The impact of the EU Emissions Trading System on oil consumption in Europe:

An empirical analysis based on a DDD model

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Abstract

Whether the emissions trading scheme (ETS) can achieve energy conservation reduction in European countries is crucial for these countries to achieve sustainable economic and environmental development. This study investigates the oil and petroleum products conservation effects of the European Union's permit trading policy implemented in 2005. Using country-level panel data of different sectors from 1995 to 2019, we apply the difference-in-difference-in-difference (DDD) model to examine the effects on oil consumption. In addition, we investigate the drivers of oil consumption in the agricultural sector, as oil is the dominant energy source in global and European agriculture. Based on the results, we derive recommendations for policy makers on how to limit the consumption of oil as a fossil fuel, particularly in agricultural markets.

Keywords: EU Emissions Trading System, oil conservation, DDD model, agricultural oil consumption

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Abbreviations

CO_2	Carbon dioxide
DDD	Difference-in-difference-in-difference
DID	Difference-in-difference
ETS	Emissions Trading System
EU	European Union
EU ETS	European Union Emissions Trading System
GDP	Gross domestic product
GHG	Greenhouse gases
R&D	Research and development

1. Introduction

In 2020, oil (oil and petroleum products) remains the most important energy source with a share of almost 32 % in the European Union (EU), followed by natural gas with 24 % (Eurostat, 2022a). The dominance of fossil fuels can also be observed in individual sectors. It is well documented that fossil fuels are the dominant source of energy in global and European agriculture, with oil accounting for 55% of total consumption (Eurostat, 2021). With the introduction of the Green Deal, the EU targets climate neutrality by 2050, and the EU's farm-to-fork strategy requires sustainable agriculture to move significantly away from fossil fuels. Grubb et al. (2015) consider three important pillars for an effective transition to a low-carbon system. The first pillar includes energy efficiency measures through standards and public involvement. Carbon taxation and emissions trading systems (ETS) form the second pillar of carbon pricing. Policies for government-supported low-carbon technologies and infrastructure form the final pillar. The EU introduced the European Union Emissions Trading System (EU ETS) in 2005, whose primary goal is the mitigation of greenhouse gases (GHGs) and whose longer-term goal is to encourage innovation leading to a transition to low-carbon energy (Baranzini et al., 2017). In this work, we investigate the impact of the EU ETS on oil consumption and whether its extension to the non-regulated agricultural sector could contribute to energy saving. We further examine which factors determine oil consumption in agriculture.

Theoretically, in terms of energy structure, the ETS is expected to substitute high-carbon energy for low-carbon energy by increasing the cost of high-emitting fossil fuels, thereby significantly reducing their consumption (Delarue et al., 2008; Gambhir et al., 2014; Li & Jia, 2016). The impact in terms of energy savings is similar to that of a carbon tax. Martin et al. (2014) show that a carbon tax on manufacturing equipment has led to a reduction in energy consumption in the UK. Schmitz et al. (2011) analyse the energy consumption and carbon dioxide (CO_2) emissions of the glass industry in the EU and find, using EU ETS data, that the average intensity of fuel consumption and direct CO_2 emissions decreased from 2005 to 2007. However, they do not establish causality and do not link the decline to the introduction of emissions trading policies. This paper fills this gap by analysing the impact of the European scheme on the consumption of oil and petroleum products across various sectors in Europe. Therefore, we extend the difference-in-difference (DID) model of Hu et al. (2020), which analyses Chinese ETS to assess the impact of the policy on energy conservation, by adding a third difference and apply it to European countries.

In the scope of the energy transition, agriculture faces a double challenge: on the one hand, it must reduce its dependence on fossil fuels, and on the other hand, it must provide society with bioenergy as a substitute for fossil fuels in addition to food. However, current agriculture is itself highly dependent on fossil fuels. The idea of involving farmers in a national permit trading scheme was pioneered in Australia by Maraseni (2009), but to date, no system involves the sector. Energy use in agriculture long ago attracted the attention of the US scientist Cleveland (1995), who studied the productivity of energy use in US agriculture. Other scholars examine the agricultural energy use in non-European countries such as Pakistan and China (Chandio et al., 2019; Fei & Lin, 2017). The analysis of driving forces for oil demand in the European agricultural sector has to our knowledge been neglected in past research.

A thorough understanding of how regulated industries responded to the EU ETS is crucial for not only improving the domestic policy but also other carbon trading schemes around the world. Therefore, this work first employs a difference-in-difference-in-difference (DDD) approach to evaluate the impact of the EU ETS on oil consumption, whereby agriculture is included in the control group. Thereafter, our study examines the drivers of oil consumption in the agricultural sector. This paper contributes to the literature in the following three aspects. First, it adds to the literature of empirical ex-post analyses on macro-level to evaluate the effectiveness of the ETS. Second, we broaden the scope of the DDD model to assess the impact of the CO_2 ETS on energy conservation. Finally, this paper has extended the empirical evidence on the determinants of oil consumption by applying the analysis to the agricultural sector in Europe.

The results suggest that the implementation of the EU ETS significantly reduces the oil demand in Europe and hence the extension of the EU ETS to non-regulated sectors could result in energy conservation. Moreover, the key driver for oil reduction in the agricultural sector is technical progress.

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

2. Related Literature

This section reviews the literature by presenting different strands of literature. The first part focuses on ETS impact studies, and the second on determinants of energy consumption. The last part provides background on energy consumption in the agricultural sector. The second and third strand help to identify the relative drivers of oil consumption, which are included in the econometric models in Chapter 3.

2.1 Background of EU ETS and related research

The EU ETS is a market-based system that sets a quantitative limit on carbon emissions and allows the market to determine a price on carbon so that emissions can be reduced in the most cost-effective way. It covers carbon dioxide, nitrous oxide, and perfluorocarbons from over 11.000 power stations and manufacturing plants in the member states of the EU, Iceland, Liechtenstein, and Norway. The cap of an ETS determines the number of permits supplied, while the demand for permits depends on output and the emissions intensity of regulated entities. Companies under the scheme are allowed to trade these allowances, with one EU Allowance Unit (EUA) corresponding to one tonne of CO_2. The EU ETS covers several sectors that account for about 45% of total greenhouse gas emissions in the EU. These sectors are electricity and heat generation, energy-intensive industries such as oil refineries, steel mills and the production of metals, cement, glass, ceramics, pulp, paper, acids and bulk organic chemicals, and commercial aviation within the European Economic Area (European Commission, 2022).

In the first year after the launch of the EU ETS, the price was relatively high, peaking at around EUR 26 in early 2006. However, in the same year, the price dropped drastically to zero and remained at this level for the rest of the pilot phase. In the first year of the second phase, the price started at around EUR 21 and peaked at around EUR 27 in mid-2008 before starting to fall as the financial crisis deepened. The EU carbon price has been relatively low for a period of 10 years since the end of 2008 and has been rising again since the beginning of 2018. As a result, there have been concerns in the public debate that the price was too low to incentivise investment in technological developments that promote energy efficiency, reduce energy consumption, and lead to subsequent CO_2 reductions (Zhang et al., 2016).

The EU ETS, as it is the largest multi-country, multi-sector permit trading system, has been the object of several studies examining its effects of the ETS. The literature includes competitive analyses (Castagneto-Gissey, 2014; Graichen et al., 2008; Qi et al., 2021), the evaluation of investment incentives in low-carbon technology (Hoffmann, 2007; Rogge et al., 2011), and studies assessing its GHG abatement.

In the existing literature, studies confirm the effectiveness of the ETS in reducing GHG emissions. Anderson & Di Maria (2011) show, using dynamic panel estimation techniques, that during the two-year pilot phase (2005-2007) of the EU ETS, emissions decreased by almost 3 %. The majority of the emission reduction occurred predominantly in the EU-15 countries. In the second phase(2008-2012), according to Martin et al. (2016), companies regulated by the EU ETS emit significantly up to 26 % less carbon. On the other hand, the following researchers suggest that the impact of the ETS should be taken with caution. Based on a cross-country panel data set of the European power market Clò et al. (2017) conclude that low prices, and an overallocation of allowances resulted in a limited impact of the ETS on emission reduction. Carrilho-Nunes & Catalão-Lopes (2022) investigate the impact of the participation of Portugal in the EU ETS and support the unclear effects on emissions. Bel & Joseph (2015) use historical data to assess the impact on GHG emissions during the first two trading periods of the EU ETS taking into account the impact of the financial crisis. They claim that the drop in emissions observed between 2005 and 2012 is mainly a consequence of the economic downturn and not due to the implementation of the EU ETS. The findings of Howie & Atakhanova (2022) reveal that despite the introduction of the ETS in Kazakhstan CO_2 emissions and CO_2 emissions intensity in the country's power sector are continuously growing. Overall, the literature shows that the evidence on the impact of the EU ETS is inconsistent.

A whole body of research looks at emissions trading policies in China using the DID and DDD methodologies. As the world's largest carbon emitter, China launched test emissions trading programmes, known as pilot projects, in a number of provinces and cities, including Beijing and Tianjin, in 2013. The study by Zhang & Wu (2022) uses the DID method and the synthetic control method (SCM) to assess the impact of the ETS introduced in 2013 on energy conservation and emission reduction in pilot provinces and cities in China. The conclusions of the study show that the ETS has contributed greatly to the overall energy conservation and emission reduction efforts of the provinces and cities that have participated in it.

According to Hu et al. (2020), the Chinese pilot policy has reduced energy consumption of regulated industries in the study regions by nearly 23% and carbon emissions by 15%. Improving technical efficiency and adjusting industrial structure are identified as the key drivers. However, the study finds that the CO_2 emissions trading system has a positive but insignificant impact on the share of fossil fuels in total energy consumption. This impact could be due to the fact that coal plays a leading role in China's energy composition. The results are based on a 10-year panel data set where a DID model was applied to evaluate the impact. The econometric models do however not take the non-stationarity problem of the data into account which might lead to spurious results (Baumohl & Lyocsa, 2009).

Tan et al. (2022) apply a different methodology. They investigate the impact of an ETS on the energy consumption and mix of the industrial sector by applying a distributional dynamics approach. They conduct the assessment using a firm-level dataset from the Hubei pilot project in China. The main results show that most companies reduce their relative energy consumption under the ETS, leading to a decrease in total energy consumption. Since coal accounts for most of the total energy consumption in China, the saving effect is mainly due to the decrease in coal consumption. However, it would take a long time to complete the energy transition.

Overall, we find evidence that a permit trading system has an impact on energy consumption. The studies that focus mainly on Chinese carbon markets differ in models applied and variables included. In the next section, we consider literature that looks at factors influencing oil demand.

2.2 Determinants of energy consumption

Empirical studies on the determinants of energy consumption provide inconsistent results, depending on several factors such as estimation method, development stage of the economy, data use, and sample size (Samuel et al., 2013).

Given oil's prominent position as the main energy source, accounting for a third of primary energy consumption in the EU countries it is of great interest to examine how oil consumption responds to changes in oil prices and real production. Cooper (2003) and Narayan & Wong (2009) conclude that oil consumption responds relatively inelastically to changes in oil prices. Goodwin et al. (2004) document that the own-price elasticity of oil consumption ranges from 0.25 in the short run to 0.64 in the long run. As for the response of oil consumption to changes in real output, Narayan & Wong (2009) show that oil consumption in Australia is more sensitive in terms of magnitude and statistical significance. In contrast, the same coefficient was found to be insignificant in Narayan & Smyth (2007) analysis for a group of Middle Eastern countries. Contrary to this, Wadud et al. (2009) find no statistically significant long-run relationship between oil consumption, real output and oil prices in the US before a structural break occurred during the 1973 oil shock. However, after the second oil shock in 1978, the results show a stable long-run relationship.

Moreover, spending on research and development (R&D) is used in econometric literature as a measure of innovation (Bointner, 2014). It is a public good with specific characteristics that imply that its effects are neither unidirectional nor direct. The efficiency gains resulting from innovation and technological development do not always lead to lower energy consumption. On the contrary, they can result in a significant increase in the input of energy factors, the so-called "rebound effect." The rebound effect arises in part from the increased consumption of energy services resulting from technological efficiency gains in the provision of those services. The energy savings that could otherwise be realized are offset by this higher demand (Sorrell & Dimitropoulos, 2008). Yuxiang & Chen (2010) address the relation between public R&D and the decomposition of the energy structure in China and find that an increase in government expenditure leads to an increase in energy intensity.

The literature on factors influencing oil consumption emphasises the importance of price, income, and technological development. Furthermore, in the next section, we look at what additional variables influence the agricultural sector.

2.3 Energy consumption in the Agricultural sector

Accurately accounting for the energy consumption in food production is extremely difficult, as food is a very composite product. The amount of energy required to get it "from farm to fork" varies considerably from one product to another due to changes in acreage, growing methods, processing and storage efficiencies, production and consumption season, and transportation needs. The food supply chain consists of several sequential steps such as agricultural production, processing and distribution, retail, and end-of-life management, each requiring energy for its specific processes (Rokicki et al., 2021).

Monforti et al. (2015) illustrate that the food supply is dominated by energy derived from fossil fuels, followed by nuclear energy and renewable energy sources. Agricultural production is responsible for about a third of the embedded energy, with livestock and dairy products containing a significant amount of energy per tonne of product, while vegetables and bread are less energy intensive. As Woods et al. (2010) indicate the substantially higher energy use in animal production results from the fact that animals are fed crops and the amount of energy accumulates. The energy embedded in food products is often divided into direct and indirect energy use. Following Pelletier et al. (2011) generally, direct energy flow measures the energy input used in a particular phase of a product such as the use of machinery (e.g. cultivation of fields with tractors) and the operating of livestock stables and greenhouses, while indirect energy flow includes the cumulative energy input used to produce the inputs in a particular phase of a product or service. Direct energy use in animal husbandry includes managing extensive stock, heating systems for young animals, and ventilation systems for pigs and poultry. Paris et al. (2022) gather data from a large number of studies investigating energy consumption in EU livestock farming. In most systems, feed is the predominant category of energy consumption. In terms of individual livestock categories, the studies evaluated show that energy requirements vary widely, ranging from dairy cows and bulls to pork production, broiler chicken and egg production.

The energy input for the cultivation of arable crops is influenced by the employed farming system. Bailey et al. (2003) compare energy use in conventional and integrated arable farming systems in the UK based on the technology and inputs necessary to produce 1 kg of each crop and the total energy used in each system. According to the findings, the integrated system seems to be the most efficient in terms of overall energy consumption. However, in terms of energy efficiency or energy consumption per unit of production, the results are less coherent. A study conducted by Dalgaard et al. (2001) in Denmark focuses on the comparison between energy consumption in organic and conventional agriculture. The results show that energy consumption in the organic farming scenarios was lower than for conventional farming. However, total crop production in the country was also lower.

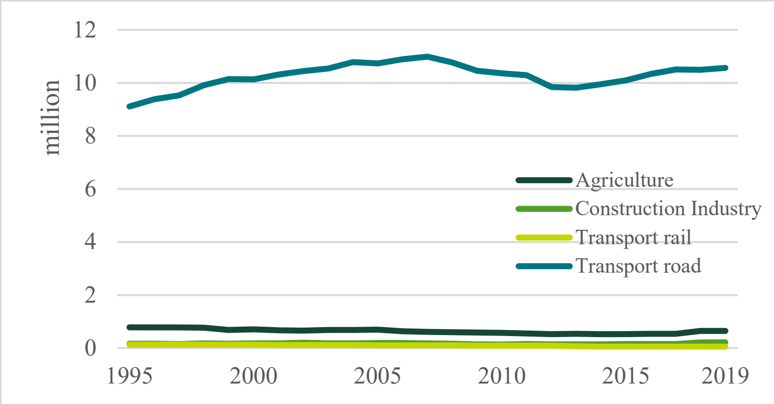
Another important energy consumer in crop production is irrigation, which mostly requires electricity, natural gas, and diesel fuel (Mérida García et al., 2019).

3. Research design

This section first briefly describes the data used, followed by a two-part methodology. The first part of the methodology discusses the econometric technique (DDD method) used to study the impact of the EU ETS on oil demand, and the second part uses an econometric procedure to explore the variation in oil consumption in European agriculture.

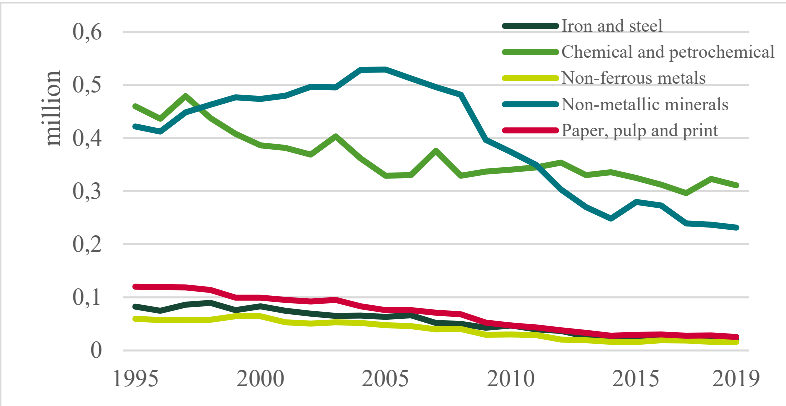
3.1 Data

In this study, we exploit annual data provided by Eurostat (2022b) at the sectoral level for European countries on oil consumption across the time period 1995- 2019 (Table 1 and Table2). The primary sample includes 39 countries and 23 sectors. A large amount of data is unavailable for various countries and sectors. To minimize the distortions of the data, and ensure the accuracy of the results, the selected sample contains 23 countries (see Appendix 1) from which the majority belongs to the EU and hence are included in the permit trading scheme. The non-EU countries Türkiye, North Macedonia, and Albania form the control group since they have not implemented the EU ETS. The 9 included sectors (see Appendix 1) are Iron and steel, chemical and petrochemical, non-ferrous metals, non-metallic minerals, paper and pulp, construction, rail transport, road transport, and agriculture and forestry, whereby the last 4 sectors are not regulated by the EU ETS and hence form the control group for the following DDD method in chapter 3.2.



Source: (Eurostat, 2022b)

Figure 1 Oil consumption (TJ) in non-regulated EU-27 sectors (1995-2019)



Source: (Eurostat, 2022b)

Figure 2 Oil consumption (TJ) in regulated EU-27 sectors (1995-2019)

3.2 Specification of DDD model

The traditional difference-in-difference (DID) model is a quasi-experimental method commonly applied in policy evaluation. The model was first brought forward by Ashenfelter & Card (1985) and over the years improved by Bertrand et al. (2004), Lee & Kang (2006), and Donald & Lang (2007). Cross-sectional difference and time series difference are two perspectives that the difference-in-difference approach uses to study the treatment effects of a policy. As an exogenous variable, the policy change inevitably changes the external circumstances of groups such as individuals, firms, and nations, and causes variations in these groups at time t. By eliminating the influences of time and location, the difference-in-difference model quantifies the impact of policy. The method typically includes a treatment group and a control group, using longitudinal data to provide a suitable counterfactual for estimating a causal effect. The effect of the policy is represented by the average treatment effect on those treated (ATT).

Pioneering research in environmental economics introduces a third difference to the standard DID model, e.g. to capture the additional level of countries or industries (Athey & Imbens, 2006; Berck & Villas-Boas, 2015), resulting in the difference-in-difference-in-difference (DDD) model. One of the most recent papers by Qi et al. (2021) examines the impact of a carbon trading pilot policy on the low-carbon international competitiveness of China's industry by applying a DDD approach. In this study, we develop a model of the impact of the EU ETS on industries' oil and petroleum products consumption across Europe based on a DDD model:

$$
\begin{aligned}
Oil_{ijt} = \alpha_0 + \alpha_1 ETS_i * sector_j * post_t + \alpha_2 ETS_i * post_t \\
+ \alpha_3 ETS_i * sector_j + \alpha_4 sector_j * post_t + \alpha_5 X_{ijt} \\
+ \mu_i + \gamma_j + \delta_t + \varepsilon_{ijt}
\end{aligned}
\tag{1}
$$

where i is the country, j is the industry, and t is the year. The explained variable Oil_{ijt} is the logarithm of the oil and petroleum product consumption of each industry in each country. The dummy variable for the carbon trading system, ETS_i , takes a value of 1 in countries with the EU ETS in place and 0 otherwise. The dummy variable for industries covered by the EU ETS is $sector_j$, which takes the value of 1 for covered sectors and 0 for uncovered sectors. $post_t$ is the dummy variable for the implementation time of the permit trading system policy, which is 2005. If the EU ETS has been implemented (t>2005), $post_t$=1, and in the period before the implementation (t<2005) $post_t$=0.

X_{ijt} represents the set of control variables for the oil consumption, which is visible in the table 1 of descriptive statistics, and table 3, and μ_i, γ_j, and δ_t are fixed effects of countries, sectors, and the year, respectively. ε_{ijt} denotes the stochastic error affected by time. The standard errors estimated by model coefficients are grouped at the country level, removing heterogeneity. Therefore, the overall effect of the EU ETS on the oil consumption of industries in this analysis equals the coefficient obtained by multiplying three terms $ETS_i * sector_j * post_t$, further named DDD estimator.

3.2.1 Further specification of DDD model variables

As one of the objectives of the EU ETS is to achieve a transition towards low-carbon energy and energy conservation, we selected oil consumption as the dependent variable to measure the effectiveness of the market-oriented policy. The variable oil consumption is measured in Terajoule (TJ), as oil and petroleum products are an aggregated sum of crude oil, NGL, refinery feedstocks, additives and oxygenates, and other hydrocarbons, excluding the biofuel portion.

The existing literature presented in chapter 2, has demonstrated that energy consumption could be affected by a set of macroeconomic variables. Given this, we selected the following control variables (see Appendix 1 for sources):

$R\&D_{ijt}$ is a key determinant of technological development and innovation. This study employs a metric that measures the proportion of total national R&D expenditure, expressed as a percentage of gross domestic product (GDP). It covers basic, applied, and experimental development and comprises spending in the four major sectors of business activity, government, higher education, and private non-profit. There are other useful indicators for measuring R&D in the power sector, such as energy-related R&D, the number of patents, and renewable energy R&D, but these data are fragmentary and lack consistent measurement. Therefore, the wider R&D indicator is the best available measure. GDP_{ijt} per capita in constant 2015US$ is a proxy for per-capita income. It is selected, in accordance with Kolawole et al. (2017) and Keho (2016) that investigate the relationship between energy consumption and economic growth. $price_{ijt}$ is the variable for the oil price in (USD/bbl). The variable is included based on the previously mentioned studies, which investigate the price elasticities of oil to estimate its own price elasticity. As a trade indicator, $export_{ijt}$ is included. Export values are the current dollar amounts of exports expressed as a percentage of the base period's average (2000). Moreover, $oil_export_{ijt}$is the export of oil products in (PJ) covers the amounts having crossed the national borders, including re-exports of oil imported for processing.

The descriptive of the main variables of the DDD model are listed in Table 1.

Table 1. Descriptive statistics of the main variables in DDD model

Variable	Observ.	Mean	Std.Dev.	Median	Min.	Max.
Oil	5175	57970	217337	3731	0	1794779
GDP	5175	28796	22054	25406	1469	112253
R&D	5175	1.445	0.884	1.28	0.085	3.87
price	5175	3.795	0.663	3.963	2.339	4.75
Oil_export	5175	451.117	752.825	172.873	0.126	4773.894
export	5175	1.67	0.582	1.748	0.592	2.576

Note: this table reports the descriptive statistics of the variables included in the DDD model used in this study from 1995 to 2019

3.2.2 Testing of a DDD model

In this research we conduct tests on the expected effects and parallel trend hypothesis in a dynamic effect estimation to assure the reliability of the estimation results from the DDD model. We constructed the models as follows:

Expected effect test

To evaluate whether the demand for oil and petroleum products has been affected by the expected effect before the implementation of the carbon trading policy, we set up the following model:

$$\begin{aligned} Oil_{ijt} = \beta_0 &+ \beta_1 ETS_i * sector_j * post_t + \beta_2 ETS_i * post_t \\ &+ \beta_3 ETS_i * sector_j + \beta_4 sector_j * post_t + \beta_5 ETS_i \\ &* sector_j * d_t + \beta_6 X_{ijt} + \mu_i + \gamma_j + \delta_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

, where d_t is a dummy variable for the time before the implementation of the EU ETS (t=2002, t=2003, t=2004). If the coefficients of β_5 in d2002, d2003, and d2004 are significantly different from 0, the level of oil consumption has been affected prior to the implementation of the policy.

Parallel trend hypothesis test

According to the parallel trend assumption, the difference between the treated and untreated groups would have been the same in the post-treatment period as it was in the pre-treatment period if no treatment had occurred. This assumption is crucial for the presumption of consistency in the estimated results of the DDD analysis. The following model tests whether this is valid for our treatment and control groups prior to the policy implementation. In addition, we perform a dynamic effect analysis of the EU ETS.

$$\begin{aligned} Oil_{ijt} = \beta_0 + \beta_t \sum_{t=1996}^{t=2019} &ETS_i * sector_j * d_{t_i} + \beta_1 ETS_i * post_t \\ &+ \beta_2 ETS_i * sector_j + \beta_3 sector_j * post_t + \beta_4 X_{ijt} \\ &+ \mu_i + \gamma_j + \delta_t + \varepsilon_{ijt} \end{aligned} \tag{3}$$

, where d_t is a dummy variable denoting the year (t=1996, 1997, …,2019). d2010 takes the value 1 in year 2010 and otherwise 0. The change in the coefficient β_t in Equation (3) is the central factor. Theoretically, the circumstances under which the DDD model supports the parallel trend hypothesis are that 1996-2004 do not have statistical significance whereas 2005–2019 do.

Further tests

Given the similarity between oil prices and stock prices, we can assume that the oil market operates like a financial market. We can further assume that no test for cointegration is required and that the time series are not cointegrated. Therefore, first differences are sufficient, and an error correction model is not necessary. In finance, the central reasoning is arbitrage and what distinguishes finance from everything else is the so-called 'efficient market hypothesis' (Jordan, 1983). That is saying that all prices are martingales and, if there are exceptions, those exceptions should be resolved by the idea that below a certain level of prices, traders would make an infinite profit by buying; and conversely above that level of prices, traders would make an infinite profit by selling. A corollary is that efficient markets do not cointegrate.

3.3 Determinants of agricultural oil consumption

The secondary objective of this research is to determine the main driving forces of oil consumption in the Agricultural sector. Therefore, we apply a panel data model for the same European countries as in the previous model. The panel is balanced, meaning there are no missing observations, hence we have i= 23 countries and t=24 time periods.

3.3.1 Model specification and setting of variables

Many scholars among them Somoye et al. (2022), and Luqman et al. (2019) suggest adopting a dynamic framework to capture the evolution of energy consumption over time. According to Gujarati& Porter (2009), the key reasons for using time lags are psychological, technological, and institutional nature. Despite those reasons for the purpose of determining the factors impacting oil consumption a first-difference panel data model is sufficient since it transforms a non-stationary series into a stationary one. All variables except for dummies and indices are converted into the natural logarithmic form in the econometric model. Converting the variables into the natural logarithmic form has the following advantages: First, the elasticity can be derived from the results of the coefficients. Second, the nonlinearity in the series can be removed. The proposed econometric panel model after transformation looks as follows:

Function in log form

$$OIL_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 RD_{it} + \beta_3 add\_value_{it} + \beta_4 price_{it} + \beta_5 arable_{it} + \beta_6 yield_{it} + \beta_7 employ_{it} + \beta_8 irr\_high_{it} + \beta_9 cattle_{it} + \beta_{10} chicken_{it} + \mu_i + \gamma_{it} \quad (4)$$

, where OIL_{it}, the dependent variable, measures oil consumption in terajoules (TJ), where oil is an aggregated sum of crude oil and petroleum products. The selection of the following independent variables is done considering the main findings from the research described in the literature review section. On this basis, GDP_{it} per capita is included as a proxy for income. RD_{it} stands for technological development and innovation, measured in national expenditure on R&D as a percentage of GDP, and $price_{it}$ is the price of oil in (USD/bbl). To capture the size, structure and productivity of the agricultural sector, $arable_{it}$ is included, which measures the share of arable land in total agricultural land, add_value_{it} indicates the share of the added value of agriculture, forestry, and fishing to the national GDP , $yield_{it}$ is the cereal yield (kg per hectare), irr_high_{it} is a dummy variable that specifies whether the irrigated agricultural area of a country is greater than 10 %. $cattle_{it}$and $chicken_{it}$ represent the animal stocks. $\mu_i + \gamma_{it}$ are two error terms, the first of which is constant over time and the second of which is time-varying. In the next section, we perform a test to verify the specification of this model.

The descriptive statistics of the main variables of the agricultural model are listed in Table 2.

Table 2. Descriptive statistics of the main variables in agricultural model

Variable	Observ.	Mean	Std.Dev.	Median	Min.	Max.
Oil	575	30573	40469	14172	212.425	206830
GDP	575	34246	30893	30686	1469	189290
R&D	575	1.445	0.885	1.28	0.085	3.87
price	575	54.836	31.749	53.15	11.66	115.64
Ad_value	575	4.209	5.02	2.38	0.214	36.411
Arable	575	26.227	12.97	25.514	6.261	60.8
Yield	575	820617	4009625	5087	1729.7	31553279
Employ	575	10.281	11.383	5.38	0.68	56.36
Irr_high	575	0.315	0.465	0	0	1
Cattle	575	3912368	4713521	1781000	183640	21256247
Chicken	575	61299	75143	25487	72	353561

Note: this table reports the descriptive statistics of the variables included in the agricultural model used in this study from 1995 to 2019.

3.3.2 Econometric tests

We use a panel data analysis with two main models - the first differences model and the random effect model - to estimate the parameters given in equation (1). In the regression model, the former is assumed to be an individual-specific constant term. The second model illustrates that the disturbance is individual-specific, similar to noise. The disadvantage of the random effects model is that it assumes that the correlations between the different effects and regressors are zero. Least squares estimation provides reliable and effective estimates when it is assumed that the correlations are the same in all countries. We use the Hausman test to compare first differences and random effects models (Hausman, 1978; Greene, 2000). To verify that a more efficient model also produces consistent results, the test compares it to a less efficient but consistent model. It can be concluded that the first differences model is better than the random effects model in a panel analysis if the null hypothesis that each effect is uncorrelated with the other regressors is rejected.

In this model, we again make the assumption that we made earlier, namely that given the similarity between oil prices and stock prices, we can assume that no test for cointegration is required and that the time series are not cointegrated. Therefore, first differences are sufficient, and an error correction model is not needed. The validity of the model is ensured, without applying further panel cointegration tests.

3.4 Limitation of econometric methodology

Country-level studies provide a thorough and easily communicable estimate of policy impacts on the whole economy or specific sectors for both scientists and policymakers, which is one of their main advantages. However, this method has the disadvantage of not being able to establish causality and is potentially subject to aggregation errors.

More specifically, an analysis based on sector-level data will inevitably count some emissions from non-treated (non-participating) companies as EU ETS emissions and vice versa, as participation in the EU ETS is determined by capacity thresholds for combustion plants and for narrowly defined industrial processes. This problem can be solved by using micro-data at the company or plant level. With microdata, it is also possible to compare the results of treated and non-treated establishments before and after the policy change, which helps researchers calculate more reliable estimates of the causal impact of the EU ETS. Future research could help shade light on the drivers of the effectiveness of the EU ETS such as industrial structure or technical efficiency and explore the underlying mechanism through which the ETS reduces energy consumption.

The econometric analysis is also affected by the small sample size, especially when we have a potentially large number of regressors in a country-specific framework. In the study, sixteen countries such as Croatia, Germany and Latvia were excluded from the dataset due to inconsistencies, especially Germany as one of the largest energy consumers in the EU could change the result of the estimation. Future research can address this issue and expand the sample size by including more OECD countries in the control group. Eurostat does not provide these data, but the International Energy Agency (IEA) could be used as a potential source. Moreover, one must account for heteroskedasticity across time and country which is here done by applying cluster-robust standard errors.

In the second part of the analysis, several variables, in particular tractors per hectare and organic farming methods, were removed from the regression due to inconsistencies, even though these factors are important drivers of fuel consumption in the agricultural sector and could have contributed to the completeness of the analysis (Fei & Lin, 2017). Furthermore, existing data on agricultural energy consumption in the EU are often fragmented and have data deficiencies, whereas Eurostat provides the most comprehensive data set available. Future research could work with more consistent data and explore the relationship between the omitted variables and energy consumption.

4. Empirical results

This chapter presents our results in two steps. The first subsection shows the effects of the adoption of an emission trading policy on energy consumption in the regulated sectors. In a second step, we explore the determinants of oil consumption in the agricultural sector.

4.1 Impact of EU ETS on oil consumption

Following the presentation of the main regression results, we evaluate their robustness by means of various tests.

4.1.1 Regression results

Based on Equation (1), this study estimates our DDD model with multidirectional effects and empirically estimates the impact of the EU ETS on oil consumption in various industries, with Table 3 presenting the results. We used the 'fixest' package (Berge,2018) in RStudio to estimate the model with more than two levels. As oil consumption is a demand function, it is influenced by the price of oil and hence non-stationarity might cause spurious results. Therefore, to convert a non-stationary time series into a stationary one, we apply the differencing technique to the logarithm of the variables. In the case of the first difference, we obtain the difference between the value and that of the previous period. While the logarithmic transformation can help stabilise the variance of a time series, differencing can stabilise the mean of a series by removing changes in the time level.

The results display that the coefficients of DDD in all three columns are significantly negative when the various fixed effects and control factors at different levels are taken into account. The coefficient of the DDD estimator is (-0.864), meaning that if a sector in an EU country, is treated by the policy, the oil and petroleum product consumption decreases on average by approximately 86%. The benchmark results in column 1 show that the carbon policy has a strong conservation effect on industry oil consumption, specifically that the introduction of the EU ETS reduces industry oil demand on average by 86%.

Table 3. Regression results

	Dependent variable:		
	(1)	(2)	(3)
	Oil	Oil	Oil
ETSxsectorxpost	-0.864***	-1.041***	-1.041***
	(0.22)	(0.077)	(0.077)
ETSxsector	-0.996*	-2.314***	-2.314***
	(0.454)	0.052	(0.052)
ETSxpost	0.333	0.871***	0.872***
	(0.178)	(0.088)	(0.088)
GDP	0.398	-0.321***	-0.321***
	(1.156)	(0.069)	(0.069)
RD	-0.198*	0.162*	0.162*
	(0.095)	(0.073)	(0.073)
Price	-0.152**	-0.394**	-0.394**
	(0.049)	(0.132)	(0.132)
Oil_export	0.023	0.666***	0.667***
	(0.089)	(0.015)	(0.015)
Export	-0.262	-0.496***	-0.496***
	(0.569)	(0.068)	(0.068)
Time-fixed effect	YES	YES	YES
Industry-fixed effect	YES	YES	
Country-fixed effect	YES		
Observations	5175	5175	5175
Adj. R-squared	0.565	0.266	0.263

Note: Robust standard errors are in parenthesis; ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

For the control variables GDP per capita, R&D, and oil price are considered in more detail. GDP per capita has a positive but not significant impact on oil consumption. The trend suggests that a 1% increase in GDP would increase oil consumption by almost 0.4% on average, but there is no statistically significant relationship. R&D expenditure as a percentage of GDP has a statistically significant negative impact on oil consumption. The results indicate that a 1% increase in R&D expenditures causes an average reduction in energy consumption of 0.198 %. The own price elasticity of oil consumption is significantly negative, meaning that a 1% price increase in oil reduces the consumption by 0.152%. The coefficient of both export variables does not have a significant impact on oil demand. There is no empirical evidence that the increase in trade openness or the fact that the country is an exporting country for oil or oil products has an impact on energy consumption.

4.1.2 Robustness tests

We run a number of robustness tests to assess the accuracy and validity of our findings. They confirm the overall significance of the DDD estimator and provide insight into the dynamic evolution of the EU ETS impact on oil consumption over time.

Expected Effects

We first examine whether the effects of an ETS on oil demand had the anticipated effects to assess the robustness of our DDD model. The test findings for the anticipated effects in the first year (2004), the two years prior (2003, and 2004), and 3 years prior (2002, 2003, and 2004) following the introduction of the carbon trading pilot are shown in Columns 1, 2, and 3 of Table 4. The findings demonstrate that the coefficients of the interaction term between the emissions trading pilot and the dummy variables are not significant for one, two and three years before the implementation of the system. This shows that the industries did not adjust to reduce oil consumption before the launch of the emissions trading pilot. The EU ETS thus exhibits strong exogeneity.

Parallel trend hypothesis test and dynamic effect analysis

As the introduction of an ETS is a dynamic adjustment process, it is important to consider the dynamic marginal effects of the system on energy consumption. The parallel trend test and the results of the regression of the dynamic impact of an ETS policy on oil consumption are shown in column 4 of Table 4. They directly reflect that there were no significant differences in the level of oil demand before the introduction of the pilot in 2005 - in other words, it supports the parallel trend hypothesis. The regression coefficients after the introduction of the ETS (ETS*sector*d2005 to ETS*sector*d2012) show that the EU ETS had no immediate statistically significant impact on consumption levels in the first eight years after its introduction. The regression coefficients (ETS*sectors*d2012 to ETS*sectors*d2019) are all significantly negative, showing that the EU ETS has a positive impact on energy savings over time after 2012.

Table 4. Test results

Variable	(1) expected effect	(2) expected effect	(3) expected effect	(4) dynamic effect
DDD	-0.895 ***	-0.920**	-0.924 **	-0.494 *
	(0.236)	(0.244)	(0.243)	(0.189)
ETSxsectorxd1996				-0.524
				(0.427)
ETSxsectorxd1997				-0.483
				(0.460)
ETSxsectorxd1998				-0.560
				(0.472)
ETSxsectorxd1999				-0.571
				(0.487)
ETSxsectorxd2000				-0.457
				(0.430)
ETSxsectorxd2001				-0.484
				(0.415)
ETSxsectorxd2002			-0.044	-0.524
			(0.131)	(0.421)
ETSxsectorxd2003		-0.264	-0.267	-0.747
		(0.197)	(0.203)	(0.476)
ETSxsectorxd2004	-0.365	-0.386	-0.390	-0.869
	(0.221)	(0.231)	(0.234)	(0.483)
ETSxsectorxd2005				-0.537
				(0.511)
ETSxsectorxd2006				-0.592
				(0.521)
ETSxsectorxd2007				-0.474
				(0.521)
ETSxsectorxd2008				-0.746
				(0.548)
ETSxsectorxd2009				-0.814
				(0.539)
ETSxsectorxd2010				-0.884
				(0.547)
ETSxsectorxd2011				-1.002
				(0.521)
ETSxsectorxd2012				-1.000
				(0.501)
ETSxsectorxd2013				-1.075 *
				(0.505)
ETSxsectorxd2014				-1.133 *
				(0.523)
ETSxsectorxd2015				-1.248 *
				(0.514)
ETSxsectorxd2016				-1.319 *
				(0.541)
ETSxsectorxd2017				-1.299*
				(0.522)
ETSxsectorxd2018				-1.145 *
				(0.497)
ETSxsectorxd2019				-1.101*
				(0.475)
Time-fixed effect	YES	YES	YES	YES
Industry-fixed effect	YES	YES	YES	YES
Country-fixed effect	YES	YES	YES	YES
Observations	5175	5175	5175	5175
R-squared	0.565	0.565	0.565	0.565

Note: the control variables are the same as those used in the Eq. (1). Robust standard errors are in parenthesis; ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

4.2 Determinants of oil consumption in agriculture

This section first presents the results of the econometric model to identify the drivers of oil consumption in agriculture and then evaluates the choice of the econometric model.

4.2.1 Regression results

Table 5 presents the estimated results based on equation (4) for the determinants of oil and petroleum consumption for the European sample.

Table 5. Regression results for determinants of agricultural oil consumption

	Dependent variable: Oil
GDP	1.366***
	(0.253)
RD	-0.247**
	(0.089)
ad_value	-0.188
	(0.117)
price	-0.244***
	(0.053)
Arable	0.039***
	(0.011)
Yield	-0.082
	(0.167)
Employ	0.073***
	(0.014)
Irr_high	0.002
	(0.196)
Cattle	0.877**
	(0.282)
Chicken	0.128
	(0.096)
Observations	575
R2	0.217
Adjusted R2	0.171
F-statistics	15.049***

Note: Robust standard errors are in parenthesis; ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

The results display a positive income elasticity, a negative own-price elasticity of oil, and a negative coefficient for R&D. Hence, a 1% increase in the oil price reduces consumption by 0.244%, while the same percentage increase in GDP raises the consumption by 1.366%. A percentage increase in technological development lowers the oil consumption in the agricultural sector by 0.244%. The three coefficients are all highly significant.

The coefficient of arable land indicates a positive relationship, meaning that a higher percentage of arable land in the total area (km2) results in significantly higher consumption of oil and petroleum products. According to the obtained results, an increase in the proportion of arable land by 1% increases the energy consumption by 0.04%.

Value added in the agricultural sector does not have a statistically significant impact on oil demand in the agricultural sector.

An increase of 1% in the cattle stock causes a significant increase of 0.877% in oil and petroleum product consumption. In contrast, other animal stocks such as chicken (0.128) do not significantly impact energy consumption. In summary, we find three relevant factors, which we discuss in more detail in the following chapter.

In summary, we find the three relevant agricultural factors: technological progress, arable land, and cattle stock, which we discuss in more detail in the following chapter.

4.2.2 Test results

The results of the Hausmann test display that the calculated value of the test statistic of 30.177 is sufficient to reject the null hypothesis at a level of 5% and even 1%. Since this is the case, we confirm the choice of the first differences model rather than the random effects model.

5. Discussion and policy implications

This chapter discusses the findings of the two estimates in separate sections. Each section concludes with policy recommendations. First, we discuss the impact of the ETS on oil consumption, and what this implies for a potential extension to non-regulated sectors. Then we derive policy recommendations for the agricultural sector to reduce oil consumption.

5.1 Expanding the EU ETS to further sectors

Our estimators for model (1) suggests that the EU ETS contributes to energy savings. Thus, we come to the same conclusion as Hu et al. (2020), who indicate that the implementation of a carbon trading policy in China has led to a significant reduction of fossil fuel consumption, especially coal, by 22.8%. However, when comparing the magnitude of the energy-saving effect in the two studies, it is noticeable that the spectrum differs significantly, with Hu et al. (2020) observing a saving of 22% while we observe an effect of 86%. The reason for this could be the different study areas, as China is a developing country where coal is the highest energy supplier. Hu et al. (2020) focus on coal, while the present study focuses on oil, which is the predominant energy source in Europe. However, we do not consider the substitution between fossil fuels in this study. This effect can be taken into account in future research when comparing the effects on the energy-mix. Apart from this, the results are also in line with the general estimates of Tan et al (2022). Their study shows that under the ETS pilot project in Hubei in China, the primary peak of the distribution of relative coal consumption decreases from 0.07 to 0.02 over the ten-year period.

Comparing the magnitude of the estimators, we find that the DDD estimator is relatively high (-0.864). A possible explanation for this could be the construction of the model itself. The sectors are not weighted, but each sector is assigned an equal weight. In estimating the model, the sectors are not considered volume-weighted, but each sector is assigned an equal weight. Looking at the shares of the individual sectors in the total oil consumption of the regulated sectors, it is noticeable that the non-metallic minerals and chemicals and petrochemicals sectors account for the largest share of consumption. If a sector has a high volume and this sector then reduces its consumption, the DDD estimator is to a certain degree distorted, as the estimator is interpreted as an average treatment effect. In this case, we have two sectors with comparatively high volume and three sectors with low volume (see Chapter 3, Figure 2). The same bias exists in the control group, where the road transport sector has a significantly higher consumption. The transport sector has a high oil consumption, which has tended to increase in recent years. A solution could be a weighted estimation, but this is not possible within the DDD model as the sectors are only included as dummy variables. This restriction extends the limitations noted in chapter 3.4. In conclusion, we can state that the average reduction of 86% is potentially overestimated and that the actual impact of the policy is smaller.

In the broader context of analyses of the EU ETS impact on energy efficiency and carbon abatement, our study contradicts several findings suggesting that the EU ETS has negligible, insignificant impacts. Using panel data from 14 industrial sectors, Zhang et al. (2016) analysed energy efficiency in Sweden. According to the results of the regression analysis, neither the EU ETS nor the CO2 tax had a significant impact on energy efficiency over the period. However, there was a relationship between the energy tax and higher energy efficiency. Wang et al. (2019) estimated the causal impact of the ETS pilot in China from 2006 to 2016 on CO_2 emissions using a DID approach. The results suggest that energy efficiency improvement significantly reduced CO_2 intensity but had an insignificant impact on emission levels. Our results contradict the above-mentioned studies.

The finding that GDP is not significant is not consistent with the results of numerous studies that have examined the demand for energy and, in particular, crude oil and oil products. Fiebig et al. (1987) found that the income elasticity of energy consumption in a sample of 30 countries ranged from 1.24 for the US, 1.35 for Brazil and 1.64 for India. Ibrahim & Hurst (1990) examined the short-run income and price elasticities of energy demand in 13 emerging economies, and the income elasticity was positive. In addition, Lin & Zeng (2013) indicated that the elasticity of gasoline demand in China ranges from 0.49 to 0.16 for price and from 1.01 to 1.05 for income. The long-run price and income elasticities for South African gasoline demand were reported by Akinboade et al. (2008) to be 0.47 and 0.36, respectively.

The significant negative impact of R&D on oil demand is consistent with most of the above studies which indicate that technological improvements have led to lower oil consumption in the EU between 1995 and 2019. The result confirms the conclusions of Shahbaz et al. (2022), who estimate a 0.1527% decrease in consumption in China. From a conceptual point of view, it is likely that R&D influences energy consumption in many ways or through different pathways. Yao et al. (2019) show that R&D can, on the one hand, reduce energy consumption by promoting energy-saving innovations. By enabling more effective technologies that minimise emissions, R&D spending tends to reduce dependence on natural resources. On the other hand, a higher share of spending on R&D can lead to higher energy consumption due to energy efficiency improvements. Our results contrast with the study by Berner et al. (2022), which shows the existence of the rebound effect in Europe and the United States.

The own price elasticity of oil consumption is estimated to be 0.152, which is quite similar to the price elasticity estimates reported by other researchers such as Cooper (2003) and Altinay (2007). Cooper's estimates of short- and long-term price elasticities range from -0.026 to -0.289 in Sweden and Denmark. The difference could be due to the different methodology and period (1991-2000). Altinay showed as a result that the short- and long-term price elasticities in Türkiye are -0.10 and -0.18, respectively.

Considering the results of the dynamic impact analysis, which indicate that the EU ETS did not have an immediate impact on energy demand, we qualify the previous results. The estimation shows that the EU ETS had no statistically significant impact on oil consumption in the first eight years after the policy was introduced. This result does not necessarily contradict the previous estimates, but it does constrain them. It is, however, consistent with the findings of many researchers who studied the effectiveness of the first phase (2005-2007) of the EU ETS and concluded that the ETS was ineffective in the first years. As Ellermann and Buchner (2007) found, the lack of reliable historical data on emissions at the installation level meant that the EU ETS was not stringent enough in the first trading period. Low allowance prices and over-allocation are the reason for the limited impact on emission reductions, according to Clò et al. (2017). Anderson & Di Maria (2010) estimate the reduction effects in the pilot phase to be small, while Bel & Joseph (2015) attribute this effect more to the economic downturn. The less stringent design and over-allocation of allowance prices are reflected in the finding that the reduction effect was relatively small, which is supported by our findings of an insignificant effect of the EU ETS on oil consumption during the first and second phase of the trading scheme. The European Commission amended the original EU ETS Directive in January 2008 to address the misallocation. Furthermore, the regression shows that there is a significant negative impact on oil demand after 2012, indicating that the more stringent design of the EU ETS is achieving its objectives. Furthermore, at the beginning of the third phase of the EU ETS, additional sectors such as the chemical industry and non-ferrous metals were included from 2013 onwards, which could also explain the significant decrease in the consumption of oil and petroleum products. Overall, the EU ETS has some lagging effects on energy consumption. An explanation for this effect could be that the permit system indirectly affects energy demand and installations, and companies gradually reduce or replace energy consumption to meet the required GHG emission reduction targets. Hu et al. (2020) found the same effect in the Chinese pilot system.

Based on these findings, we can derive policy implications from our research. As the results suggest that the EU ETS policy has an empirically negative impact on oil consumption, we conclude for policy makers that an extension of the scheme to non-regulated sectors such as transport, agriculture and forestry promotes driving the energy transition away from carbon-intensive energy. In view of the current Ukraine crisis, the EU aims to reduce its reliance on Russian fuel imports by taking measures to reduce fossil energy consumption. The expansion of the EU Emissions Trading Scheme can be another instrument to approach independence. Some countries, such as Germany, have already expanded the EU ETS in 2021 to include a national emissions trading scheme that includes additional sectors such as transport and buildings to further reduce GHG emissions and moving to a low-carbon economy to achieve the goal of climate neutrality. However, with regards to the agricultural sector, Ancev (2011) argues against the inclusion of the agricultural sector. In the study, additional costs such as administrative, monitoring, verification, audit, enforcement, sanctioning, and trade costs are included in a cost-benefit comparison. The results do not provide evidence of a significant cost benefit that agriculture can contribute to an ETS. Therefore, based on the estimation of the drivers of energy consumption, we develop further policy recommendations to reduce energy consumption in the agricultural sector.

5.2 Drivers of agricultural oil consumption

After analysing the general impact that an extension of the ETS to different sectors may have, we have seen that this instrument may not be as suitable for the agricultural sector. Therefore, we propose below alternative measures to reduce carbon emissions in the agricultural sector that could prove effective.

The results of the agricultural analysis display a positive income elasticity of oil demand and a negative own-price elasticity of oil, which confirms the results in chapter 4.1.1 as well as those of the existing literature (see chapter 5.1), with the difference that the impact of GDP on oil demand is significant in the agricultural sector.

Moreover, the findings reconfirm that technological innovation is an important driver of energy consumption reduction; in fact, it is the main driver in the agricultural sector. In their study, Pelletier et al. (2011) present several technology-based methods for increasing energy efficiency in agriculture.

One explanation for the positive correlation between the share of arable land and energy consumption could be that arable land requires more complex land management than grassland, which relies on machinery and thus fuel consumption.

Contrary to expectations, the results do not provide empirical evidence that the high use of irrigation systems has a significant impact on oil demand. A study conducted in Spain by Soto-García et al. (2013) suggests that the most influential factor for energy use in irrigation systems is water withdrawal. Mo et al. (2011)

point out that as water scarcity increases, so does the embodied energy associated with water provision.

Livestock estimates suggest that cattle farms on average have a greater impact on energy demand than other livestock farms, which is consistent with the conclusions of Paris et al. (2022). However, compared to their results, our study does not distinguish between dairy and beef production, which leads to less detailed results.

Apart from whether the agricultural sector is included in the EU ETS, we can develop policy recommendations based on the estimation of factors influencing energy consumption. The estimation led to the conclusion that technological innovations are the most important factor in reducing energy consumption in agriculture, especially in the management of land and livestock. Technology-based methods for increasing energy efficiency in agriculture include technological advances, such as more efficient engines and appropriate transport systems, and improved agricultural techniques e.g. better fertilisation, and soil conservation agriculture (Pelletier et al., 2011). One modern agricultural technique is so-called precision agriculture, a method of locally differentiated and targeted management of agricultural land. This measure serves economic and ecological improvement. The saving of inputs primarily refers to an improvement in indirect energy use, namely the reduction in the use of fertilisers and pesticides and the targeted reduction in the use of machinery, which leads to lower fuel consumption. It is recommended that national spending on research and development and on the development and diffusion of innovative technologies be increased to achieve the goals of transitioning away from fossil fuels. The results also suggest that reducing livestock and cropland alone has the potential to reduce oil demand. However, we do not recommend that policy should aim to reduce these factors directly, as the key role of the agricultural sector is to ensure food supply. Nevertheless, it is important to consider these factors when designing a policy to identify possible side effects of a policy approach.

In general, this analysis suggests that the focus of agricultural policy design should be on technical development in the sub-areas of cattle husbandry and land management, both of which are covered by precision farming technology.

6. Conclusion

In this study, we answer the question of whether the EU ETS can play a positive role in energy saving and which factors affect oil consumption in the agricultural sector. Therefore, we conducted a quasi-natural experiment with a DDD model to empirically investigate the impact of the emissions trading policy on oil consumption, followed by a panel data regression of oil consumption in the agricultural sector. Our results lead us to the following conclusions.

First, the introduction of an emissions trading policy in Europe leads to a significant reduction in the consumption of oil and oil products in regulated industries, implying that the EU ETS contributes to the long-term goal of promoting a low-carbon energy transition. This is the first empirical study to examine the impact of the EU ETS on energy demand with oil as an energy source at a cross-country and cross-sectoral level, which is an important complement to current studies focusing on the impact of the European and Chinese ETS on energy conservation.

Secondly, we can conclude that the inclusion of additional, so far unregulated sectors such as the transport sector, various industrial sub-sectors and the agricultural sector could further reduce oil demand in Europe and contribute to greater independence from oil exports.

Third, technological development is an important driver for reducing energy consumption. In both the DDD model and the agricultural model, research and development has a significant impact on the consumption of oil and oil products. This finding can be a useful input for policymakers to design new policy or improve existing ones.

The agricultural sector faces the challenge of limiting oil and fossil fuel consumption while providing biomass for renewables and maintaining food production. In our analysis, we see that particular the increase in cattle production and the cultivation of land increase energy consumption. Therefore, it is important to address these factors and promote precision farming, which is an agricultural practice aiming to minimise input use.

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Appendix 1

Table 7 in the Appendix 1 displays the countries included in the DDD model, and in the agricultural estimation. Table 6 presents an overview of the regulated and non-regulated sectors, whereby treatment YES response to a regulated sector and NO to an unregulated sector. Table 9 defines the variables and shows the sources from which the variables are retrieved.

Table 6. Countries included in the study

number	Country	Treatment
1	Austria	YES
2	Belgium	YES
3	Bulgaria	YES
4	Czech Republic	YES
5	Denmark	YES
6	Finland	YES
7	France	YES
8	Greece	YES
9	Hungary	YES
10	Ireland	YES
11	Italy	YES
12	Luxembourg	YES
13	Netherlands	YES
14	Poland	YES
15	Portugal	YES
16	Romania	YES
17	Slovenia	YES
18	Spain	YES
19	Sweden	YES
20	United Kingdom	YES
21	Albania	NO
22	North Macedonia	NO
23	Turkiye	NO

Table 7. Sectors included in the study

number		Sector category	Treatment
1	Industry sector	Iron and steel	YES
2	Industry sector	Chemicals and petrochemicals	YES
3	Industry sector	Non-ferrous metals	YES
4	Industry sector	Non-metallic minerals	YES
5	Industry sector	Pulp, paper, and printing	YES
6	Industry sector	Construction	NO
7	Transport sector	Rail	NO
8	Transport sector	Road	NO
9	Other sectors	Agriculture and forestry	NO

Table 8. Variables definitions

Variable	Description and measure	source
Oil	Oil and petroleum consumption in end-use sectors (TJ)	Eurostat
GDP	GDP per capita (constant 2015 US$)	OECD
RD	national expenditure R&D (% of GDP)	OECD
price	Average Cost of Total Crude Imports USD/bbl; Crude Oil Prices: Brent	OECD, FRED
Oil_export	Exports of oil products (PJ); Comprises the amounts having crossed the national borders	IEA
export	Export value index (2000 = 100)	worldbank
Ad_value	added value of agriculture, forestry and fishing (% of GDP)	worldbank
arable	Arable land (% of land area)	FAO
yield	Cereal yield (kg per hectare)	FAO
agr_exp	agricultural raw materials exports (% of merchandise exports)	worldbank
employ	Employment in agriculture (% of total employment) measures industry size	worldbank
Irr_high	dummy variable for irrigated agricultural land; takes value 1, if percentage of irrigated land is >10%	worldbank FAO
cattle	Stocks in number of heads for live animals	FAO
chicken	Stocks in number of 1000 heads	FAO

Appendix 2

Estimation outputs

Table 9. Output of DDD estimation

	Estimate	Std. Error	t value	Pr(>|t|)
ETSxsectorxpost	-0.864824	0.220212	-3.927.240	0.0007201***
ETSxsector	-0.996335	0.453748	-2.195.787	0.0389457*
ETSxpost	0.333078	0.178452	1.866.479	0.0753608
GDP	0.398903	1.156.521	0.344916	0.7334330
RD	-0.197850	0.095486	-2.072.024	0.0501875
Price	-0.152431	0.048937	-3.114.860	0.0050466**
Oil_export	0.023463	0.089618	0.261807	0.7959056
Export	-0.261968	0.569163	-0.460269	0.6498403
Observations	5175			
Adj. R-Squared	0.565361			

note: ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

Table 10. Output of regression for determinants of agricultural oil consumption

	Estimate	Std. Error	t value	Pr(>|t|)
GDP	13.664.038	0.2530910	53.989	1,01E-04***
RD	-0.2465970	0.0895456	-27.539	0.006087**
ad_value	-0.1877418	0.1165416	-16.109	0.107775
price	-0.2440518	0.0525915	-46.405	4,36E-03***
Arable	0.0398594	0.0109186	36.506	0.000287***
Yield	-0.0824265	0.1671077	-0.4933	0.622033
Employ	0.0734086	0.0141222	51.981	2,86E-04***
Irrgiagtion_high	0.0020392	0.1962823	0.0104	0.991715
Cattle	0.8774808	0.2823777	31.075	0.001986**
Chicken	0.1280393	0.0961952	13.310	0.183737
Observations	575			
R-Squared	0.21732			
Adj. R-Squared	0.17111			
F-statistic	150.493			2.22e-16

note: ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

Table 11. Output of dynamic effect test

	Estimate	Std. Error	t value	Pr(>|t|)
DDD	-0.494162	0.189707	-2.604.874	0.0161700*
DD_ETS_sector	-1.336.323	0.526860	-2.536.390	0.0188072*
DD_ETS_post	0.112334	0.199945	0.561825	0.5799148
ETSxsectorxd2019	-1.101.491	0.475311	-2.317.410	0.0301755*
ETSxsectorxd2018	-1.145.883	0.497823	-2.301.788	0.0311905*
ETSxsectorxd2017	-1.299.462	0.522299	-2.487.969	0.0209089*
ETSxsectorxd2016	-1.319.587	0.541487	-2.436.969	0.0233576*
ETSxsectorxd2015	-1.248.896	0.514602	-2.426.915	0.0238706*
ETSxsectorxd2014	-1.133.488	0.523907	-2.163.528	0.0416321*
ETSxsectorxd2013	-1.075.207	0.505169	-2.128.408	0.0447465*
ETSxsectorxd2012	-1.000.492	0.501291	-1.995.831	0.0584791
ETSxsectorxd2011	-1.002.461	0.521271	-1.923.107	0.0675053
ETSxsectorxd2010	-0.884322	0.547737	-1.614.501	0.1206713
ETSxsectorxd2009	-0.814167	0.539396	-1.509.406	0.1454243
ETSxsectorxd2008	-0.746130	0.548051	-1.361.424	0.1871613
ETSxsectorxd2007	-0.474116	0.521600	-0.908965	0.3732193
ETSxsectorxd2006	-0.592274	0.521144	-1.136.487	0.2679812
ETSxsectorxd2005	-0.537615	0.511403	-1.051.255	0.3045524
ETSxsectorxd2004	-0.869448	0.483407	-1.798.585	0.0858205
ETSxsectorxd2003	-0.747221	0.476214	-1.569.086	0.1309001
ETSxsectorxd2002	-0.524621	0.421534	-1.244.550	0.2263929
ETSxsectorxd2001	-0.484070	0.415156	-1.165.996	0.2561015
ETSxsectorxd2000	-0.457566	0.430248	-1.063.494	0.2990926
ETSxsectorxd1999	-0.571580	0.487061	-1.173.529	0.2531325
ETSxsectorxd1998	-0.560303	0.472891	-1.184.846	0.2487205
ETSxsectorxd1997	-0.483840	0.460333	-1.051.064	0.3046379
ETSxsectorxd1996	-0.524354	0.427367	-1.226.942	0.2328133
GDP	0.622943	1.198.308	0.519852	0.6083584
RD	-0.206514	0.100098	-2.063.127	0.0510982
Price	-0.152128	0.048409	-3.142.555	0.0047295**
Oil_export	0.031721	0.093729	0.338434	0.7382451
Export	-0.322964	0.571978	-0.564644	0.5780283
Observations:	5175			
Adj. R-Squared:	0.565924			
RMSE:	244302			

note: ***, **, and * represent significance levels of 1%, 5%, and 10% respectively, and standard errors are clustered at the country level

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