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Abstract

This study examines the potential spillover effects of the EU ETS price trend on agricultural carbon emissions using panel data regression. Despite agriculture's significant contribution to greenhouse gas emissions, it remains excluded from the EU ETS, the primary mechanism for addressing emissions. Despite not being directly covered by the EU Emissions Trading System (ETS), agriculture may experience spillover effects from this policy, affecting emissions, land use, and environmental sustainability. Panel data regression analysis reveals potential spillover effects of ETS prices on agricultural emissions, though with some uncertainty. Robustness tests highlight the influence of GDP on emissions and ETS prices but raise questions about the model's accuracy in capturing spillover effects. Further investigation suggests potential simultaneous or reverse causality bias, emphasizing the need for better data and instrumental variables in future research. Future research should focus on improving data quality, including monthly or quarterly data, and employing instrument variables to mitigate potential confounding variables and causal biases.

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1:Introduction

Agricultural emissions have a significant impact on the European Union (EU), contributing substantially to the region's greenhouse gas (GHG) emissions and presenting challenges for climate change mitigation and environmental sustainability. Despite accounting for around 10% of total GHG emissions in the EU, the agricultural sector is not included in The European Union Emissions Trading System (EU ETS), the primary mechanism for addressing emissions issues (European Commission, 2022). This study aims to identify spillover effects of EU ETS prices on agricultural sector emissions. Understanding and addressing these spillover effects is crucial for ensuring the effectiveness and fairness of climate policies while safeguarding the viability of agricultural systems. Exploring these spillover effects also enables policymakers, researchers, and stakeholders to better understand the interconnectedness of climate and agricultural policies.

Recent studies by Zhao et al. (2023) have found that the EU ETS has spillover effects on electricity prices in the northern countries of Europe. This suggests that the EU ETS can have an indirect impact on sectors that legislators may not have initially intended. Zhao's (2023) study focuses solely on a sector already within the EU ETS and its spillover effect on price variation, particularly in the northern countries known for their strong focus on climate issues.

In contrast, this paper takes a different approach by examining a sector outside the EU ETS and aiming to identify spillover effects on its emissions rather than its prices. Furthermore, it considers the EU as a whole rather than focusing on specific regions.

The remainder of this work is organized as follows: Section 2 presents a brief overview of related literature, while Sections 3 and 4 outline the research design, including data and methodology. Section 5 presents our empirical findings. Finally, Section 6 discusses our findings and draws policy implications, and Section 7 concludes our work.

2. Literature review

2.1 Background of EU ETS and related research

The European Union's Emissions Trading System (EU ETS) functions as a cap-and-trade system, as described by the European Commission (2022). It operates as a market-based environmental policy mechanism aimed at controlling and reducing pollution by offering economic incentives for emissions reductions. A cap is set to limit the total amount of greenhouse gases emitted by covered facilities, which decreases over time in line with the EU's climate targets, ensuring emissions reduction over the years. Companies can buy and sell emission allowances within these limits, with each allowance granting the right to emit one ton of carbon dioxide equivalent. Failure to surrender enough allowances to match emissions results in significant fines for companies. While companies primarily purchase allowances, some may receive a limited number for free from EU governments. Companies can also use saved allowances from previous years (European Commission, 2022).

The EU ETS was introduced in 2005 and has since undergone several phases of changes. Phase one, from 2005 to 2007, served as a trial period to test price formation in the carbon market and establish infrastructure for monitoring emissions levels, covering mainly power and manufacturing industries. Phase two, from 2008 to 2012, expanded to include Norway, Iceland, and Liechtenstein, with aviation added toward the end of this phase. Phase three, from 2013 to 2020, underwent significant reforms, including a shift toward auctioning allowances instead of free allocations, and added sectors focused on chemicals and aluminium manufacturing and usage. The fourth phase began in 2021 and continues onwards, with its beginning outlined by a legislative proposal for system revision not yet enforced (European Commission, 2022)
The EU: s ETS has a potential problem, that being an oversupply in allowances, that threatens to undermine its goals. In the first two phases, most allowances were allocated for free combined with the downturn of the global economy in 2008, decreased demand and emissions, it caused a surplus of allowances. The presence of the surplus has resulted in persistently low prices for allowance that some think may discourage companies in the EU from taking actions to reduce emissions and investing in low carbon methods. A way to try and fix this problem has been the shift in phase three from giving free allowances away and start auctioning them instead. (European Commission, 2022)

Some existing research provides evidence of the effectiveness of the Emissions Trading System (ETS) in reducing greenhouse gas (GHG) emissions. Abrell et al. (2011) found in their study on the European Union Emissions Trading System (EU ETS) that it notably impacted emissions reduction, particularly during the second phase of implementation. Specifically, it induced emission reductions, with significant differences in abatement behaviour observed across phases. Sectors such as non-metallic minerals and basic metals contributed most to these reductions, while electricity and heat sectors did not show significant cuts. Another study by Grubb et al. (2012) examined the EU ETS and its impact on abatement, investment, innovation, and profits. They found evidence suggesting some degree of emissions reduction in certain sectors, though insufficient to meet long-term targets. However, determining actual emissions reductions within the EU ETS context is challenging due to factors such as surpluses of allowances being greater than verified emissions, leading entities to cover their emissions by purchasing surplus allowances rather than implementing abatement measures. Lin and Jia (2019) studied ETS price influences on GDP and emission reduction in China, finding that as ETS price levels increase, GDP is projected to decrease, suggesting a trade-off between environmental goals and economic growth. They also found that low ETS prices may undermine the effectiveness of the carbon market in reducing emissions, while higher prices are associated with greater reductions in CO_2 emissions, albeit at higher economic costs.

However, some researchers find less evidence of ETS effectiveness. Bel and Joseph (2015) assessed the impact of the EU ETS on greenhouse gas emissions during its first two trading phases, focusing on disentangling effects from the 2008/09 economic crisis. They found that much of the emission reduction during these phases is primarily attributed to the economic recession rather than the EU ETS. The study highlights that oversupply of allowances in the market has resulted in decreased allowance prices and diminished incentives for investments in low-carbon technology.

Additionally, there is evidence of ETS having spillover effects on different markets. Research from Zhao et al. (2023) examined price linkage and risk transmission (spillover effects) between electricity and carbon markets (EU ETS) in northern Europe. The study confirmed the presence of spillover effects between carbon and electricity markets, with varying degrees and characteristics. The analysis investigated how changes in price and volatility in one market affect the other, focusing on the intermediary role of energy markets. These spillover effects were categorized as volatility and return spillover effects, with volatility being more easily transferred between markets than return. Out of 28 market groups analysed, 21 exhibited volatility spillovers, while 15 groups showed return spillovers (Zhao et al., 2023).

2.2 Spillover effects on the Agricultural sector

Yip et al. (2020) conducted a study examining volatility spillover between crude oil and commonly traded agricultural commodities, exploring their connection to oil's low and high volatility. Their findings reveal that the net volatility spillover effect from crude oil to all agricultural commodities tends to decrease to a significantly negative value during periods of low oil volatility. Conversely, this effect shifts to a positive range during high oil volatility, showing a sharp increase when oil transitions from stable low volatility to stable high volatility. These results suggest that the volatility spillover effect is closely tied to the volatility of crude oil, exhibiting distinct patterns in low and high volatility scenarios

3.Data

The study utilizes data provided by the World Bank on EU ETS prices, along with data from the Eurostat database. All collected data are in panel format, covering the period from 2005 to 2021 across the 27 current members of the European Union as of 2024. In total, there are twelve datasets available; however, each estimation will only utilize five datasets. This is due to the inclusion of three robustness tests for other sectors, where emissions and emissions tax data for those sectors will be analysed instead of agriculture. The various variables used in this study, along with their sources, are summarized in Table 1 below.

Table 1

VARIABLE	DESCRIPTION	INDUSTRY	SOURCE
ETS_PRICE	EU ETS price is US dollars per ton of carbon dioxide (CO2) equivalent	EU ETS	World Bank
AGRICULTURE EMISSIONS	Carbon dioxide (CO2) emissions in thousands of tons in crop and animal production, hunting and related service activities	Agriculture	Eurostat (code A01)
MANUFACTURING EMISSIONS	Carbon dioxide (CO2) in thousands of tons includes 33 industry articles	manufacturing	Eurostat (code C)
MINING/QUARRYING EMISSIONS	Carbon dioxide (CO2) in thousands of tons	mining/quarrying	Eurostat (code B)
HEATING/COOLING EMISSIONS	Carbon dioxide (CO2) in thousands of tons only includes heating and cooling for households	Heating/cooling	Eurostat (code HH_HEAT)
TAX_EMISSIONS_AGR	The revenue collected from pollution taxes in millions of euros (only carbon dioxide)	Agriculture	Eurostat (code A01)
TAX_EMISSION_MAN	The revenue collected from pollution taxes in millions of euros (only carbon dioxide)	manufacturing	Eurostat (code C)
TAX_EMISSION_MIN	The revenue collected from pollution taxes in millions of euros (only carbon dioxide)	mining/quarrying	Eurostat (code B)
TAX_EMISSIONS_HEAT	The revenue collected from pollution taxes in millions of euros (only carbon dioxide) Eurostat lacks that specific data set, so households are used instead, EP_HH.	Heating/cooling	Eurostat (Code EP_HH)
GDP	Annual gross domestic product at current prices in millions of euros	-	Eurostat (code -)
FOOD_PRICE	Harmonized Index of Consumer Prices is for food and non-alcoholic beverages	-	Eurostat(code CP01)

4. Methodology

To estimate potential spillover effects of the EU ETS on the agricultural sector, this study constructed the following log-log model: $\boldsymbol{lnY_{it} = \beta_0 + \beta_1 lnETS\,price_t + \beta_2 lntax_{it} + \beta_3 lnGDP_{it} + \beta_4 lnfood_{it} + \gamma_i} + \varepsilon t$

Where the dependent variable lnY_{it} is the emissions by EU member i in the agriculture sectors in years t, measured in thousands of tons. The independent of interest are $lnETS\,price_t$ is EU: s ETS price measured in US dollars per ton of emissions. The price is the same for all EU member states so this variable ($lnETS\,price_t$) lack individual (entity) data and is in year t. $lntax_{it}$ is the first control variable and measures the revenue collected by EU member i from pollution taxes (only carbon dioxide) in millions of euros in years t. The next control variable $lnGDP_{it}$ annual gross domestic product by member stat i measured at current prices in millions of euros per year t. $lnfood_{it}$ is a harmonized index of consumer prices is by EU stat member i in years t measured for food and non-alcoholic beverages. The model also includes a country fixed effect γ_i by a set of dummy variables. Where 26 dummy variables are created with one country serving as the reference category, in this instance being Austria. This helps to account for differences in economic, social, cultural, or institutional characteristics that are not explicitly measured in the dataset but could have an effect on emissions levels.

The model is a log-log meaning that every variable, except for the γ_i, are transformed using the natural logarithm function. The reason for having a log-log model when estimating the spillover effects are because many entity's (countries) have a non-linear relationship between the dependent variable lnY_{it} and $lnETS\,price_t$ variable, as figures 2 to 5 shows in appendix. The log-log model can help linearize the relationship between variables by transforming them using the natural logarithm. This is important as this study uses the ordinary least squares (OLS) estimator that assumes a linear relationship between the independent variable and the dependent variable. The objective of the OLS is to find the line that minimizes the sum of the squared differences between the observed dependent values and the values predicted by the model.

Something that is not in the estimations of the model is time fixed effects that works the same way country fixed effects does however with time trends. The reason it is not in the estimations is because the ETS prices are the same for all the countries, shown in Appendix figure 1. This means the model cannot control for unobserved factors that may vary systematically across time periods however are common to all units, such factors as global recessions, seasonal effects, and pandemic.

This study dose a type of sensitivity test, to evaluate the robustness of the main regression. The goal of the test is to observe if the main independent variable, the $lnETS\,price$, is stable when adding another controlling variable in one at a time. The technique is particularly valuable where it helps to identify which variables have the most influence on a particular result. The test assist in the evaluation and in understanding the robustness of the model. An unstable main independent variable that gains or loses its significance when a control variable is included could suggest several interpretations about the relationships between the variables.

To further evaluate the robustness of the results three additional sensitivity test are made for sectors that are in the EU: s ETS. The mining and quarrying sector, the manufacturing sector and the heating/cooling sector is used and utilize the same model as the main, the agricultural sector, but the dependent variable lnY_{it} and the control variable $lntax_{it}$ use data for respective sector. By applying the model to multiple sectors, we can verify that the observed effects are either unique or not unique to the agricultural sector, therefore we can judge if the model can capture spillover effects or not. It also ensuring that our model performs consistently across these varied sectors, thus strengthening the validity of our findings.

It is important to address potential biases that might arise in the results. One such bias is simultaneous causality bias, where both the dependent variable and the independent variable influence each other. This complicates the determination of the true direction of causality and may lead to an overestimation of the actual effect. Another potential issue is reverse causality, where the causal relationship could be opposite to what is assumed in the analysis. Additionally, omitted variable bias may occur if an unobserved variable affects both the dependent and independent variables, thereby exacerbating the bias.

A common method to mitigate these biases is the use of an instrumental variable, which correlates with the independent variable but not with the error term. This approach helps in isolating the true causal effect. However, this method is not employed in this thesis.

5. Results

This section presents the results of our regressions and evaluates their robustness. We begin by examining the main regression for the agricultural sector to assess the effects of the EU ETS price trend on agricultural carbon emissions and determine if there are any spillover effects. Following the presentation of the main regression results, we evaluate their robustness using three additional tests.

5.1 Regressions results

To interpret the log-log model 1% change in an independent variable is associated with a β_i1% for the dependent variable holding constant all other variables in the model.

The main regression results in Table 2 display that the coefficients on the $lnETS\ price_t$of the log-log model are significantly positive on a 10% level when country fixed effects and all control variables are included. The coefficient of the $lnETS\ price_t$estimator is 0.02 meaning that if the $lnETS\ price_t$increases by 1% the carbon emissions in the agricultural sector increases 0.02%. For the control variables $lntax_{it}$ on agriculture, $lnGDP_{it}$and the $lnfood_{it}$ should also have a closer look. The $lntax_{it}$ on agriculture are positive, but insignificant even on the 10% level. The trend suggests that a 1% increase in tax emissions on agriculture would increase agricultural emissions by roughly 0.004% but there is no significant relationship. $lnGDP_{it}$has a statistically significant level of 1% and has a positive impact on agricultural emissions. The result indicates that a 1% increase in $lnGDP_{it}$causes an increase in agricultural emissions by almost 0.3%. The coefficient of the $lnfood_{it}$is negative and does not have a significant impact. It suggests that a 1% increase in the $lnfood_{it}$would have roughly 0.17% reduction in emissions. How probable this estimate can interpret causally is discussed in section 6.

Table 2. Regression results: Agriculture

lnY_{it}	(1)
VARIABLES	Log-log
$lnETS\ price_{t}$	0.0200*
	(0.0115)
$lntax_{it}$	0.00445
	(0.0102)
$lnGDP_{it}$	0.297***
	(0.0762)
$lnfood_{it}$	-0.173
	(0.138)
Constant	3.659***
	(0.657)
Observations	395
R-squared	0.992
Country-fixed effect	YES

Standard errors in parentheses

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

5.2 Robustness tests

This study runs several robustness tests to assess the accuracy and validity of the findings and the model. They provide insight into EU ETS impacts on the agricultural sector and the impact it has on sectors that are in the system. First, looks at the sensitivity test on agriculture emissions. Secondly, it looks at three regressions for three sectors that are in the EU ETS to check if the model can estimate any effects that should have a direct impact.

5.2.1 Robustness tests, Sensitivity Test

In Table 3 first column (1), that only contains the $lnETS\ price_t$, has a significant positive impact at the 1% level. The coefficient on the $lnETS\ price_t$is 0.0318 meaning if the $lnETS\ price_t$was the only variable impacting the agricultural emissions 1 % increase on the price would increase roughly 0.03% emissions. When $lntax_{it}$ is added in the second column (2) the significant and the coefficient stay the same. Column (3)
$lnGDP_{it}$is added and the $lnETS\ price_t$ significant level becomes 10 % and the coefficient decreases to 0.022. $lntax_{it}$non-significant, and the coefficient becomes smaller. $lnGDP_{it}$is itself significant at the 1% level and the coefficient is 0.226. The last column (4) is the whole model, and the addition of $lnfood_{it}$does not change much for $nETS\ price$, just the coefficient becomes a little smaller to 0.02, and the significant level stays the same. $lntax_{it}$coefficient is somewhat bigger however changes nothing to its non-significant. $lnGDP_{it}$stays the same significant level, at 1%, and the coefficient becomes quite bigger to 0.297. In this sensitivity test the biggest changes to the regressions of the model when $lnGDP_{it}$is added as this addition weakens the $lnETS\ price_t$ variable, the primarily focus on in this study, statistical significance. This sensitivity test suggests that there could be several possible interpretations about the relationships between the variables in the model and will be discussed further in the next chapter.

Table 3. Sensitivity Test: Agriculture

lnY_{it}	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
VARIABLES	Log-log	Log-log	Log-log	Log-log
$lnETS\ price_t$	0.0318***	0.0318***	0.0220*	0.0200*
	(0.0114)	(0.0115)	(0.0114)	(0.0115)
$lntax_{it}$		0.00648	0.00361	0.00445
		(0.0105)	(0.0102)	(0.0102)
$lnGDP_{it}$			0.226***	0.297***
			(0.0513)	(0.0762)
$lnfood_{it}$				-0.173
				(0.138)
Constant	6.606***	6.623***	3.760***	3.659***
	(0.0546)	(0.0609)	(0.652)	(0.657)
Observations	395	395	395	395
R-squared	0.992	0.992	0.992	0.992
Country-fixed effect	YES	YES	YES	YES

5.2.2 Robustness tests, different sectors

This section will look at three different sensitivity tests made from three different sectors. All industries are in the EU ETS and have the same variables as the main regression except for the emissions and emission tax that are the same data as the agricultural one however for each respective sector. Table 4 is a sensitivity test on the mining and quarrying sector where in column (1) $lnETS\ price_t$ is significant, at 10% level, positive with a coefficient of 0.0337.

Column (2) adding $lntax_{it}$ variable for mining and quarrying the $lnETS\ price_t$ becomes more significant, at a 1% level, and the coefficient becomes a little bigger at 0.0343. The emission tax variable itself is negative coefficient, differently from main regression when it was positive, and is not significant. When adding $lnGDP_{it}$ in column (3) $lnETS\ price$ loses its 1% to a 10 % significance much similar to the first column. $lnGDP_{it}$ is positive and non-significant and

$lntax_{it}$ stays roughly the same. The last column (4) ETS price loses all its significant levels and $lnGDP_{it}$ gains significantly at 1% level. $lnfood_{it}$ is also significant at a 1% level and has a negative coefficient at -1.037.

Table 4. Sensitivity Test: Mining and quarrying

	(1)	**(2)**	**(3)**	**(4)**
$\boldsymbol{lnY_{it}}$	**OLS**	**OLS**	**OLS**	**OLS**
VARIABLES	**Log-log**	**Log-log**	**Log-log**	**Log-log**
$\boldsymbol{lnETS\ price_t}$	**0.0337***	**0.0343****	**0.0339***	**0.0219**
	(0.0174)	**(0.0174)**	**(0.0177)**	**(0.0173)**
$\boldsymbol{lntax_{it}}$		**-0.0108**	**-0.0111**	**-0.0138**
		(0.0142)	**(0.0145)**	**(0.0141)**
$\boldsymbol{lnGDP_{it}}$			**0.00915**	**0.438*****
			(0.0811)	**(0.116)**
$\boldsymbol{lnfood_{it}}$				**-1.037*****
				(0.207)
Constant	**6.555*****	**6.518*****	**6.402*****	**5.715*****
	(0.0828)	**(0.0960)**	**(1.038)**	**(1.015)**
Observations	**395**	**395**	**395**	**395**
R-squared	**0.984**	**0.984**	**0.984**	**0.985**
Country-fixed effect	**YES**	**YES**	**YES**	**YES**

Table 5 is in the manufacturing sector and has the same structure as the other sensitivity test. In all the columns (1) to (4) we see no significance in the $lnETS\ price_t$however it is significant at least at 5% on all other controlling variables except for GDP in column (3). In the coefficients of the variables almost all is positive, very much like the main regression in Table 2, however not $lnGDP_{it}$in column (3) but then in (4) it becomes positive. $lnfood_{it}$ are negative similar to Table 2.

Table 5.Sensitivity Test: Manufacturing

	(1)	**(2)**	**(3)**	**(4)**
	OLS	**OLS**	**OLS**	**OLS**
$\boldsymbol{lnY_{it}}$				
VARIABLES	**Log-log**	**Log-log**	**Log-log**	**Log-log**
$\boldsymbol{lnETS\ price_t}$	**0.0108**	**0.0113**	**0.0121**	**0.00423**
	(0.00801)	**(0.00798)**	**(0.00814)**	**(0.00772)**
$\boldsymbol{lntax_{it}}$		**0.0236****	**0.0225****	**0.0375*****
		(0.0111)	**(0.0113)**	**(0.0108)**
$\boldsymbol{lnGDP_{it}}$			**-0.0185**	**0.265*****
			(0.0373)	**(0.0532)**
$\boldsymbol{lnfood_{it}}$				**-0.665*****
				(0.0940)
Constant	**10.16*****	**10.09*****	**10.33*****	**9.754*****
	(0.0382)	**(0.0480)**	**(0.480)**	**(0.458)**
Observations	**395**	**395**	**395**	**395**
R-squared	**0.996**	**0.996**	**0.996**	**0.996**
Country-fixed effect	**YES**	**YES**	**YES**	**YES**

Table 6 is on the heating and cooling sector where we see in $lnETS\ price_t$column (1) and (2) significantly at 5 % level then in (3) and (4) at the 1% level. When adding $lntax_{it}$ for heat and cooling the impact of $lnETS\ price_t$reduces a little in its

coefficient however increases again when
$lnGDP_{it}$ is added and lowed somewhat when $lnfood_{it}$ is includes. $lntax_{it}$ for heating and cooling have negative coefficients in all columns and is only significant in column (2). $lnGDP_{it}$is only significant in (3) columns and loses it when $lnfood_{it}$is added, it also has a negative coefficient in all columns$lnfood_{it}$is in column (4) the only variable with the $lnETS\ price_t$that is significant, both at a 1% level.

Table 6. Sensitivity Test: Heating/cooling

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
lnY_{it}				
VARIABLES	**Log-log**	**Log-log**	**Log-log**	**Log-log**
$lnETS\ price_t$	**0.0310****	**0.0265****	**0.0447*****	**0.0375*****
	(0.0131)	**(0.0126)**	**(0.0129)**	**(0.0126)**
$lntax_{it}$		**-0.342*****	**-0.109**	**-0.0691**
		(0.0615)	**(0.0786)**	**(0.0763)**
$lnGDP_{it}$			**-0.335*****	**-0.0508**
			(0.0731)	**(0.0892)**
$lnfood_{it}$				**-0.762*****
				(0.146)
Constant	**8.745*****	**11.59*****	**13.88*****	**13.44*****
	(0.0618)	**(0.516)**	**(0.708)**	**(0.689)**
Observations	**390**	**390**	**390**	**390**
R-squared	**0.990**	**0.991**	**0.992**	**0.992**
Country-fixed effect	**YES**	**YES**	**YES**	**YES**

These sensitivity tests on different sectors that are all in the EU ETS framework all have several different possible interpretations between the impact of the ETS price on emissions that will help evaluate the level of robustness of the main regression. This is discussed in the next section.

6. Discussion

This chapter will be divided into two parts. The first part will discuss the statistical significance of the main regressions and how the model estimates the effects ETS has on agricultural emissions. The second part will examine the positive coefficient the ETS price has in all the regressions and how that can interpret the relationship between cause and effect.

6.1 The significance of the results

The results for the main regression on agriculture in Table 2 show no significance at a 5% level or lower for the $lnETS\ price_t$ on the agricultural emissions. The 10% level statistically significance impact suggests that the $lnETS\ price_t$ has some probability of having a spillover effects on lnY_{it},the agricultural sector's emission however, the risk is also high that impact is from randomness. One could speculate that not having any spillover effects is expected. As having a system, such as the EU ETS, having no impact on a sector, such as agriculture, that is not in that system is reasonable. However, the results from previous study of Zhao et al (2023) found it that the volatility of ETS price had a spillover effect on the prices in electricity markets in northern counites. This indicates that ETS price might have an effect on agriculture making it more credible that their can exists some spillover effect. The study from Yip et al (2020) finds that spillover effects from price volatility between crude oil and agricultural commodities exist giving more evidence that ETS price changes might spillover to the agricultural sectors. However, those study did not look at how ETS price or price changes effected emissions, such as this study does, and the Zhao's study on the electricity market is in the ETS unlike the agricultural sector. The differences in the studies leading the main results in Table 2 to similar spillover effect more uncertain.

This raises the question of how well the model in this paper is constructed to capture the presence or absence of spillover effects. To evaluate the model robustness, we see if the ETS price is stable when adding other variables. In Table 3 in the first robustness test ETS price is significant before we add the $lnGDP_{it}$suggesting the model is not most stable. However, it could just suggest that there are several possible interpretations about the relationships between all different factors.

One possibility why ETS price could lose its significance is that GDP is a confounding variable that influences the air emissions for agriculture and ETS price. Evidence of this being true is from Lin and Jia (2019) study on ETS price influence on GDP and emission reduction in China. They found the relationship of ETS price increasing GDP and emissions decreases. They suggest that there is a trade of between economic growth and emission levels, were an increase in GDP increases emissions. The main results in this study finds a $lnGDP$ to be statistically significant and has a positive coefficient suggesting a similar relationship.
The significance in ETS price before might have been due to an omitted variable bias that with GDP has been corrected. The previous model without the GDP might have been mis specified, causing the significance for ETS price. The new model is a more accurate picture of the true relationship revealing that the ETS price was not truly significant. One way to statistically counter the confounding effect is by using an instrumental variable that is correlated with the independent variable but not with the confounder.

Table 4 to Table 6 tries to evaluate if the model is able to capture any effect ETS price might have on a different sector, in the system, emissions level. Table 4 and Table 5 show no significance to ETS price while Table 6 does suggest that of these three sectors the ETS price impacts heating/cooling sector the most. The effectiveness of the EU ETS policy is not university agreed on and there is evidence for it both its success and shortcomings. Abrell et al (2011) and Grubb et al(2012) finds some significance impact for EU ETS first two phases in both reduction of emissions and abatement in some sectors. In Abrell study they find ETS having most effect in the non-metallic minerals and basic metals sectors while in this study in Table 4, mining and quarrying, finds no significance when $lnfood_{it}$ is added. Abrells paper finds no significant emission cuts for the heating sector while this paper finds ETS price has most statistically significant in heating/cooling sector. It is not a 100 % true comparison for the sectors examine for both studies but the sectors are vervy similar. The revelation that this paper found the opposed result from the Abrell study for two sectors brings in to question if the model is able to capture any true impact ETS price might have on sectors emission. Bel and Joseph (2015) does not find evidence that EU ETS have a significant effect on emissions level but that the economic recession have had a bigger effect. This brings back the conversation of GDP being a stronger variable in the model to predict emission levels for almost all sectors looked at in this study. $lnGDP$ is significant in almost all sectors, except the heating/cooling sector, this study looked at and Bel study suggest that is the main contributor to emission levels. However, these three studies only looked at phases one and two so the true relationship might have changed.

Grubb et al (2012) mentions how the surpluses of allowances has made it challenging to estimate the actual emission reduction where companies can cover their emissions by purchasing surplus allowances rather than implementing abatement measures. Bel and Joseph (2015) also highlights this problem where the oversupply of allowances in the market have resulted in a decrease in ETS prices. Figure 1 in appendix the low value in ETS can bee seen in the first two phases relative to more recent times. Lin and Jia (2019) finds that low ETS prices in China tends to undermine the effectiveness of reducing emissions. Such a relationship seems to exist in the EU ETS however it cannot be for certain. Might be something for future researchers to look at for the EU ETS.

6.2 The causality of the results

The coefficient from Table 2 on $lnETS\ price_t$ is 0.02 because the model is log-log it means that a 1 % increase of ETS price has a 0.02 % increase in emissions on agriculture. This signifies that the spillover effect ETS price has on emissions for agriculture is arguably negative to society at large when it comes to reducing carbon emissions. Having the price of ETS go up and that resulting in more pollution is a relationship that arguably goes against the main goals of the EU agenda for sustainable development. These also goes against the previous research that has been made. Abrell et al (2011) finds that ETS has a reduction in emissions, so does Grubb et al (2012). Lin and Jia (2019) looked at ETS price in China and found it also reduce emissions, Bel and Joseph (2015) finds that GDP had most to attribute to emission reduction but not that ETS increase emissions. Because all other robustness tests made in this study, table 4 to 6, also have a positive coefficient there must be an underlying factor at play.

One candidate that can explain what we are observing is that there is simultaneous, or even reverse, causality. The price might affect the emission level but the emission levels might also affect the price. It could also simply be a reverse causality bias, where the true causal relationship may be reversed from what is assumed. In this case it might not be that the ETS price is what affects the levels of air emissions but that the levels of air emissions are what affects the ETS price. For example, if the air emissions in the EU has gone up then the EU issues fewer allowances to trade and the ETS price goes up. Because the ETS price has a positive coefficient for all sectors done in this study it makes the evidence for simultaneous causality bias or reverse causality bias more likely. One way to solve these biases is the use of an instrument variable, one that strongly correlates with ETS price but that do not correlate directly with the emission levels. The low value of ETS prices, resulting from the oversupply of allowances, might also undermine the ETS's effectiveness in reducing emissions. Lin and Jia (2019) find a similar issue in China. However, in the EU, the effect might be so profound that the ETS is now enabling more emissions rather than discouraging them. Future research is needed to prove if this is the cause.

6.3 Limits

Something that could mislead the results is the absence of time fixed effects. Time fixed effects could have been useful to control for the effects of variables that change over time but are constant across countries. This could have reduced omitted variable biases, however because all the countries had the same ETS price as data this could not be included in the model.

Having an instrument variable would solve some biases, omitted variable biases, simultaneity bias and reverse causality bias

Few observations for just 18 years because of annual data, the ETS price not having that much variation plus the low value of ETS price the first two phases.

7. Conclusion

In this study, we are trying to answer the question of whether the EU ETS price have any spillover effects on the agriculture sectors carbon emissions. Therefore, we conducted a panel data regression with a log-log model to empirically investigate the impact of ETS price trend on agricultural emissions, followed by sensitivity tests for the agricultural, the manufacturing, mining and quarrying and heating/cooling sectors. Our results lead to the following conclusion.

First, the main results from Table 2 shows that the $lnETS\ price_t$ has some probability of having a spillover effects on the agricultural sector with a 10 % significance giving it a somewhat high risk the results are random. Previous research suggests that ETS price have had slipover effects on electricity markets before but not on emissions just its price volatility. The test robustness from the sensitivity analysis, show that $lnETS\ price_t$ is very significant before $lnGDP_{it}$as a control variable. This suggests that the GDP variable could influence both $lnETS\ price_t$ and $lnY_{\boldsymbol{it}}$ on emissions. Previous studies in China show that ETS prices has a negative effect on economic growth and development in trade of with higher reduction in emissions. To ensure that the model can capture the full spillover effect ETS price might have on agricultural emission an instrument variable should be added. However, because the lack of significance for two out of three robustness tests and that some of previous studies have difficulty in assessing ETS effectiveness in some sectors. The results from these robustness tests and previous research makes it unclear if there really are no spillover effects or if the model is unable to capture the spillover effects correctly.

Secondly, we conclude that the positive coefficient of the ETS price for all the regressions that were made suggest that there could be a simultaneous or reverse causality bias. Where the true relationship could be that the carbon emissions are what affects the ETS price not the ETS price is what affects the emissions levels. However, none of the previous studies have find such a relationship, to be certain an instrument variable is probably be needed to find the true relationship.

For future research, both better data, preferably monthly or quarterly, and the use of an instrumental variable are needed. This could address the potential confounding variables and the potential simultaneous or reverse causality bias. Future studies can also seek to observe whether the low value of ETS prices undermines the effectiveness of emission reduction, as seen in China. Additionally, many researchers hypothesize that the oversupply of allowances has diminished incentives for investments in low-carbon technology. Studies should be incentivized to investigate the causes and effects of low ETS prices in the EU.

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Appendix

Figure 1 shows price trend of ETS between 1990 to 2023 over time (US dollar/tCO2e)
Figure 2 to 5 shows for 5 EU countries scatter plots ETS price on Y axis and air emissions for agriculture on X axis show a non-linier relationship

Figure 1 ETS price trend

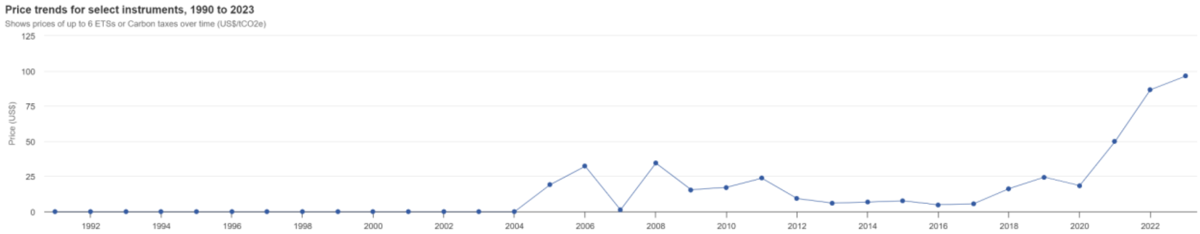


Figure 2 Scatter plot for Sweden

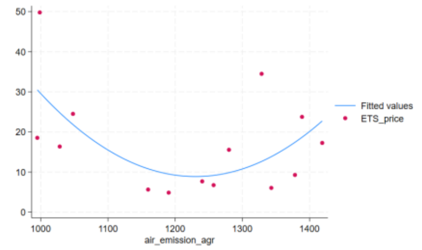


Figure 3 Scatter plot Belgium

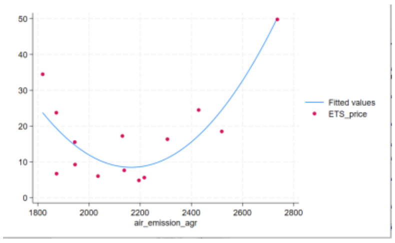


Figure 4 Scatter plot Austria

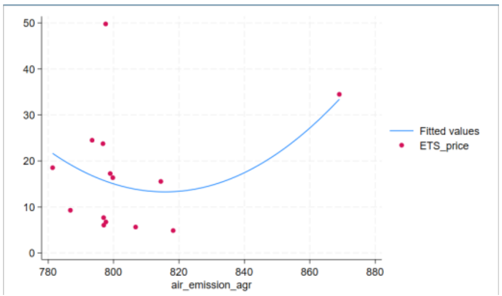
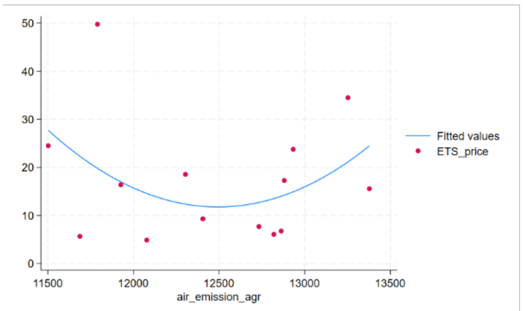


Figure 5 Scatter plot France



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