EU Emission Trading and Aluminium Imports: Evidence for Carbon Leakage

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Abstract

While carbon pricing is considered the most effective policy to cut emissions, offshoring of emissions, defined by the carbon leakage rate, is potentially a major drawback. Recent literature on carbon leakage from the EU Emission Trading Scheme (EU ETS) exhibits a major discrepancy between analytical forecasts and empirical observations of carbon leakage. The former predicts a leakage rate of 2 - 50%, and the latter is unable to show any significant leakage. Aside from synchronising the theoretical and empirical literature, this paper aims to tackle this discrepancy by investigating trade data from the EU Aluminium sector. The Aluminium sector is in a unique position because most of its emissions are indirect which means it does not receive free allowance allocations. The proposed regression model uses EU ETS monthly allowance price data from all four phases to predict monthly net aluminium imports while controlling for domestic industrial demand. A number of commonly used autoregressive tests and corrections are applied to reduce the serial correlation in the error term. This paper additionally proposes a new autoregressive correction, which minimises the Lagrange Multiplier. For phase IV of the EU ETS, a percent-increase in allowance price is associated with an increase in Aluminium imports of €1.12 million, which empirically demonstrates the existence of significant carbon leakage from the EU ETS. The serially correlated error terms call for further investigation of EU Aluminium trade to gain a more robust understanding of the magnitude of carbon leakage.

1 Introduction

Climate change has been identified by a large scientific consensus to be one of the most pressing issues that humanity is currently facing. Similarly in agreement, a variety of economic studies have identified carbon pricing as the most adequate measure to counteract global warming while minimising harm to economic development (Baranzini et al., 2000; Klenert et al., 2017). Over the last 30 years, a range of different carbon pricing schemes have been implemented on a regional, national and supranational level (Steinebach et al., 2021). Today there are over 60 carbon pricing policies which cover around a fifth of global emissions at a variety of different prices. Regional differences in the price for CO_2 emissions give rise to the potential for these emissions to escape regional jurisdictions in a phenomena described as carbon leakage (World Bank, 2022). More precisely, carbon leakage refers to the increase in carbon emissions outside a country's territory that are linked to its climate policies. To ensure the effectiveness of its climate policies and to stop carbon-intensive industry from relocating, it is in the interest of governments to minimise the amount of carbon leakage that is associated with a climate policy. Based on the amount of carbon leakage that is estimated from a climate policy, a country might decide to accompany that policy with certain leakage protection mechanisms such as a carbon border adjustment mechanism (CBAM). The EU, for example, is planning to introduce a CBAM in October 2023 (European Commission, 2023).

Considering the real-world policy decisions that stem from carbon leakage estimates, it is important that these estimates are as precise and reliable as possible. There is, however, a striking gap between current ex-ante and ex-post estimations of carbon leakage with the empirical literature being unable to confirm any of the leakage rates that have been forecast by economic models. To help close that gap, this paper aims to support the empirical demonstration of carbon leakage by contributing in three distinct ways: Firstly, it lays out the differences and similarities between the theoretical and empirical literature on carbon leakage. Secondly, this paper highlights why the European aluminium sector is particularly well suited for the empirical study of carbon leakage and how the trading data from this sector can be useful for empirical research. Lastly, carbon leakage is empirically demonstrated by introducing a novel autocorrelation procedure to regression residuals from aluminium imports and allowance price. The remainder of this article is structured as follows: The next section (2) will briefly review the analytical and econometric literature on carbon leakage from the EU ETS and highlight the differences between them. Section 3 is going to lay out why the aluminium industry is particularly suited for the demonstration of carbon leakage while section 4 will explain the econometric methodology that was applied. The results are presented in section 5 and section 6 concludes the findings while suggesting future research steps.

2 Literature Review

2.1 Carbon Leakage

Today, 78.3% of global GHG emissions remain untouched by any sort of carbon pricing policy and only 4% of global emissions are found to be priced at an adequately high level (World Bank, 2016; 2022). This creates the potential for arbitrage between producing carbon intensive goods in a region with a low or no carbon price and importing it from such a region into a region with a high carbon price. In the context of carbon pricing, carbon intensive imports from non-regulated areas to regulated areas are referred to as carbon leakage. Carbon leakage had been anticipated theoretically before the implementation of carbon pricing schemes in what is referred to as the 'pollution haven hypothesis' (Levinson and Taylor, 2008). This hypothesis states that, as developed nations tighten their environmental regulations, companies will move polluting processes to the developing world, where environmental standards are less stringent. As carbon pricing is just another form of environmental regulation, this hypothesis has been used to predict carbon leakage (Aldy and Pizer, 2015). The pollution haven hypothesis considers two distinct channels: relocation and international competition. The former occurs through domestic firms moving their production to unregulated areas while the latter refers to those firms losing market share in benefit of competing companies from unregulated areas (Naegele and Zaklan, 2019). Both channels have been investigated with a variety of results although most papers seem to agree that environmental regulations do not constitute, in general, a sufficient financial burden to seriously disadvantage domestic firms (Caccia and Baleix, 2020). The two channels described by the pollution haven hypothesis can also be applied to carbon leakage although another more sophisticated way to describe the channels of carbon leakage dominates recent research (Gerlagh and Kuik, 2014). In this new approach domestic carbon prices can affect international emissions through three distinct channels: International trade, the energy market and technology spillover. How each of these channels affects carbon leakage is illustrated in figure 1.

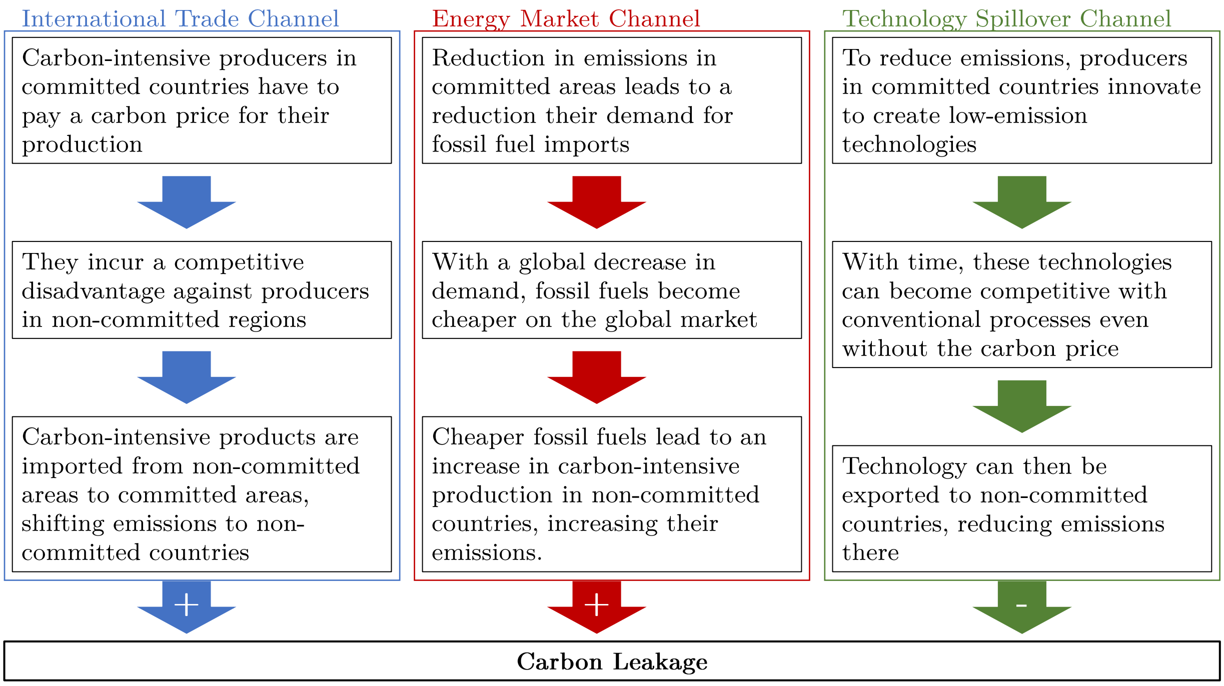

Figure 1: Illustration of the Different Carbon Leakage Channels. Adapted from Yu et al. (2021)

The international trade channel refers to what has been explained above by the pollution haven hypothesis. The disadvantages in domestic production that are caused by carbon pricing directly lead to carbon-intensive imports. The reduced competitiveness of abating areas can lead to either multi-national companies moving their production to different countries or international competitors taking over domestic market shares. The international trade channel is also influenced by international capital movement. If a non-abating country has a competitive advantage in a certain area, it will attract more foreign direct investment, resulting in increased production capacities. The energy market channel refers to the fossil fuel market where the country that has committed to a carbon price will lead to a decrease in demand. This will in turn decrease the market prices of fossil energy commodities and thereby increase the consumption of countries that have not committed to a carbon price. Since this mechanism increases emissions outside the committed country, it falls under the umbrella of carbon leakage. The technology spillover channel, unlike the other two, actually leads to a decrease in emissions from non-committed countries. It therefore, does not add to carbon leakage but rather subtracts from it. As committed countries introduce a carbon price, it can be expected that their carbon-intensive industries will start to develop technologies that allow them to produce more environmentally friendly as this allows them to circumvent high carbon prices. These technologies will eventually also be available to non-committed countries, potentially reducing emissions there, even though the country never adopted an emission-reduction policy. Technology spillover can therefore reduce the carbon leakage effect although it is still counted as one of the channels in which a country's carbon pricing policy can affect emissions elsewhere (Yu et al., 2021). Since the implementation of carbon pricing systems, economic research has concerned itself with the possibility of carbon leakage. Globally, the regionally different measures that followed the implementation of the Kyoto protocol in 2005 were found to have increased carbon-intensive imports from non-committed countries to committed countries by 8% (Aichele and Felbermayr, 2015). More recent studies have used the 'carbon leakage rate' as a basis for comparing carbon leakage estimations. The carbon leakage rate is defined as the increase in related carbon emissions outside a country that is implementing regulation divided by the total regulation-induced reduction of emissions within the country (Barker et al., 2007). This newly defined carbon leakage rate is illustrated in figure 2. The carbon leakage rate is commonly expressed as a percentage and on a global level has been found to be between 4% and 7% for GHG regulations that followed the Paris agreement (King and Bergh, 2021). Global estimates of carbon leakage have been criticised for being very uncertain, though (Aichele and Felbermayr, 2015). Section 2.2 and 2.3 review analytical and empirical carbon leakage rate estimations for the EU ETS.

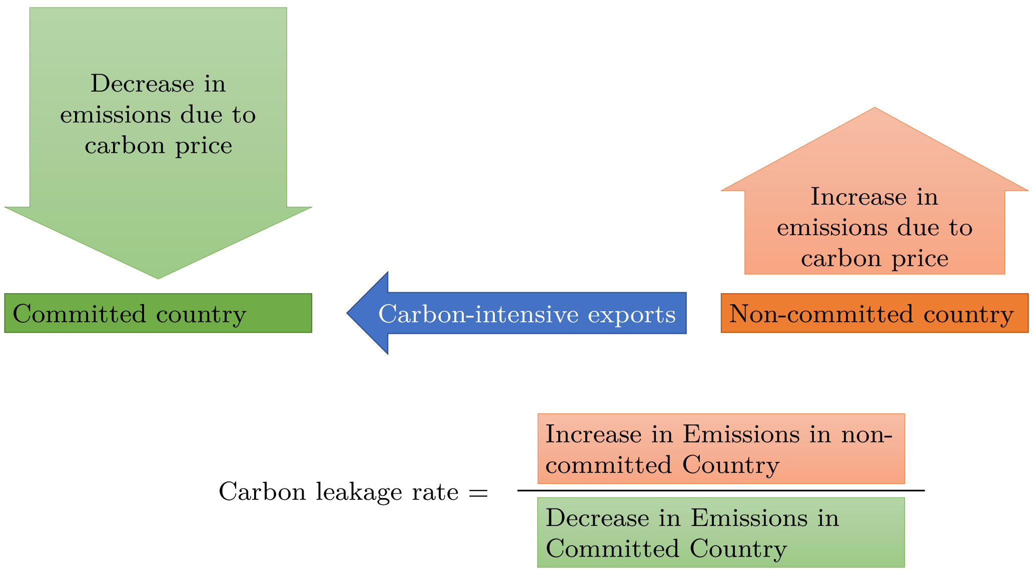

Figure 2: Illustration of the Carbon Leakage Rate and its Computation

2.2 Predictive Modelling of Carbon Leakage from the EU ETS

A number of studies have attempted to estimate the carbon leakage rate that is associated with the EU ETS. There is a large amount ex-ante research which estimates carbon leakage primarily through computed general equilibrium (CGE) models. The different studies differ mainly in their data sources and the channels of carbon leakage that they consider as well as the industries that they include in their research (Yu et al., 2021). Some articles use data from the Global Trade Analysis Project (GTAP) to calibrate their models (Böhringer et al., 2017; Gerlagh and Kuik, 2014; Kuik and Hofkes, 2010) while others use the CGE-based models GDynE (Antimiani et al., 2016) or PACE (Alexeeva-Talebi et al., 2012). Demailly and Quirion (2006) is the only predictive paper that we are aware of which does not use a CGE based model but instead a spatial model. All mentioned ex-ante studies are summarised in table 1.

Study	Inudstrial sector	Period	Leakage rate	Model
Antimiani et al. (2016)	Multi-sectoral	2010 - 2050	16% - 49%	CGE(GDyneE)
Böhringer et al. (2017)	Multi-sectoral	2011	17% - 20%	CGE(GTAP)
Demailly and Quirion (2006)	Cement	2005 - 2011	50%	Spatial Model
Kuik and Hofkes (2010)	Cement & steel	2005 - 2008	2% - 35%	CGE(GTAP-E)
Alexeeva-Talebi et al. (2012)	Non-ferrous, steel & minerals	2004 - 2020	10% - 15%	CGE(PACE)
Gerlagh and Kuik (2014)	Multi-sectoral	2007 - 2020	-1% - 10%	CGE(GTAP-E)

Table 1: Ex-ante studies that model carbon leakage from the EU ETS. Adopted from Yu et al. (2021)

The approach that Gerlagh and Kuik (2014) take, stands out because they are the only study that considers the technology spillover channel. This channel predicts a decrease of emissions in third countries which explains why the result range for this study includes a negative carbon leakage rate. With the possibility of an insignificant leakage rate, this is the only predictive paper that seems to line up with the empirical research which are listed in table 2. The fact that Gerlagh and Kuik (2014) lines up with the empirical research appears likely to be just coincidental because the technology spillover channel impacts competitiveness in the long-term whereas most of the empirical studies focus on short-term trade fluctuations.

2.3 Empirical Studies on Carbon Leakage from the EU ETS

Comparing table 1 and 2 very clearly shows that all predictive modelling studies have found very significant carbon leakage rates while none of the empirical studies were able to confirm those leakage rates. To understand why this could be the case and how this paper plans to improve the empirical research, we ought to have a look at the previous papers.

Study	Inudstrial sector	Period	Leakage rate	Method
Branger et al. (2016)	Cement & steel	2005 - 2012	No evidence in the short run	ARIMA & Prais-Winsten
Reinaud (2008)	Aluminium	2005 - 2006	Not statistically significant	Prais-Winsten
Sartor (2012)	Aluminium	2005 - 2011	No evidence	Johansen Cointegration
Naegele and Zaklan (2019)	Multi-sectoral	2004 - 2011	No evidence	Panel Data
Healy et al. (2018)	Cement & Aluminium	2000 - 2016	No evidence	Panel Data
Boutabba and Lardic (2017)	Cement & steel	2005 - 2015	Negligible	Rolling Cointegration

Table 2: Ex-post studies that study carbon leakage from the EU ETS

Reinaud (2008) was one of the first empirical papers to be published on carbon leakage from the EU ETS. It examines carbon leakage in the aluminium sector for phase I of the EU ETS using a time series regression with Prais-Winsten transformation. Phase I of the EU ETS was a trial phase in which almost none of the certificates were auctioned and instead given to emitters for free. Furthermore, the “cap” of the EU ETS did not actually decrease (Climate Action Network Europe, 2006). Thus, the carbon price would have not affected the aluminium industry disproportionately to its international competitors and it is no surprise that carbon leakage was not observable. Sartor (2012) investigated the same sector with a similar methodology but for phases I and II. In phase II, certificates were still mainly assigned to emitters freely although now the “cap” to the number of certificates was 1.9% lower than the reference emissions from 2005 (European Commission, 2007). Branger et al. (2016)

investigate pretty much the same time frame but while the previous two papers included the USD/EUR exchange rate as a control variable, Branger et al. (2016) only use the industrial outputs of the EU and the BRICS countries (Brasil, Russia, India, China, South Africa). This appears sensible when investigating the steel and cement sector in which the world market is greatly influenced by the BRICS countries. Naegele and Zaklan (2019) also look at the first two phases only, although they are the first paper to consider transport costs as a control variable. Their approach is more sophisticated in that it is not only multi-sectoral but also looks at a variety of bilateral trade connections rather than just the overall trade flows in and out of the EU. The literature on carbon leakage from the EU ETS seems to be limited to phases I and II which might be caused by the fact that after the beginning of phase III the price for certificates collapsed to less than 10 Euros/ton and only recovered in 2018. A price of below 10 Euros/ton is generally seen as not impactful enough to influence trade flows (Boyce, 2018), so naturally research on carbon leakage for this period is not very attractive either. Since 2018 though, the price has continuously risen to above 80 Euros/ton in 2022. This implies that the analysis by Healy et al. (2018) might have equally been set out to fail. The recent increase in emission allowance price desperately calls for a new econometric analysis of carbon leakage, though. Yu et al. (2021) demonstrate this by concluding that econometrics-based research on carbon leakage is "far from enough". Branger et al. (2016), Reinaud (2008) and Sartor (2012) all try to account for serially correlated errors by using different time series procedures. This paper adds to that by trialling a different set of procedures on a more recent set of trading data.

3 Emission Allowances for the European Aluminium Sector

3.1 Free Allocations of Emission Allowances

The EU ETS has been the first major emission trading system to be implemented, it has long been the ETS that covers the most emissions, and it is one of the only ETS's that has seen a high enough price for it to be impactful, at least for some of its history. However, there have been numerous issues with the EU ETS over time that should not go unmentioned. One topic that a lot of the issues are related to is the free allocation of emission allowances. The EU is traditionally an organisation in which national member states and the union in form of the EU commission are haggling over regulation competencies. The EU ETS became subject to exactly this haggling which is reflected in the history of freely allocated emission allowances. The EU ETS is divided into different phases with four different phases having started to date. Each phase saw a few new legislative additions to the EU ETS.

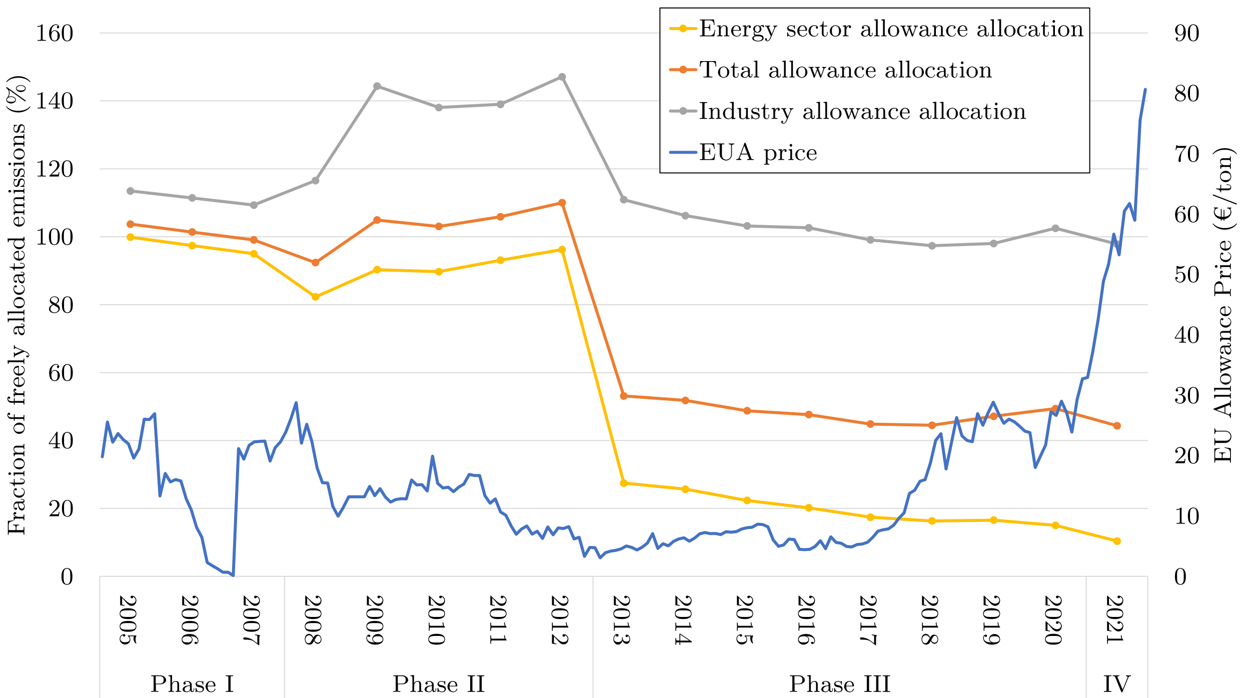

Figure 3: Allowance Price and Percentage of Free Allocations Across Different Phases of the EU ETS

Phase I lasted from January 2005 until December 2007 and could be described as merely a trial phase. Emitters had to possess emission allowances, but all allowances were freely allocated based on the emissions from the previous year. Nonetheless, this led to a relatively stable carbon price between 10 and 30 euros/ton and the overall emission cap was actually reduced by the intended 1.7% every year. However, it was later discovered that the verified end emissions actually increased by 1.9% between 2005 and 2007 (European Commission, 2008). In phase II, which lasted from 2008 till 2012, some of the emission allowances were supposed to be auctioned off. This way emitters would actually have to pay for their emissions and governments could collect money from selling the allowances. Unfortunately, the member states oversaw the auctioning or free allocation of allowances to emitters on their territory. Although they had the possibility of auctioning them off, most countries freely allocated almost all their emission certificates, leading to an oversupply of allowances. It can be assumed that this tendency for free allocations rather than auctioned allocations was largely due to member state governments anticipating carbon leakage to other EU member states. In a practically borderless market, game theory dictates that they could not have allowed their industry to have a competitive disadvantage in case other member states were giving out allowances freely (Bailey, 2010). Because of the free allocations and since emissions were naturally sinking at the time due to the 2007/08 financial crisis (Eurostat, 2022), in all years from 2009 on, there were more freely allocated emission certificates than there were eventual emissions. Naturally, this oversupply led to a diminishing price: between 2009 and 2017 the price was never higher than 20€/ton as can be observed in figure 3. Learning from this, in phase III, which lasted from 2013 until 2020, the EU commission took control of the allowance allocations. This can be seen in Figure 3 where the percentage of freely allocated allowances steeply drops in 2013. Overall, only about half of all emissions have been freely allocated since 2013. However, the share of free allocation varies wildly by sector. The emissions covered by the EU ETS can roughly be divided into two sectors: Energy and industry. Energy makes up around 60% of covered emissions with the rest being various types of industry. While the energy sector received less than a third of its emission allowances for free, the industrial sector continues to receive around 100% of its emission certificates in freely allocated allowances. The EU commission explained this by stating that "sectors at a significant risk of carbon leakage receive a higher share of free allowances" (European Commission, 2021a). As can be inferred from figure 3, most of the industrial sector has been placed in this category. Martin et al. (2014) comment on this, stating that the current allocation strategy by the EU commission results in 'substantial overcompensation for given carbon leakage risk'. The changes for phase IV are not as drastic as the previous changes before a new phase. The annual cap will reduce at an increased pace of 2.2% instead of the 1.74% from phase III. The commission has also announced that their free allocations will focus on "sectors at the highest risk of relocating their production outside of the EU [and on] new and growing installations [based on] more stringent criteria and improved data" (b). With the planned introduction of a CBAM by the EU this year, one can speculate that the practice of freely allocating allowances could finally come to an end, though (2023).

3.2 The Unique Position of the Aluminium Sector

For its lightweight properties, aluminium has been described as playing a key part in reaching climate goals within the transportation sector (Belingardi, 2014). Currently, the global average emissions for the production of a ton of aluminium are estimated at $14-17tCO_2$ (Saevarsdottir et al., 2020). For its importance in this study, it is important to understand where those emissions come from, though. In the production process, aluminium is turned from alumina into metal through the Hall-Héroult process which is an energy-intensive electrolysis. Thus, only 2t or 13% of the emissions associated with the production of a ton of aluminium are direct emissions, meaning they originate from the production process itself (International Aluminium, 2023). The remainder of emissions is mainly made up of indirect emissions from the electricity production with an average of 10t of CO2-emissions being caused by the electricity mix used (Saevarsdottir et al., 2020). This has important effects for its coverage under the EU ETS: The EU ETS covers direct emissions from the industry and energy sector with the industry sector receiving 100% of its allowances for free while the energy sector has to purchase the majority of its allowances in auctions. Since the aluminium industry is part of the industrial sector, it receives allowances for 100% of its direct emissions for free. However, the direct emissions only make up around 13% of the total emissions from the aluminium production process. The indirect emissions coming from the electricity mix make up around two thirds of the total emissions, and, since they turn into direct emissions in the energy sector, they only receive a small part of their allowances for free. As such, the aluminium sector is unique, because it is the only sector that is at real risk of carbon leakage but does not receive the majority of its total emissions covered by free allowances. This makes the aluminium sector the perfect ground for empirical studies on carbon leakage.

4 Methodology

4.1 Empirical Strategy

We aim to test the hypothesis of carbon leakage occurring from the EU Aluminium sector for any of the EU ETS phases. We expect no carbon leakage in phase I or II due to free allocations but anticipate carbon leakage in phase III or IV because the power sector stopped receiving free allocations then. Following Reinaud (2008) and Sartor (2012), we will test the hypothesis by trying to find a correlation between monthly EU ETS allowance price and monthly net aluminium imports into the EU. If the hypothesis of carbon leakage is correct, we should see that an increase in allowance price leads to an increase in aluminium imports. This impact would occur via an increase in electricity prices that would ultimately disadvantage EU Aluminium producers and lead to an increase in net imports. We estimate the effect of the EU emission allowance on EU Aluminium imports during the period 2005-2021 using monthly data. To this end, and in the spirit of Branger et al. (2016), we propose the following empirical model:

$$N_t = \beta_0 + \beta_{1,i} log(E_t) \times P_i + \beta_2 log(I_t) + \beta_{3,j} M_j + \varepsilon_t \tag{1}$$

Where N_t is the value of the net aluminium imports in month t, E_t is the average emission allowance price in that month, and I_t is a monthly EU industrial output value. The data structure of these variables and their sources are described in more detail in section 4.2. P_i is a dummy for each phase i of the EU ETS and M_j is a dummy for each month j of the year.

In previous trials, variables for shipping costs and a dummy for major changes in tariffs were also included but they turned out not to be significant, so they were dropped from the regression. To prove carbon leakage, we expect β_2 (effect of EU allowance price) to be positive. That's because this would mean that an increase in CO2 allowance price would lead to an increase in aluminium imports. We included the phase dummy to see how the effect of the allowance price varies for the different phases. We expect the strongest positive effect of the allowance price during phase III and IV. We expect β_2 to be less significant or not significant at all during phase I and II since allowances were allocated freely. β_3 should be positive throughout because the industrial output is expected to have a positive effect on aluminium imports. That is because the industrial output index proxies the demand for aluminium. With an increase in demand, more of the supply will be imported, causing this expected positive correlation.

4.2 Data

Data for different variables was taken from a variety of sources which are explained below. All data was taken monthly from January 2005 until December 2021:

N_t : Monthly net aluminium imports into the EU-27
This data was taken from Eurostat Trade-by-HS database (Eurostat, 2022). The HS-code for Aluminium is 76. The data was extracted in May 2022. The data is only EU-27 (without UK) because Eurostat offers all their EU data only for the current members. This is a limitation to the study because the UK formed part of the EU ETS for phases I to III. The EFTA states Norway, Iceland and Liechtenstein also form part of the EU ETS but unfortunately monthly data for their imports is hard to come by, so they could not be included which forms another limitation. This is aggravated by the fact that Norway and Iceland are the biggest primary aluminium producing countries covered by the EU ETS, and the 8th- and 11th-largest primary aluminium producers in the world (Brown et al., 2018). To compute the net aluminium imports the exports were subtracted from the imports. It should be noted that the imports were generally larger than the exports, making the EU a net aluminium importer. This meant that all values were positive except for September 2009, in which the exports were slightly larger than the imports. This negative value meant that the net aluminium imports variable (N_t) could not be included logarithmically in the regression because the logarithm of a negative value is undefined.

E_t : EU ETS future allowance price
The EU ETS allowance price was taken from investing.com in May 2022 (Investing.com, 2022). The monthly price was taken as the opening price on the first trading day of every month. There are two sudden drops in the allowance price data between February and May 2007 as well as between April and July 2009. The price during those time ranges was practically zero so the values from those dates have been excluded from the regression.

The reason the price went to zero in 2007 was the announcement that certificates will not be allowed to be carried to the next phase and in 2009 the outcome of the Copenhagen climate summit which was generally seen as disappointing (Krukowska, 2012).

I_t : Monthly EU industrial output
The EU industrial output was also taken from Eurostat (Eurostat, 2022). It gives an index of all industrial activity within the EU-27 which based at 100 in the year 2010. The data was extracted in May 2022.

4.3 Testing Serial Correlation

Serial correlation means that a variable is to some degree correlated with a lagged observation of itself. One of the Gauss-Markov assumptions for ordinary least squares (OLS) regression is that there is no serial correlation in the errors (Johnson, Wichern, et al., 2002). This is because, depending on what causes the serial correlation of the errors, this can lead to a bias in the regression coefficient estimates or an exaggerated tendency to reject the null-hypothesis. Several common tests for serially correlated errors will be applied in this paper:

Durbin-Watson Statistic
The Durbin-Watson statistic is a test for estimating the level of serial correlation at the first lag ($\varepsilon_t \sim \varepsilon_{t-1}$). The test value is calculated using equation 2:

$$DW = \frac{\sum_{t=2}^{t=T}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{t=2}\varepsilon_t^2} \tag{2}$$

If the serial correlation at the first lag is given by $\varepsilon_t = \delta\varepsilon_{t-1} + u_t$, then equation 2 simplifies to $DW = 2(1-\delta)$. This means that in the case of no first lag serial correlation($\delta \approx 0$), the Durbin-Watson statistic should be close to 2 (Durbin and Watson, 1950; 1951).

Breusch-Godfrey Test
In addition to the first-order serial correlation of the Durbin-Watson statistic, the Breusch-Godfrey test also includes the possibility for higher-order serially correlated errors. This means that it additionally assesses the possibility of errors being correlated at a lag of two or higher. The test uses an auxiliary regression that adds the lagged error terms to the original regression (Godfrey, 1978). In our case, the original regression is given in equation 1 and the auxiliary regression with lagged error terms is given in 3:

$$log(N_t) = \beta_0 + \beta_{1,i}log(E_t) \times P_i + \beta_2 log(I_t) + \delta_1\varepsilon_{t-1} + \delta_2\varepsilon_{t-2} + \cdots + \delta_p\varepsilon_{t-p} + u_t \tag{3}$$

The null hypothesis in this case states that all coefficients for lagged errors should be zero ($\delta_1 = \delta_2 = \cdots = \delta_p = 0$). The test assesses this by performing a Lagrange multiplier test to see whether the new R^2 follows a chi squared distribution which it would in case the null hypothesis was true.

Ljung-Box Test
The Ljung-Box test also assesses serial correlation in higher orders (Ljung and Box, 1978). Its test statistic is given in equation 4:

$$Q(\hat{\delta}_k) = n(n+2)\sum_{p}^{k=1}(n-k)^{-1}\hat{\delta}_k \tag{4}$$

Under the null hypothesis that there is no serial correlation, $Q(\hat{\delta}_k)$ should again follow a chi squared distribution.
All three tests estimate different aspects of serial correlation in the error term of an OLS regression. They were used to thoroughly assess the results from the OLS regression as well as the effect of using different correction procedures which are presented in subsection 4.4.

4.4 Correcting Serial Correlation

Serially correlated error terms in regression often stem from not including all the relevant independent variables because dependencies that have not been included lead to continued periods of over- or underestimation by the model. As such, including phase and monthly dummies in the regression model in equation 1, can already be seen as an attempt to reduce autocorrelation in the error term. Similarly, additional variables were included at an earlier stage in the regression but they were shown to neither have an impact on the autocorrelation nor to even show any significant correlation with the dependant variable. The additional variables (USD/EUR Exchange rate and Baltic Exchange Dry Index) have therefore been included from the regression. With additional variables being unable to solve the autoregressive error term, there are a range of statistical remedy procedures that can be applied to the regression.

Procedures that correct for serial correlation in the first lag often follow the same principle: They consider that errors are correlated as an autoregressive process of order 1 (AR(1)). This means the error term in an OLS equation should be to some degree dependant on a once-lagged version of itself ($\varepsilon_t = \delta\varepsilon_{t-1} + u_t$). To let the error term become equal to the partially lagged term, a lagged version of the regression equation has to be multiplied by the factor δ and subtracted from itself. The result of applying this transformation to the original regression from equation 1 is shown in equation 5:

$$log(N_t) - \delta log(N_{t-1}) = \beta_0(1-\delta) + \beta_{1,i}(log(E_t) - log(E_{t-1})) \times P_i + \beta_2(log(I_t) - \delta log(I_{t-1})) + (\varepsilon_t - \delta\varepsilon_{t-1}) \quad (5)$$

The difficulty in this is that the degree of serial correlation in the error term which is expressed in the value of δ is not known initially. There are a number of procedures to determine the best value for δ so that it best corrects the observed serial correlation. Four common procedures as well as one novel transformation (Lagrange-Multiplier Minimisation) are explained below:

Cochrane-Orcutt Procedure

The Cochrane-Orcutt procedure simply estimates the value of δ by performing a regression analysis between the error term and it's lag. This regression follows equation 6 which has been referenced previously (Cochrane and Orcutt, 1949):

$$\varepsilon_t = \delta\varepsilon_{t-1} + u_t \quad (6)$$

Prais-Winsten Transformation

The Prais-Winsten transformation is exactly the same as the Cochrane-Orcutt procedure with the only exemption lying in how δ is applied to the auxiliary regression in equation 5. While the Cochrane-Orcutt procedure loses the first observation due to the applied differencing, the Prais-Winsten transformation estimates a replacement for the first observation, using equation 7 (Prais and Winsten, 1954):

$$\sqrt{1-\delta^2}y_1 = \beta_0\sqrt{1-\delta^2} + (\sqrt{1-\delta^2}X)\beta + \sqrt{1-\delta^2}\varepsilon_1 \quad (7)$$

Hildreth-Lu Estimation

The Hildreth-Lu estimation finds δ through iteration by applying different values of δ to the auxiliary regression and choosing the value that minimises the residual sum of squares (Hildreth and Lu, 1960)

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Lagrange-Multiplier Minimisation

This method has been added by the author to the commonly used autocorrelation procedures. It builds up on a similar principle to the Hildreth-Lu Estimation by trialling different values of δ and optimising for some performance metric. Rather than minimising the residual sum of squares, though, it finds the δ-value for which the Lagrange Multiplier of the Breusch-Godfrey test is minimal. That way it ensures minimal autocorrelation for at least one test metric. The results from this procedure should be interpreted with care because its statistical validity has not been subject to thorough investigation. As such, it is unclear whether the estimators from this procedure can still be labelled as giving the best fit, which is what validates the Hildreth-Lu Estimation.

First Differences

Taking the first differences is a common procedure to remove serial correlation. Rather than using the absolute values of the regression variables, this procedure attempts to show a correlation by using the time differences of each variable. This means each observation is replaced by the difference between the observation at t and the observation at $t-1$. With equation 5 in mind, it should be apparent that this procedure can also be thought of as simply setting δ to 1.

5 Results

Figure 4 shows the evolution of net Aluminium imports into the EU over time. It also shows the fit of the linear regression model that is based on equation 1. We can see that the model offers a reasonable fit but there are prolonged periods in which the model continuously under- or overestimates the net imports. For example, between July 2010 and December 2012, the model continuously underestimates the net imports, and for the whole year of 2009 the model continuously overestimates them. These time-correlated periods of estimating wrong in the same direction are more easily seen in the model residuals and they mean that the error term is autocorrelated which can also be seen in the autocorrelation function. Both the residuals and the autocorrelation function are in appendix A.

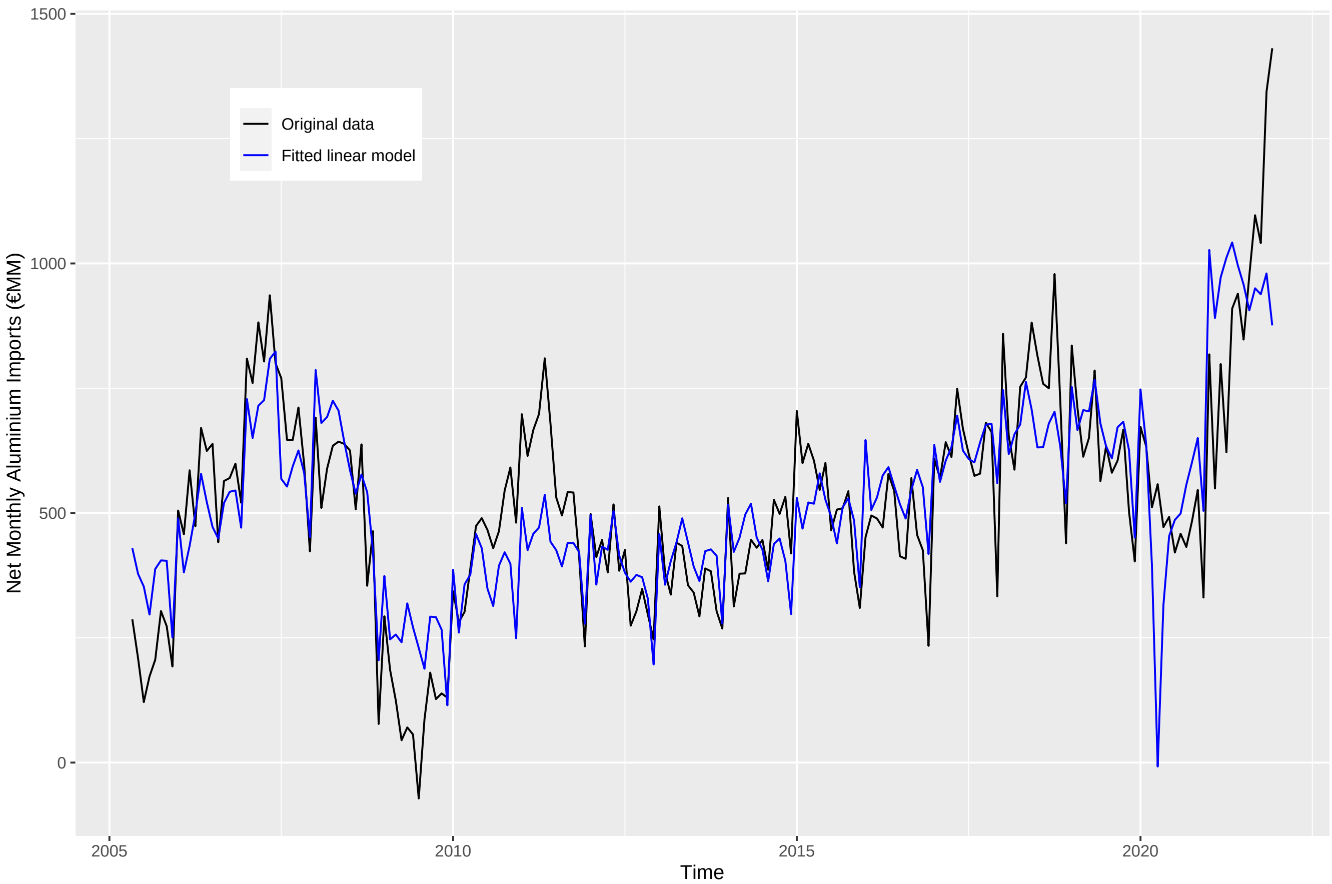

Figure 4: Recorded Net Aluminium Imports in €Million and Predictions by OLS

Section 5.1 discusses the results of attempting to reduce the autocorrelationand section 5.2 interprets the results of the different regressions.

5.1 Effectiveness of Serial Correlation Correction Procedures

A number of procedures that attempt to treat the autoregressive error term were presented in section 4.4. These have been applied to the ordinary regression and were tested using the autocorrelation test from section 4.3. The resulting δ-values of each procedure as well as their test performance are shown in table 3. For each test statistic, their significance is indicated. A significant test result means that the test rejects the null hypothesis of zero autocorrelation which means that autocorrelation is still present in the regression's error term. As explained in section 4.3, the Durbin-Watson statistic indicates likely autocorrelation the further the difference to the value 2. Thus, the closer the statistic is to 2 for a given regression, the lower the likelihood of serial correlation in the error term. This can be seen in table 3, where all of the insignificant Durbin-Watson statistic values are relatively close to 2. For the Breusch-Godfrey and Box-Ljung test, a lower value generally indicates a lower likelihood of autocorrelation. Table 3 shows that the different autocorrelation tests show quite different results. The Durbin-Watson statistic only finds autocorrelation in the ordinary least squares (OLS) regression and indicates that all procedures are successful in removing autocorrelation. The Breusch-Godfrey test finds that only the LM_min procedure is successful in removing autocorrelation and the Box-Ljung test finds that none of the procedures are successful.

Table 3: Results of the Autoregression Tests for Different Procedures

		Autocorrelation tests		
	δ	Durbin-Watson	Breusch-Godfrey(LM)	Box-Ljung(X^2)
OLS	0	0.63751^{***}	89.877^{***}	234.45^{***}
LM_{min}	0.63	1.9561	0.031845	60.108^{***}
Prais-Winsten	0.843	2.4761	14.808^{***}	56.04^{***}
Cochrane-Orcutt	0.847	2.4841	15.232^{***}	56.281^{***}
Hildreth-Lu	0.86	2.5089	16.60^{***}	57.101^{***}
First Differences	1	2.6913	27.586^{***}	64.763^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

The Hildreth-Lu and the Lagrange Multiplier Minimization (LM_{min}) procedures choose a value for δ by optimising a certain regression statistic. These statistics are shown across the full range of δ-values in figure 5. The figure shows how the value sum of squared errors (SSE) and the Lagrange multiplier (LM) vary for different values of δ and how they have different minima. The δ for which the SSE is minimal (0.86) is the value that will be applied for the Hildreth-Lu procedure and the value for which the LM is minimal (0.63) will be applied in the Lagrange-Multiplier Minimisation procedure.

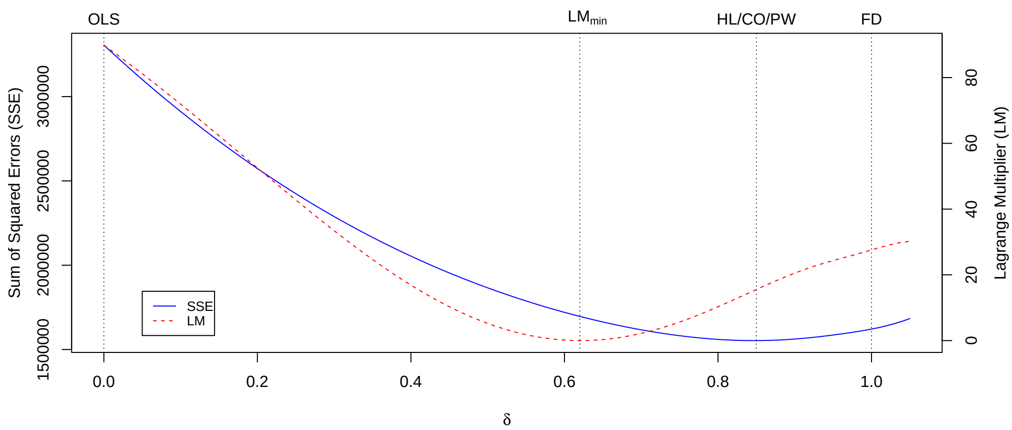

Figure 5: Sum of Squared Errors and Lagrange Multiplier across Different Values for δ

From table 3 we saw that the δ-values for the Hildreth-Lu (HL), Cochrane-Orcutt (CO) and Prais-Winsten (PW) procedures are very similar. The autoregressive performance indicators are also very similar, so that, instead of evaluating each of these procedures individually, we will henceforth compare their average ($\delta \approx 0.85$). This average is shown in figure 5 and table 4. Overall, the Lagrange-Multiplier Minimisation (LM_{min}) procedure appears to perform best because it removes autocorrelation for two out of three of the main statistical tests for serial correlation in the error term. However, care should be taken in evaluating the results from this transformation because it does not minimise the SSE which means that it might not offer the best possible regression fit.

5.2 Interpretation of Regression Coefficient Results

Table 4 shows the results for the different regressions. It does not include the regression coefficients for the monthly dummies. These are shown in appendix B.

Table 4: Results

	Dependent variable:			
	Net Aluminium Imports (€MM)			
	OLS	LM_{min}	CO/PW/HL	First Diff.
	($\delta = 0$)	($\delta = 0.63$)	($\delta \approx 0.85$)	($\delta = 1$)
$log(I_t)$	24.388***	14.523***	6.072*	3.214
	(2.012)	(2.842)	(3.306)	(3.376)
$log(E_t) \times$ Phase I	−40.323***	−2.034	9.010	9.613
	(14.499)	(16.829)	(16.879)	(16.468)
$log(E_t) \times$ Phase II	−23.874*	−12.968	−5.365	−4.191
	(14.119)	(20.827)	(27.753)	(30.477)
$log(E_t) \times$ Phase III	−0.941	22.293	27.468	−52.969
	(14.625)	(21.402)	(33.209)	(55.236)
$log(E_t) \times$ Phase IV	72.836***	112.159***	120.431***	12.523
	(13.287)	(20.833)	(34.559)	(62.071)
Constant	−1,963.425***	−441.270***	−116.304**	−104.645***
	(205.980)	(109.455)	(55.123)	(23.686)
Observations	200	199	199	199
R^2	0.663	0.577	0.573	0.585
Adjusted R^2	0.633	0.540	0.535	0.548
Resid. Std. Error (df = 182)	134.759	96.220	92.372	94.381
F Statistic (df = 16; 182)	22.384***	15.505***	15.261***	16.006***
Note:				*p<0.1; **p<0.05; ***p<0.01

The coefficients from the OLS regression suggest that during phase I and II, the EU allowance price had a negative impact on carbon leakage and during phase IV it had a positive impact on carbon leakage. This could be explained by the fact that during phase I and II, emitters got allowances freely allocated. At high allowance prices, there might have been a possibility that emitters were able to reduce their process emissions (without reducing production output) for less than the price of the allowance. This would have then enabled them to obtain additional capital by selling the emission allowance, thereby giving them a competitive advantage. This theory is deemed superfluous, however, when considering the fact that adjusting for serial correlation annihilates the significance the phase I and II negative coefficients. The positive correlation between the allowance price and net aluminium imports as well as the positive impact of the EU industrial output stay highly significant throughout all serial correlation adjustments apart from the First Differences procedure. The persistence of the former appears to be a real indicator for carbon leakage. The results of the First-Differences procedure do not indicate any significant correlation for any of the tested independent variables. This is especially interesting for the industrial index because the correlation between this and the net imports could be seen as a given.

That is because a strong correlation between industrial demand and metal imports has been proven empirically before (Kim et al., 2016). It therefore seems very plausible that the first-differences procedure "overcorrected" for the serial correlation and in the process got rid of some of the real correlations. This would also explain why no significant correlation can be found the allowance price in phase IV for that procedure. The fact, that all other correction procedures still show a significant correlation for the allowance price in phase IV, indicates that real carbon leakage can be observed empirically in the EU Aluminium sector in phase IV of the EU ETS. Note also, that the magnitude of the correlation between the emission allowance price in phase IV and the aluminium imports increases as the autocorrelation procedures (apart from the First-Differences procedure) are applied. This again suggests that this effect is real and was not just exacerbated by the removed autocorrelation.

The coefficients from the LM_{min} regression should be interpreted because they performed the best in the statistical autocorrelation tests. These results show that for every 1-percent increase in the industrial demand index, there is a €140,000 increase in Aluminium imports. Correspondingly, for every 1-percent increase in allowance price in phase IV, the aluminium imports are expected to increase by €1.12 million. The coefficients from phase I to III are found to be insignificant, so no effect on the Aluminium imports is expected during this time frame.

6 Conclusion

Using monthly data for aluminium imports and ETS allowance prices, carbon leakage was shown to be present for phase IV of the EU ETS. Autocorrelation in the errors is tackled using a variety of treatment methods which remove part of the autocorrelation. These treatment procedures include the use of monthly and longer period dummy variables, the inclusion of additional regression variables and the application of commonly used statistical transformations. Additionally, a new transformation which minimises the Lagrange Multplier is introduced and trialled by the author. Three commonly used statistical tests are applied to evaluate the remaining autocorrelation. While the conventional statistical procedures can only significantly reduce one of the three test measures, the new method reduces autocorrelation in two of them. The allowance price in phase IV continues to have a significant impact on Net aluminium imports for all useful transformations. It shows that every percent-increase in allowance price is associated with an increase of €1.12 million in Aluminium imports. This shows that carbon leakage from the EU ETS can be observed empirically in the European Aluminium sector. While some test measures of autocorrelation seem to persist, this piece of research shows that the aluminium sector is the place in which empirical evidence for carbon leakage from the EU ETS can be found. With the prospect of the European CBAM coming into force soon, more research is desperately needed to empirically quantify carbon leakage and thereby support informed policy decisions. Potential future approaches should include SARIMAx regressions and difference-in-difference approaches that compare the Aluminium sector to other sectors that should have been spared from carbon leakage due to receiving free emission allowances.

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A Residuals and Autocorrelation Function

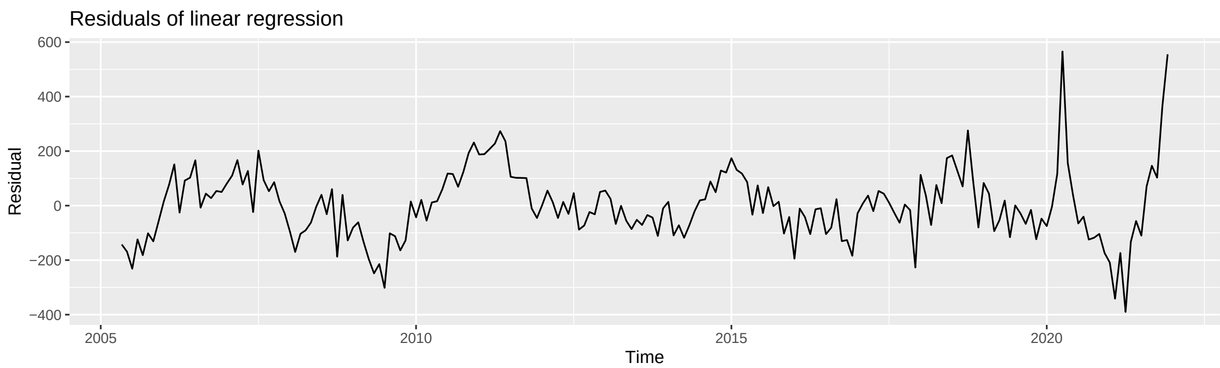

Figure 6: Residual Errors from OLS Regression

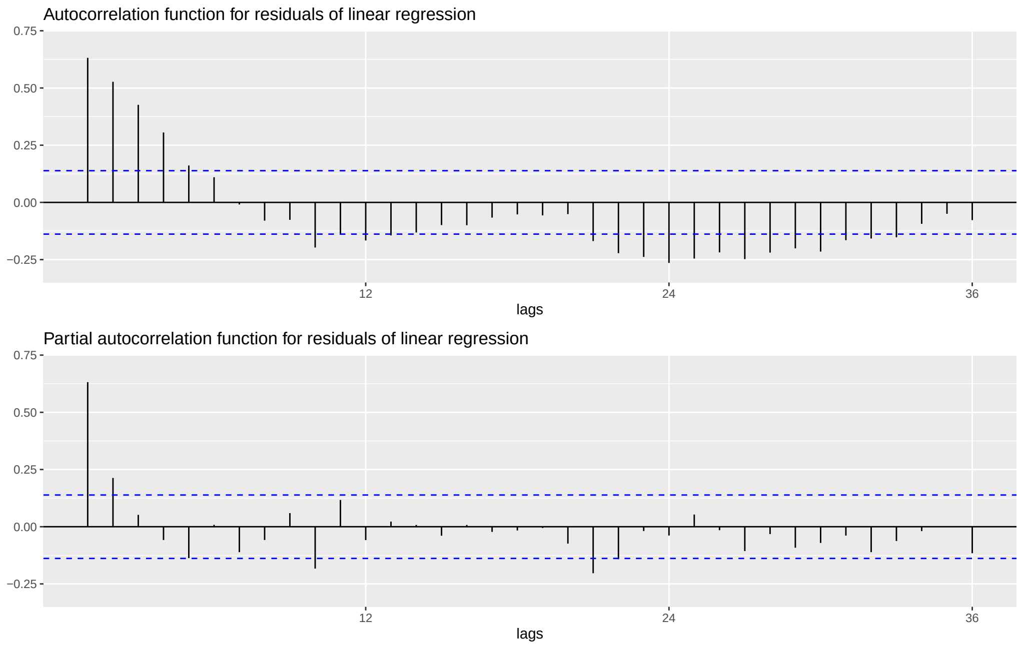

Figure 7: Total and Partial Autocorrelation Function for OLS Regression

B Monthly Dummy Coefficients

Table 5: Results for the Monthly Dummies from the Regressions

	Dependent variable: Net Aluminium Imports (€MM)			
	OLS	LM_{min}	CO/PW/HL	First Diff.
	$(\delta = 0)$	$(\delta = 0.63)$	$(\delta \approx 0.85)$	$(\delta = 1)$
February	40.039	103.512***	123.493***	133.417***
	(47.657)	(34.058)	(32.736)	(33.559)
March	57.278	89.910***	97.199***	104.907***
	(47.743)	(34.188)	(32.860)	(33.548)
April	114.787**	150.199***	170.492***	183.661***
	(47.663)	(34.044)	(32.770)	(33.575)
May	45.535	51.216	58.108*	60.960*
	(46.947)	(33.552)	(32.247)	(32.975)
June	3.604	32.061	44.140	52.540
	(47.077)	(33.821)	(32.533)	(33.243)
July	−30.214	31.293	57.323*	75.468**
	(47.127)	(33.596)	(32.223)	(32.910)
August	27.342	110.442***	143.447***	164.188***
	(47.097)	(33.549)	(32.207)	(32.948)
September	38.322	86.490**	107.441***	117.898***
	(47.071)	(33.546)	(32.212)	(32.989)
October	3.356	46.535	66.281**	78.242**
	(47.036)	(33.550)	(32.227)	(32.946)
November	−132.467***	−70.468**	−46.366	−29.190
	(47.052)	(33.553)	(32.191)	(32.883)
December	105.988**	282.078***	345.407***	394.840***
	(47.647)	(34.189)	(33.079)	(34.094)
Note:				*p<0.1; **p<0.05; ***p<0.01