provide more comprehensive firm-level information on key variables. Finally, global standards and treaties should encourage both developed and developing countries to compete in the international market while promoting sustainability.

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