The Impact of the European Union Emissions Trading System on the Competitiveness and Employment of EU Firms in 2012[†]

By HAIHANG WANG[*]

This paper examines whether the European Union Emissions Trading System has impacted the competitiveness and employment of firms in 2012—the last year of the second trading period (2008–2012). Both the OLS and 2SLS results suggest that emission constraints have a significant effect on firm-level revenues, but not on employment levels of German firms in 2012. The 2SLS results also suggest that emission constraints have a significant effect on both firm-level revenues and employment of firms in other EU countries. Finally, the results indicate that the effect of emission constraints on firm-level revenues does not differ across selected EU countries.

This paper examines the economic implications of the European Union Emissions Trading System (EU ETS). Following the approach taken in Anger and Oberndorfer (2008), I first assess the impact of the EU ETS on the competitiveness and employment of German firms in 2012, a pivotal year in the development of the EU ETS. I then perform a comparative analysis to determine if there are similar or different effects of the EU ETS on a large sample of firms in selected

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† Go to https://github.com/ricardowang/carbon_emissions to download dataset.

EU countries. Finally, I propose how the use of machine learning can help policymakers determine firm-specific emission constraints that both achieve emission reductions and maintain firms' relative competitiveness.

The EU ETS, like many other environmental systems, was first established with the aim to counter the problem of negative externalities. In the case of the EU ETS, the negative externalities that are targeted are the consequences of global warming, the primary cause of which is widely considered to be increasing greenhouse gas emissions. The establishment of the EU ETS was largely due to its impact on reducing greenhouse gas emissions. In addition, some economists also believe that companies stand to benefit from innovations spurred by environmental regulations.

Despite the European Commission's claim that the EU ETS combats climate change "cost-effectively," the EU ETS has been met by extensive and ongoing discussions regarding its overall efficiency and its impact on the performance of companies. Several empirical papers have examined the impact from a cost perspective in the early stage of the EU ETS (2005–2007). This paper is a chronological and logical extension of their efforts. First, it focuses on the second trading period of the EU ETS (2008–2012). Second, it does not directly perform a cost-benefit analysis, as it is often difficult to quantify the benefits of reduced greenhouse gas emissions or abated global warming. Neither does this paper try to investigate the causal pathways from environmental regulations, to firm-level innovations, to increased profitability. Instead, this paper focuses on the cost side of the EU ETS; it asks several questions: does the EU ETS have a significant impact on the competitiveness and employment of firms? If so, by how much?

To answer these questions, I divide the paper into the following sections. Section I provides the background information regarding the formation and development of the EU ETS. Section II summarizes and discusses the existing literature. Section III examines the data used in this paper, verifies the relative relationship between freely allocated allowances and verified emissions in the first trading period (2005–2007), and explores the relationship for an extended period beyond the first trading period. Section IV performs an empirical analysis using the model in Anger and Oberndorfer (2008) to examine whether emission constraints, as measured by the relative relationship between freely allocated allowances and verified emissions, have an impact on the competitiveness and employment of German firms in 2012. Section V subsequently details a similar analysis of the competitiveness and employment of firms in selected EU countries other than Germany. Section VI discusses the use of machine learning in economics and recommends its use in allowance allocation in the context of the EU ETS. Finally, Section VII offers conclusions, discusses the limitations of this paper, and suggests directions for future research.

I. Background

The EU ETS is the first multinational cap-and-trade program. It aims to reduce emissions of carbon dioxide (CO_2) and other potent greenhouse gases, such as nitrous oxide (N_2O) and perfluorocarbons (PCFs). The EU ETS works under the framework of the so-called cap-and-trade principle. Companies covered by the EU ETS are allowed to emit greenhouse gases only below a predetermined maximum, also known as the cap. Under the cap, each company receives a certain number of free allowances each calendar year. However, if companies need to emit more gases than covered by freely allocated allowances, they need to either buy additional allowances on the open market (often through auctioning after 2012) or to draw on their past reserves, i.e., surplus allowances saved in previous years (EC Climate Action 2017). Each year, businesses must report their emissions and have their annual report reviewed by an accredited verifier. For each ton of carbon dioxide (CO_2) or equivalent amount of nitrous oxide (N_2O) or perfluorocarbons (PCFs) that they have emitted, companies must surrender one unit of allowances to the EU ETS. To avoid penalties, companies must surrender allowances that sufficiently match their respective emissions. According to the official fact sheet compiled by the EC Climate Action (2017), penalties include 1) buying additional allowances to make up the shortfall; 2) being "named and shamed" by having their names published; and 3) paying a fine for each excess ton of greenhouse gases emitted.

As of September 2016, the EU ETS regulates approximately 11,000 power stations and manufacturing plants as well as aviation activities in all 28 Member States in the EU plus Iceland, Liechtenstein, and Norway (EC Climate Action 2017). Its regulations, which cover over 45% of the total EU greenhouse gas emissions, have made it the world's largest cap-and-trade program. Since its inception in 2005, the EU ETS has achieved significant reductions in greenhouse gas emissions (Brown et al. 2012; Ellerman et al. 2010). A progress report from the European Commission (2009) shows that the EU ETS surpassed the target (8% reductions compared to base-year level) that was agreed upon by the EU-15 under the first commitment period of the Kyoto Protocol. The progress report also shows that all EU Member States were on track to meet the subsequent obligations under the second commitment period of the Kyoto Protocol.

The development of the EU ETS between 2005 and 2020 is divided into three phases:

(i) The first trading period (2005–2007): the scale of the regulations in the first phase established the EU ETS as the largest multinational cap-and-trade program despite its experimental nature. This phase featured activities to test price formation and build the required infrastructure to monitor, report, and verify emissions (European Commission 2017). Furthermore, the Linking Directive (2004) allowed businesses to use international credits to meet their obligations under the EU ETS; it allowed businesses to generate emission reductions units under the Clean Development Mechanism (CDM) or Joint Implementation (JI), thus linking the EU ETS with the Kyoto Protocol's project-based mechanisms (Anger and Oberndorfer 2008; European Commission 2017). Another notable feature in this period was over-allocation of allowances. More than one source has reported that the number of allowances allocated for this period systematically exceeded the verified emissions (European Commission 2009). I verify this feature of the first trading period in section II.

(ii) The second trading period (2008–2012): the second phase ran in parallel to the first commitment period under the Kyoto Protocol. The EU ETS expanded to include Iceland, Norway, and Liechtenstein (starting January 1, 2008) and aviation activities (starting January 1, 2012). It also saw the number of allowances reduced by 6.5% per year and the auctioning limit increased to 10%.

(iii) The third trading period (2013–2020): the third phase coincides with the second commitment period under the Kyoto Protocol. For this period, an EU-wide cap on emissions was established, and the cap is reduced by 1.74% per year. The EU ETS also established auctioning as the default method for allocating allowances during this period.

II. Literature Review

Environmental economics is a growing sub-field of economics. Central to environmental economics is the concept of externality. The social costs associated with negative externalities caused by market participants often justify environmental regulations. Before Michael E. Porter, the relationship between environmental regulations and companies' competitiveness had often been viewed as a trade-off between social benefits and private costs, i.e., companies must incur private costs so that individuals in society can enjoy social benefits brought about by environmental regulations. Those private costs are usually induced by firms allocating inputs of labor or capital to pollution reductions (Ambec 2011).

However, Porter (1991) argues that there is a false dichotomy in the alleged conflict between environmental regulations and competitiveness. He argues that such dichotomy stems from a static view of competition, devoid of the consideration of innovation and upgrading that might be incentivized by environmental regulations. Porter and van de Linde (1995) expand on this formative paper by contending that the environment-competitiveness debate has been framed in an incorrect way to the exclusion of a more dynamic model, in which the most successful firms have the capacity to innovate and continually improve despite the existence of environmental regulations. Together, these views are later referred to as the Porter hypothesis. In the hypothesis, Porter introduces a new concept of "innovation offsets." Porter believes that in a well-designed environmental protection scheme, the innovation offsets can more than fully counterbalance the costs of compliance. By this definition, scholars often divide the Porter hypothesis into two parts/steps: 1) a well-designed environmental regulation scheme will spur innovation; 2) innovation will, in many cases, more than offset the costs of compliance.

On the other hand, criticisms that challenge the Porter hypothesis have been raised. An assumption underlying the Porter hypothesis is that firms might otherwise ignore profitable opportunities; that is, firms often do not improve and innovate sans environmental regulations. This assumption contradicts the basic view that firms are profit-maximizing entities. As noted by Ambec (2011), Porter responds to such criticisms by arguing that firms might not make optimal choices for many reasons and that environmental regulations help firms to uncover inefficient uses of their resources and thus reach the Pareto optimum.

During the 20 years after the emergence of the Porter hypothesis, a vast body of theoretical literature has attempted to reconcile the Porter hypothesis with traditional economic concepts such as risk aversion (Kennedy 1994), bounded rationality (Gabel 1998), and market failure or organization failure. At the same time, researchers have conducted empirical studies with different approaches to testing the Porter hypothesis. As mentioned above, there are two steps in the logical chain of the Porter hypothesis. These empirical analyses focus on testing either the first step (known as the “weak” version of the Porter hypothesis), or the second (known as the strong “version” of the Porter hypothesis), or a combination of both. Most empirical tests are context-specific limited to certain firms, sectors, or countries. Furthermore, they often attempt to empirically assess the impact of environmental regulations on the business performance of firms. This approach focuses on testing the Porter hypothesis, but without looking at the causality chain, i.e., whether it is innovation or other causal factors that lead to performance changes (Ambec 2011). This approach is especially pronounced in the empirical literature surrounding the EU ETS.

As noted by Zhang et al. (2010) in their overview of previous research on the EU ETS, a large proportion of studies focus on empirically analyzing the economic effect of the EU ETS on firms’ performances. Some papers assess the impact of the EU ETS on the performance of firms in specific sectors, including the European electricity industry (Neuhoff et al. 2006), the iron and steel industry (Demailly and Quirion 2008), and the cement sector (Demailly and Quirion 2006). Others measure the impact using a large sample of companies in a specific country. For example, Anger and Oberndorfer (2008) claim that they are the first to empirically assess the impact of the EU ETS on competitiveness and employment for a large sample of German firms.

Anger and Oberndorfer (2008) find that in 2005, the EU ETS was in an overall “net long” position; that is, the verified emissions in the EU ETS in 2005 were less than the allowances freely allocated to firms. Their results demonstrate varied levels of the relative relationship between allocated allowances and verified emissions among different countries. The long position was most evident in Lithuania, while other countries—including the United Kingdom and Ireland—were short in allowances. Findings regarding the differences in the relative relationship between allocated allowances and verified emissions across countries are evident in several other studies (Ellerman and Buchner 2007; Kettner et al. 2008). Among the papers that test the impact of emission constraints under the EU ETS, Anger and Oberndorfer are the first to give an empirical analysis of the competitiveness and employment implications of emission constraints using a large sample of German companies. Their regression analysis on firms' competitiveness depends on the definition of competitiveness as a firm's ability to sell, and thus using firms' operating revenues as a proxy for firms' competitiveness. Anger and Oberndorfer use the change in the number of employees of firms to test the employment implications of emissions constraints. With these variables, they find that emission constraints, as measured by the relative relationship between freely allocated allowances and verified emissions, did not have a significant impact on the competitiveness and employment of firms in Germany that were regulated by the EU ETS in 2005.

Several limitations of their study are acknowledged in the paper as disclaimers. For example, Anger and Oberndorfer only conduct a case study for Germany because they did not have access to firm-level data for other countries through 2005. They also contend that it was too early to perform an ex-post analysis on the impact of emission constraints given that the EU ETS was established in 2005 and that the allowance allocation of the EU ETS in general, as well as of German firms, was in a long position in 2005. In addition to these two limitations, I also note that Anger and Oberndorfer do not specify the criteria they used to select the sample of German firms.

In this paper, I base my analytical methodology on the approach in Anger and Oberndorfer

(2008). However, instead of merely replicating their results, I focus on the second trading period of the EU ETS. With emissions data to date, I am able to provide a more comprehensive picture of how the relative relationship between allocated allowances and verified emissions has changed. In addition, instead of relying on the Amadeus database and Creditreform to obtain firm-level data, I use the Orbis database, which allows me to extract firm-level data of more countries for an extended period.

III. Data

This chapter is divided into two sub-sections. In the first sub-section, I discuss the relative allowance allocation in Europe. Anger and Oberndorfer (2008) calculate the allocation factors at an aggregated national level for the EU ETS countries in 2005. I verify their calculations and then extend the descriptive analysis to a longer time period in order to examine if the patterns of relative allowance allocation continue after 2005. In the second sub-section, I describe the data used to perform the empirical analyses for this study.

A. Relative Allowance Allocation in the EU ETS

For regulating purposes, each company under the EU ETS must open an account called the Operator Holding Account (OHA). Each account records relevant emissions data such as verified emissions, freely allocated allowances, and units surrendered, of an installation.[1] To calculate the allocation factor, Anger and Oberndorfer (2008) extract the verified emissions and allocated allowances from the EU Community Transaction Log and calculate them at an aggregated national level (European Union 2007). They define the allocation factor as the following:

[1] Each company may have records of multiple installations, i.e., multiple OHAs on the EU Community Transaction Log.

$$AF = \frac{FAA}{VE} \tag{1}$$

where AF denotes the allocation factor, FAA denotes the freely allocated allowances by the EU ETS, and VE denotes the verified emissions.

The allocation factor measures the allowances allocated by the EU ETS relative to the emissions verified by an accredited verifier. An allocation factor greater than one indicates that the company in question receives more free allowances than its actual emissions. An allocation factor less than one implies that the company needs to resort to other measures, e.g., emission reductions or allowances purchasing/auctioning on the open market, to comply with the regulations of the EU ETS.

Since Anger and Oberndorfer (2008), the European Environment Agency (EEA) has developed he EU ETS data viewer (2017). Rather than performing the aggregation based on disaggregated installation-level data from the EU Community Transaction Log, I can more easily and directly obtain country-level emissions data from the EU ETS data viewer for the period from 2005 to present.

Relative Allowance Allocation in 2005.—I find similar results to those found by Anger and Oberndorfer (2008) and Kettner et al. (2008). Figure 1 demonstrates that different countries have different levels of the allocation factor. The data indicate that companies in the United Kingdom ($AF = 0.850$) and in Ireland ($AF = 0.857$) are generally among those who received fewer free allowances from the government. On the other hand, companies in Lithuania, with an allocation factor of 2.044, received more than two times more freely allocated allowances than their verified emissions. Lithuania has also been identified by Anger and Oberndorfer (2008) and Kettner et al. (2008) as the country exhibiting the greatest allocation factor among all countries in 2005.

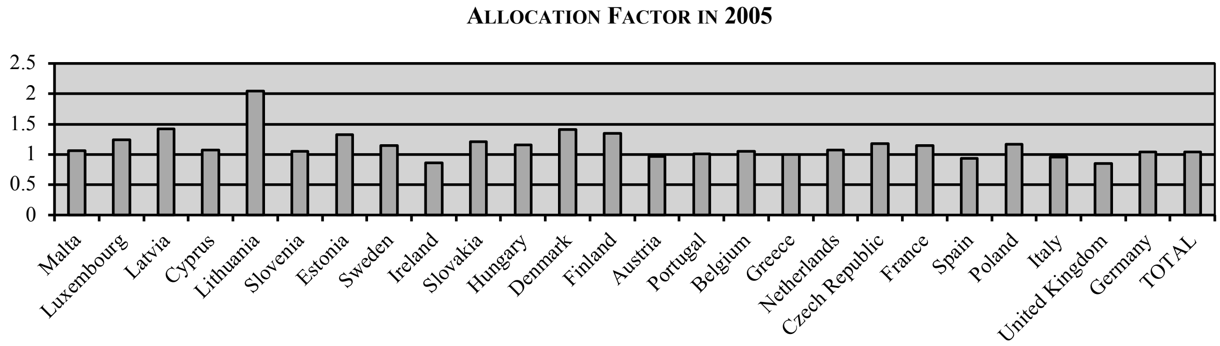

FIGURE 1. ALLOCATION FACTORS AT AN AGGREGATED NATIONAL LEVEL FOR EU ETS COUNTRIES IN 2005
HORIZONTAL AXIS: COUNTRY | **VERTICAL AXIS:** ALLOCATION FACTOR
(SOURCE: EUROPEAN ENVIRONMENT AGENCY; OWN CALCULATION)

The EU ETS was in an overall long position in 2005 ($AF = 1.041$). Among the 25 countries that were regulated by the EU ETS in 2005, only six countries[2] have an allocation factor less than one.

Changes of Relative Allowance Allocation.—In 2005, the EU ETS was in its first year of implementation. Therefore, the overall long position was not unexpected. However, it is valuable to subsequently examine whether the overall long position persists in later years. Moreover, it is also useful to investigate whether the allocation factors of those countries that were long in 2005 remain greater than one in later years, and whether those countries that emitted more greenhouse gases than covered by free allowances in 2005 continue to exhibit the same trends. To limit the scope of this study, I only analyze the allocation factors of certain countries. I also omit aviation activities in this paper. Because the EU ETS started to regulate aviation activities in 2012, companies with aviation activities tend to have a large allocation factor. I select countries based on their allocation factors or emissions levels in 2005. According to Table 1, I divide the countries into three categories: the country with the highest allocation factor in 2005, which includes only

[2] The six countries are the United Kingdom ($AF = 0.850$), Ireland ($AF = 0.857$), Spain ($AF = 0.938$), Italy ($AF = 0.956$), Austria ($AF = 0.971$), and Greece ($AF = 0.999$).

TABLE 1—CATEGORIZING COUNTRIES IN THE EU ETS

Categories	Countries
Country with the highest allocation factor in 2005	Lithuania
Countries with the lowest allocation factors in 2005	United Kingdom, Ireland
Countries with the highest level of verified emissions in 2005	Germany, Italy, Poland, Spain, France

Notes: Although the United Kingdom was also among the countries that had the highest level of emissions in 2005, I put it in the second category given that it has the lowest allocation factor among all countries.

Lithuania; countries with the lowest allocation factors in 2005, including the United Kingdom and Ireland; and countries with the highest level of verified emissions in 2005. The last category consists of five countries: Germany ($AF = 1.039$), Italy ($AF = 0.956$), Poland ($AF = 1.169$), Spain ($AF = 0.938$), and France ($AF = 1.046$).

Figure 2 shows the changes in allocation factor of the five countries with the highest levels of verified emissions in 2005. There is a steady decrease in allocation factors of German firms, from a “net long” to a “net short” position. The allocation factors of the other four countries in the category demonstrate a decreasing trend before 2008 and an increasing trend during the years between 2008 and 2012. However, those four countries overall receive more allowances than their actual emissions before 2012. The period between 2008 and 2012 also corresponds with the financial crisis. The increasing trend in those four countries is most likely due to the crisis-induced demand reduction for allowances (Abrell 2011).

Figure 3 shows the changes in allocation factors of the two countries with the lowest allocation factors in 2005. Before 2011, the allocation factor of Ireland continuously increased. Ireland evolved from the country with the second lowest allocation factor in 2005 to one of the countries with the highest allocation factors in 2012. The United Kingdom remained in a “net short” position (except for the year 2011) despite some fluctuations in the first and second trading periods.

The general trend of Lithuania in Figure 4 is similar to the four countries (excluding Germany) in Figure 2: a decreasing trend before 2008 and an increasing trend between 2008 and 2012.

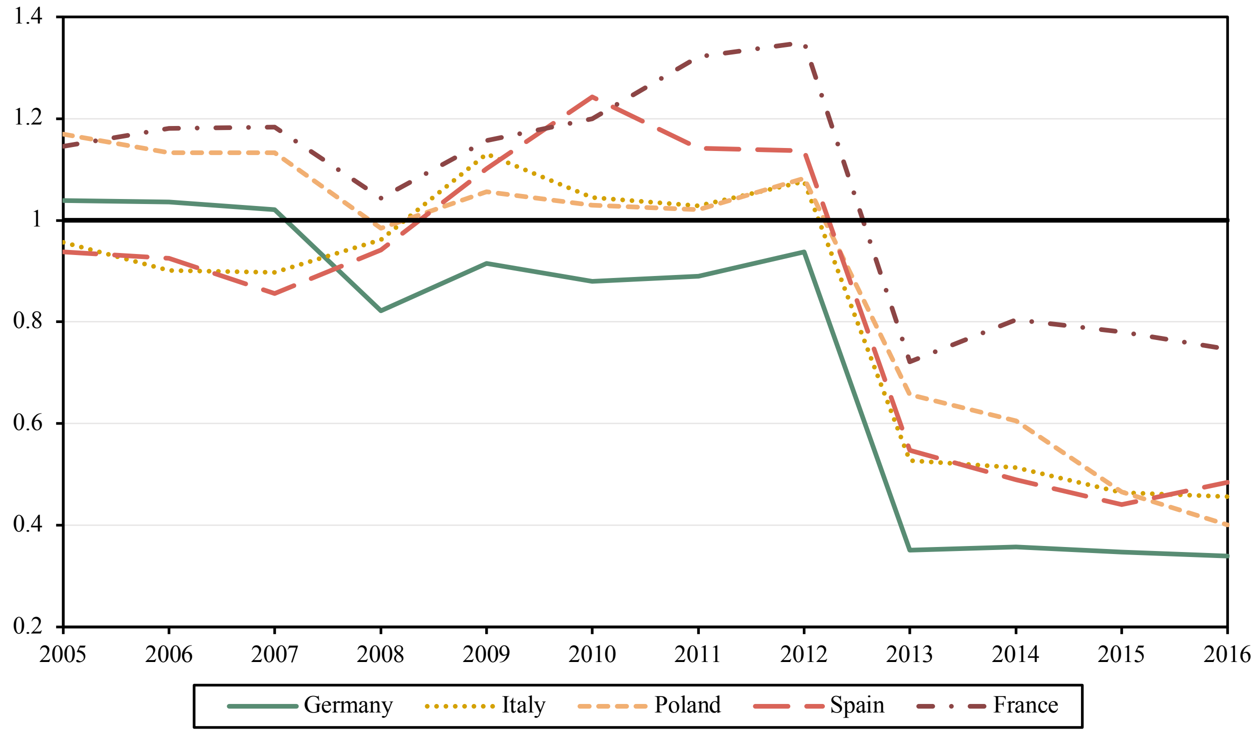

FIGURE 2. YEARLY CHANGE IN ALLOCATION FACTOR OF COUNTRIES
WITH THE HIGHEST LEVEL OF VERIFIED EMISSIONS IN 2005
(SOURCE: EUROPEAN ENVIRONMENT AGENCY; OWN CALCULATION)

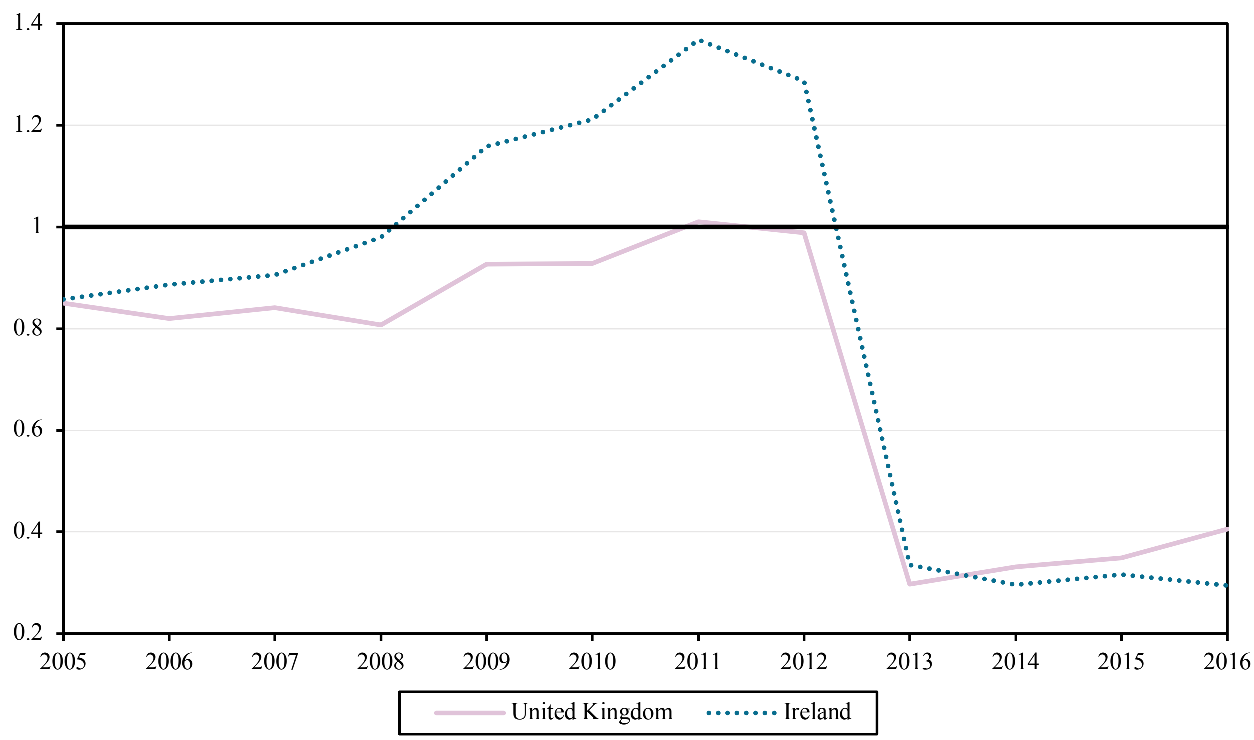

FIGURE 3. YEARLY CHANGE IN ALLOCATION FACTOR OF COUNTRIES

WITH THE LOWEST ALLOCATION FACTOR IN 2005
(SOURCE: EUROPEAN ENVIRONMENT AGENCY; OWN CALCULATION)

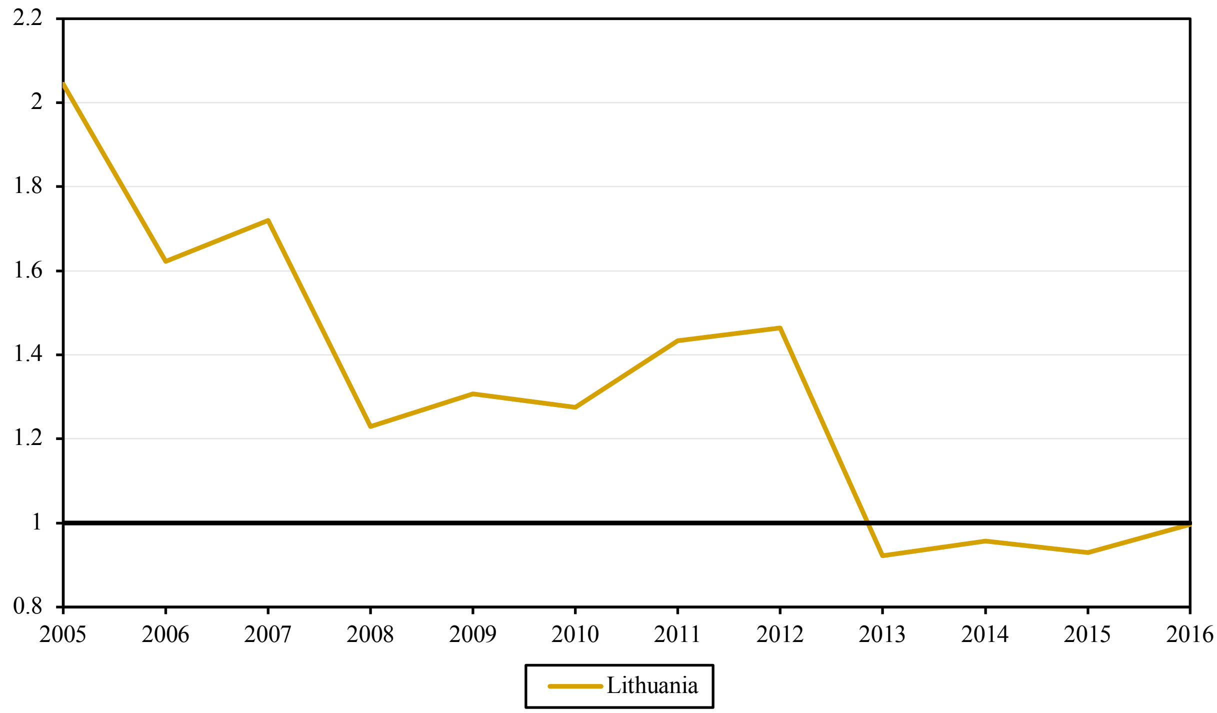

FIGURE 4. YEARLY CHANGE IN ALLOCATION FACTOR OF COUNTRIES
WITH THE HIGHEST ALLOCATION FACTOR IN 2005
(SOURCE: EUROPEAN ENVIRONMENT AGENCY; OWN CALCULATION)

One feature that all eight countries share is a steep decrease in allocation factors in 2013. All eight countries exhibit relatively low levels of allocation factors in subsequent years. This phenomenon can be explained by the introduction of the auctioning mechanism in the allowances market. In the years before 2013, when auctioning was not the default method, "allocated allowances" was almost interchangeable with "freely allocated allowances." Since 2013, auctioning has been regarded as the default method for allocating emission allowances. The Commission estimates that about 57% of the total amount of allowances will be auctioned in the period 2013–2030 (EC Climate Action 2017). This corresponds to a sizable decrease in the freely allocated allowances and thus in the allocation factors.

B. Data Used in this Paper

Varied levels of allocation factors exist not only across countries at an aggregated national level, but also among discrete firms in a single country. I first assess whether such variance in allocation factors has an impact on firms' performances in a single country. Following Anger and Oberndorfer (2008), I choose Germany as my case study. I then perform a similar analysis on firms in selected countries other than Germany, including Belgium, Bulgaria, Czech Republic, Finland, France, Italy, and Spain.

In the empirical analysis, I use firm-level emissions data from the EU Community Transaction Log to calculate allocation factors, and firm-level economic data from the Orbis database. The Orbis database includes firm-level operating revenues from 2008 to 2017, numbers of employees from 2008 to 2017, and the 4-digit NACE Rev.2 core code[3] (hereafter referred to as NACE code). *Appendix A.1* provides more information on the EU Community Transaction Log and *Appendix A.2* includes details about the Orbis database. According to the NACE code, I generate eight sectoral dummy variables, which include dummy variables for the following sectors: mining, paper and pulp, chemicals, metal, other manufacturing sectors, electricity, gas and steam, and others. *Appendix A.3* includes detailed information on how sectoral variables are generated according to the NACE code. Within the comparative empirical analysis, Czech Republic, France, Italy, and Spain are among the countries that have higher verified emissions, while Belgium, Bulgaria, and Finland exhibit moderate emissions. The selection process used aims to balance the time needed to obtain the data and the range and representativeness of countries, as it would have taken too long to gather economic data for all companies in the EU Community Transaction Log. It must be duly noted that the Orbis database does not contain all companies

[3] NACE Rev.2 has been used for statistics referring to economic activities performed from 1 January 2008 onwards. It is different from the NACE Rev 1.1. For simplicity, in this paper I will refer to NACE Rev. 2 core code as the NACE code.

covered by the EU ETS, and entries required to perform the empirical analysis are often missing for a specific company. As a result, I only select those firms with complete economic data with the exception of cases in which I could perform a single imputation: 1) if a company has revenues/employment data between the year 2008 and 2012 except the year 2009/2010/2011, and 2) if differences of the revenues/employment data before and after the year of the missing entry are relatively small. I perform a single imputation by averaging the data before and after the year of missing entry. In reality, cases with missing data that match these two criteria are extremely rare because most companies either have complete revenues/employment data or have more than one missing entry.

Despite missing entries in both the EU Community Transaction Log and the Orbis database, I produce a fairly large sample for both German firms and firms in selected EU countries. By merging the emissions data and economic data, I obtain a sample of 311 German firms regulated by the EU ETS and another sample of 922 firms in Belgium (115 firms), Bulgaria (43 firms), Czech Republic (115 firms), Finland (57 firms), France (61 firms), Italy (245 firms), and Spain (286 firms).

Table A.4.1 in *Appendix A.4* provides an overview of the descriptive statistics of all 311 German firms. As indicated in Figure 5, Germany is among the only three countries that were in the net short position in 2012, with an allocation factor of 0.938. The median allocation factor of the sample is 1.26. The results also indicate that German firms were impacted by the financial crisis but managed to recover very quickly. From Table A.4.1, it is evident that with the exception of the year 2008–2009 when the average firm revenue dropped by EUR 270.56 million and the average number of employees dropped by 135.03, German firms recovered quickly from the financial crisis. The average revenues and the average number of employees of firms in Germany had

ALLOCATION FACTORS IN 2012

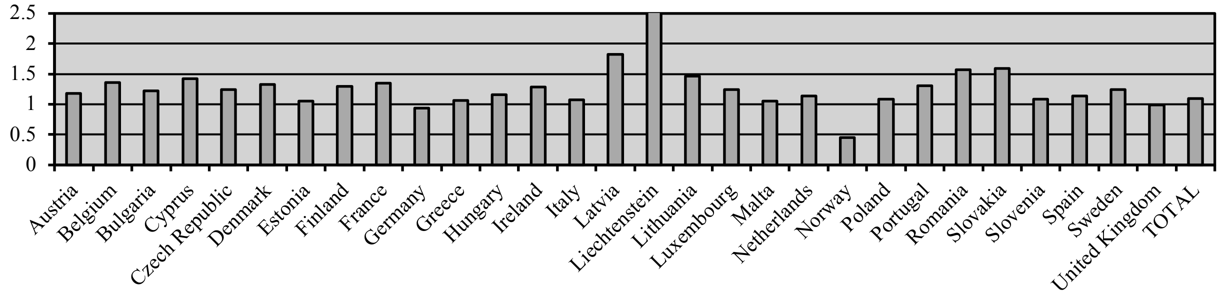

FIGURE 5. ALLOCATION FACTORS AT AN AGGREGATED NATIONAL LEVEL FOR EU ETS COUNTRIES IN 2012
HORIZONTAL AXIS: COUNTRY | **VERTICAL AXIS:** ALLOCATION FACTOR
(SOURCE: EUROPEAN ENVIRONMENT AGENCY; OWN CALCULATION)

well exceeded the levels of 2008 by the year 2012.

Table A.4.2 in *Appendix 4* provides the descriptive statistics of all 922 firms in selected EU countries. In comparison to the German sample, those 922 firms exhibit a wider spread of allocation factors, with a lower minimum and a higher maximum. The mean and median values of allocation factors are slightly greater than the mean and median values for the firms in the German sample. Economic data for the broader EU sample also indicate that European firms in general were impacted by the financial crisis, but the impact was only temporary.

IV. Econometric Analysis for a Sample of Firms in Germany

In this section, I analyze the sample of 311 German firms in the second trading period, following the model in Anger and Oberndorfer (2008). Anger and Oberndorfer (2008) adopt Balassa's (1962) definition of firm competitiveness as its "ability to sell" and approximate this ability using firm revenues. There are other possible proxies to measure a firm's "ability to sell" and a firm's competitiveness may encompass aspects other than its ability to sell. However, for simplicity and in order to draw comparable results, I follow Anger and Oberndorfer's approach by using the operating revenues as a proxy for companies' competitiveness. Employment level can be directly measured by the number of employees in a firm.

In order to assess whether the relative relationship between freely allocated allowances and verified emissions, as measured by the allocation factor, has an impact on firms' competitiveness and employment, I treat the changes in firms' revenues and number of employees between 2012 and 2011 as dependent variables. The independent variables are therefore the factors that can impact competitiveness and employment, including changes in revenue or employment in earlier years (to control for macroeconomic changes), lagged level of revenue or employment, sectoral indicators, and the allocation factor, which is the main interest of this paper. *Appendix A.5* contains the correlation table in which I report the related correlations between (dependent and independent) variables in the regression analysis. I utilize two statistical methods to compute the regression results: ordinary least squares (OLS) and two-stage least squares (2SLS). The use of instrumental variables in 2SLS is to avoid potential endogeneity of the allocation factor, which would render the regression results biased and inconsistent. These models are discussed in detail in the following sub-sections of this chapter.

A. OLS

In order to test whether the EU ETS has an impact on the competitiveness and employment of sample German firms, I first use the OLS to compute the regression results. Equations (2) and (3) represent the regression equations for competitiveness and employment, respectively. In equation (2), the dependent variable is the changes in operating revenues between 2012 and 2011, while in equation (3) the dependent variable is the changes in the number of employees between 2012 and 2011.

$$or_{12-11} = \beta_1 \cdot AF_{12} + \beta_2^T \cdot OR + \beta_3^T \cdot L + \beta_4 \cdot ne_{11-10} + \beta_5^T \cdot D + \varepsilon \tag{2}$$

$$(3) \qquad ne_{12-11} = \gamma_1 \cdot AF_{12} + \gamma_2^T \cdot NE + \gamma_3^T \cdot L + \gamma_4 \cdot or_{11-10} + \gamma_5^T \cdot D + \varepsilon$$

Where:

- or_{x-y} is the difference in a firm's operating revenues between the year x and y; ne_{x-y} is the difference in the number of employees of a firm between the year x and y; or_x is a firm's operating revenues in the year x; ne_x is a firm's number of employees in the year x
- AF_{12} is the allocation factor of a firm, measured by the quotient of freely allocated allowances in 2012 to the verified emissions of that year
- $\beta_2^T \cdot OR = \beta_{2_1} \cdot or_{11-10} + \beta_{2_2} \cdot or_{10-09} + \beta_{2_3} \cdot or_{09-08}$
- $\gamma_2^T \cdot NE = \gamma_{2_1} \cdot ne_{11-10} + \gamma_{2_2} \cdot ne_{10-09} + \gamma_{2_3} \cdot ne_{09-08}$
- $\beta_3^T \cdot L = \beta_{3_1} \cdot or_{10} + \beta_{3_2} \cdot ne_{10}$
- $\gamma_3^T \cdot L = \gamma_{3_1} \cdot ne_{10} + \gamma_{3_2} \cdot or_{10}$
- $\beta_5^T \cdot D$ and $\gamma_5^T \cdot D$ are the vector products between a vector of sectoral dummy variables (excluding the dummy variable for other sectors) and their regression coefficients
- ε is the error term.

As noted by Anger and Oberndorfer (2008), the reason for using the lagged form of revenues and employment levels and their differences in previous years is to avoid potential reverse causality and endogeneity, as it is possible that the dependent variable might have influenced these explanatory variables. However, including lagged levels and changes in revenues and employment in previous years may not completely solve the problem of endogeneity. The regression results on changes in revenue and employment using OLS are shown in column (1) in Table A.6.1 and column (5) in A.6.2 in *Appendix 6*, respectively.

TABLE 2—FIRST-STAGE REGRESSION IN THE 2SLS

Allocation factor 2012	Coefficients	Standard Error	t	P > | t |	[95% Conf. Interval]
Revenues 2012 (Mio. Euro)	.0000337**	.0000144	2.35	0.020	[5.43e-06, 0.00006]
No. employees 2012	−7.50e-06	6.29e-06	−1.19	0.235	[−.000020, 4.89e-06]

Note: 1) Heteroscedasticity-consistent standard errors are used. 2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B. 2SLS

The allocation factor in 2012 depends on the actual emissions level of that year. As common sense suggests, the emissions level can potentially be endogenous because when other factors are fixed, emissions tend to increase when economic activities increase. The increase in economic activities is often reflected by the magnitude of firms' revenues and employment. If that is the case, then the allocation factor in 2012 might be a function of the operating revenues and the number of employees in 2012. This will cause the regression analysis to suffer from endogeneity, and the OLS results will be biased and inconsistent. To avoid the endogeneity of the allocation factor, I also utilize the 2SLS to compute the regression results.

In the first stage, I run a regression with the allocation factor in 2012 as a dependent variable and operating revenues and the number of employees in 2012 as explanatory variables (also known as instruments in the 2SLS). The first-stage regression results are shown in Table 2. In the second stage, the regression equations are the same except that the potentially endogenous allocation factor in 2012 is replaced with its predicted value in the first stage. This process is mathematically shown in Equations 4 (first stage), 5 (second stage), and 6 (second stage).

The regression results for changes in revenues and employment using the 2SLS are shown in column (3) in Table A.6.1 and column (7) in A.6.2 in Appendix 6, respectively.

$$\widehat{AF_{12}} = \hat{\zeta} \cdot or_{12} + \hat{\eta} \cdot ne_{12} \tag{4}$$

$$or_{12-11} = \beta_1 \cdot \widehat{AF_{12}} + \beta_2^T \cdot OR + \beta_3^T \cdot L + \beta_4 \cdot ne_{11-10} + \beta_5^T \cdot D + \varepsilon \tag{5}$$

$$ne_{12-11} = \gamma_1 \cdot \widehat{AF_{12}} + \gamma_2^T \cdot NE + \gamma_3^T \cdot L + \gamma_4 \cdot or_{11-10} + \gamma_5^T \cdot D + \varepsilon \tag{6}$$

C. Results and Discussion

Tables A.6.1 and A.6.2 in *Appendix A.6* report detailed regression results. Columns (1), (3), (5), and (7) show regression models that are parallel to those used in Anger and Oberndorfer (2008). However, because my paper focuses on a different time period, the equivalent models specified in columns (1), (3), (5), and (7) may have the problem of overfitting or underfitting. Following Anger and Oberndorfer's approach, I also report regression results where insignificant explanatory variables are excluded. Columns (2), (4), (6), and (8) in Tables A.6.1 and A.6.2 report regression results where insignificant explanatory variables are excluded from (1), (3), (5), and (7), respectively. The last row of those four columns shows the *p*-value of the *F*-test for excluding insignificant variables.

The OLS and 2SLS Results for Changes in Revenues between 2012 and 2011.—In Table A.6.1, column (1) reports the results of the OLS with the change in revenues between 2012 and 2011 as the dependent variable. The results indicate a good fit of the econometric model, with $R^2 = 0.9158$. Column (2) shows a model excluding all insignificant variables in column (1). Column (3) presents the results of the 2SLS with the change in revenues between 2012 and 2011 as the dependent variable. The use of 2SLS increases the overall fit, with $R^2 = 0.9904$. This may be explained by the significance of revenues in 2012 in the first stage, as indicated in Table 2. Column (4) again excludes all insignificant variables in (3). Both exclusions are supported by the F-test, with p-values of 0.1311 and 0.1276, respectively. In addition, there is only a slight drop in the R^2 for two models that exclude insignificant variables ($R^2 = 0.9024$ compared to $R^2 = 0.9158$ for the OLS; $R^2 = 0.9902$ compared to $R^2 = 0.9904$ for the 2SLS).

The regression results reported in columns (1) to (4) suggest that emission constraints, measured by the allocation factor, have a significant impact on the change in German firm revenues between 2012 and 2011. Except for column (2) in Table A.6.1 where insignificant variables are excluded from column (1), the coefficients for the allocation factor or the predicted allocation factor in 2012 are all significant. This is especially evident in the 2SLS case: the coefficient of the predicted allocation factor in 2012 is significant at the 0.01 level in columns (3) and (4).

This finding is different from that in Anger and Oberndorfer (2008). Their study does not find evidence for a significant impact of emission constraints on the change in firm revenues between 2005 and 2004. The different results may be explained by the changes in German firms' relative position in allowance allocation or by the changes of the EU ETS in the second trading period. Germany shifted from a net long country to a net short country between the first and second trading periods. Moreover, the increasing use of auctioning (though it was not the default method in 2012) in the allowance allocation could have increased the burden of German firms with lower allocation factors. Despite the differences in findings, the regression results for the change in revenues conform to intuitions. Anger and Oberndorfer (2008) cite that a higher relative (grandfathered) allowance allocation is accompanied by lower compliance costs (Böhringer et al. 2005). The results indicate a positive coefficient for the allocation factor or the predicted allocation factor in both the OLS and 2SLS regressions. Given their significance, the coefficients are statistically different from 0. The results therefore imply that firms with a higher allocation factor—

with higher allocated allowances compared to verified emissions—could increase their revenues in 2012 more than those with a relatively lower allocation factor.

In addition to the allocation factor, lagged levels of revenues and employment, i.e., revenues in 2010, number of employees in 2010, and change in employment between 2012 and 2011, show a significant impact on the change in revenues between 2012 and 2011 in both the OLS and the 2SLS results. The coefficient for revenues in 2010 has a positive sign in the OLS results but a negative sign in the 2SLS results. Meanwhile, the coefficient for employment in 2010 has a negative sign in the OLS results but a positive sign in the 2SLS results. The differences between the OLS and 2SLS might be explained by correlations between explanatory variables in the first stage (operating revenues and number of employees in 2012), and revenues and employment in 2010.

Although the change in revenues between 2011 and 2010, and between 2010 and 2009, do not show a significant impact on the dependent variable in the OLS results, their coefficients are significantly negative in the 2SLS results. The negative signs of those two explanatory variables are counterintuitive, as we would either 1) expect both signs to be positive as when firms have a higher increase in revenues in previous years, it is likely that they also have a higher increase in revenues this year, or 2) expect one sign to be positive and another to be negative due to regression toward the mean. The negative signs again might be caused by correlations between explanatory variables of 2SLS in the first stage (the operating revenues and the number of employees in 2012), and change in revenues between 2011 and 2010, and between 2010 and 2009.

The positive impact of the employment change between 2011 and 2010 is noted by both OLS and 2SLS. This suggests that companies with more incoming employees between 2010 and 2011 also have increased revenues between 2011 and 2012. All sectoral indicator variables do not show a significant impact on the revenue change in 2012 with the exception of the electricity sector. The coefficient of the sectoral variable for the electricity sector is significant at the 0.05 level in the 2SLS with all explanatory variables and at the 0.01 level in the 2SLS with only significant variables. This finding indicates that companies in the electricity sector experienced less change in revenues between 2011 and 2012 compared to companies in other sectors.

The OLS and 2SLS Results for Changes in Employment between 2012 and 2011.— Column (5) reports the results of the OLS with the change in employment between 2012 and 2011 as the dependent variable. The results also indicate a good fit of the econometric model, with $R^2 = 0.9081$. Column (6) shows a model excluding all insignificant variables in Column (5). Column (4) provides the results of the 2SLS with employment change in 2012 as a dependent variable. The use of the 2SLS slightly increases the overall fit, with $R^2 = 0.9108$. Column (8) excludes all insignificant variables in column (7). The exclusion in the OLS case is supported by the F-test. There is only a slight drop in the R^2 for the OLS model that excludes insignificant regressors ($R^2 = 0.8841$ compared to $R^2 = 0.9081$). However, there is a large drop in the overall fit when excluding all insignificant variables in the 2SLS model ($R^2 = 0.5980$ compared to $R^2 = 0.9108$), which is evident in the p-value when excluding insignificant variables. The exclusion in the 2SLS case is rejected at the 0.01 level, with a p-value of 0.0086. Joint non-significance is therefore not achieved for all the variables that are not significant in the 2SLS.

The finding for the change in employment between 2012 and 2011 differs from the case of change in revenues. The regression analysis does not find evidence that emission constraints have a significant impact on a German firms' employment change in 2012. Although the coefficient for the allocation factor in both models is positive, the standard errors are large enough that the coefficient does not differ from 0.

However, the employment change between 2011 and 2010 is significant in both the OLS and 2SLS results, which suggests that companies with more incoming employees between 2010 and 2011 also have more incoming employees between 2011 and 2012. The results conform to intuitions given that we expect firms to expand and hire more employees over time. It is likely that firms that hired more employees in 2011 were still expanding and thus also hired more employees in 2012 compared to firms that were not increasing employees.

The coefficients for the lagged levels of employment and revenues, i.e., number of employees in 2010 and operating revenues in 2010, are only significant in the OLS model, with the former being negative and the latter positive. This finding demonstrates that German firms with lower levels of employment and higher levels of revenues in 2010 hired more employees in 2012. The revenue level in 2010 likely has a significantly positive impact because higher levels of revenues in 2010 translate into an overall larger size of economic activities, and firms would thus expect to hire more employees in subsequent years. Furthermore, the sectoral variable for the chemical sector shows significant impact on the change in employment between 2012 and 2011 in the OLS and 2SLS results with all variables included. Both coefficients are strongly positive, indicating that companies in the chemical sector hired far more employees between 2011 and 2012 than companies in other sectors.

Overall, we see fewer significant variables in the regression results for the change in employment between 2012 and 2011 compared to results for the change in revenues between 2012 and 2011. In addition, a majority of the significant regression coefficients reveal a significantly positive impact instead of a negative impact on the change in employment. Finally, the emission constraints, as measured by the allocation factor, do not have a significant impact on the change in employment of German firms between 2012 and 2011. One possible explanation for such deviations between change in revenues and employment might be the stringent nature of German labor and employment laws, which somewhat insulates German employment levels. German labor and employment laws are strongly biased in favor of employees.[4] For example, companies with more than five employees can elect a work council through which they can negotiate with employers on matters such as mass layoffs. In addition, employers must acquire prior approval from the employment office before mass layoffs. Such requirements can potentially explain why emission constraints have more of an impact on the change in revenues than on the change in employment.

V. Econometric Analysis for a Sample of Firms in Selected EU Countries

This chapter is divided into two sub-sections. In the first sub-section, I compare regression results for the sample of German firms in section IV and a sample of firms in selected EU countries. I run regressions without taking country-specific effects into account, assuming that the effect of emission constraints on the change in revenues/employment between 2012 and 2011 is the same across companies in different countries. This assumption is removed in the second sub-section by including the country dummy variables and interaction terms between the allocation factor and the country dummy variables. This allows me to test whether the emission constraints have different effects on firms in different countries.

A. OLS and 2SLS Results for a Sample of Firms in Selected EU Countries

Similar to my approach with German firms, I run OLS and 2SLS regressions, and the dependent and independent variables are the same as in the German case. Table A.5.2 reports the pairwise correlations between relevant variables. Tables A.6.3 and A.6.4 show regression results with the change in revenues between 2012 and 2011 and in employment between 2012 and 2011

[4] https://www.wilmerhale.com/pages/publicationsandNewsDetail.aspx?NewsPubId=90463

TABLE 3—FIRST-STAGE REGRESSION IN THE 2SLS

Allocation factor 2012	Coefficients	Standard Error	t	P > | t |	[95% Conf. Interval]
Revenues 2012 (Mio. Euro)	.0000276	.0000187	1.48	0.140	[−9.08e-06, 0.00006]
No. employees 2012	6.99e-06	4.90e-06	1.43	0.154	[−2.63e-06, 0.00002]

Note: 1) Heteroscedasticity-consistent standard errors are used. 2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

as dependent variables, respectively.

Unlike the German case—for which I found that the emission constraints have a significant impact on the change in revenues, but not on the change in employment between 2012 and 2011—the OLS results for this new set of firms suggest that there is no impact of emission constraints on either revenues or employment. However, the 2SLS results demonstrate entirely different implications. According to column (11) in Table A.6.3 and column (15) in Table A.6.4, the coefficient of emission constraints, as measured by the allocation factor, is significant in the 2SLS model even at the 0.01 level. This means that when controlled for macroeconomic factors in the first stage (as in Table 3), emission constraints have a significant impact on the change in revenues and employment between 2012 and 2011 for the sample of firms in selected EU countries. Such impact is positive in both cases, as indicated by the positive sign of the regression coefficients in columns (11) and (15). As mentioned in previous sections, the results conform to intuitions that when controlling for other factors, firms with less stringent emission constraints will have the ability to expand in revenues and employment.

The regression results across the German and EU samples suggest that emission constraints have different effects on German firms than on firms in other EU countries. The difference can again be potentially attributed to the differences in labor and employment laws in different countries. As noted in the previous section, Germany has stringent labor and employment laws that greatly limit employers' power to lay off employees. In addition, the second trading period of the

EU ETS coincides with several major policy changes in Germany, including the Harts reforms of German labor law, a set of recommendations to reform the German labor law with the aim to reduce short- and long-term unemployment. The lack of similar reforms in other countries and the differences in labor and employment laws between Germany and other EU countries may help explain the differences in the regression results.

B. Testing for Differences in Regression Functions Across Countries

Part A of this chapter focused on whether or not the results found in the previous section can be generalized to other EU countries. However, the regression excludes consideration of the distinct effects of emission constraints on firms in different countries. This sub-section therefore addresses whether there are differences in regression functions for firms across different countries. One may expect that because the selected countries differ in many respects, the regression functions should similarly differ for different countries. On the other hand, despite their differences in terms of population and economic strengths, the selected countries are all countries within the EU. Thus, from this perspective, the effect of emission constraints on revenues should be fairly similar.

To examine country differences, I first create country dummy variables that are given a value of one for a company in a certain country and a value of zero for a company not in that country. I then modify the OLS regression by including country dummy variables and the interaction terms between the allocation factor and the country dummy variables. I focus in particular on the impact of emission constraints on the change in firms' revenues. When adding the newly-created variables, equation (2) can be modified as follows:

$$(7) \qquad or_{12-11} = \beta_1 \cdot AF_{12} + \beta_2^T \cdot OR + \beta_3^T \cdot L + \beta_4 \cdot ne_{11-10} + \beta_5^T \cdot D + \beta_6^T \cdot C + \beta_7^T \cdot I + \varepsilon$$

Where:

- $\beta_6^T \cdot C$ is the vector product between a vector of country dummy variables (excluding the dummy variable for one country to avoid multicollinearity) and their regression coefficients
- $\beta_7^T \cdot I$ is the vector product between a vector of interaction terms and their regression coefficients.

Country dummy variables are used to represent Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Finland (FI), France (FR), Italy (IT), and Spain (ES). For consistency, the regressions exclude the dummy variable and interaction term that involve Belgium to avoid multicollinearity. Thus, the vector products in the equation above can be expanded as follows:

(8) $$\beta_6^T \cdot C = \beta_{6_{BG}} \cdot BG + \beta_{6_{CZ}} \cdot CZ + \cdots + \beta_{6_{ES}} \cdot ES$$

(9) $$\beta_7^T \cdot I = \beta_{7_{BG}} \cdot (BG * AF_{12}) + \beta_{7_{CZ}} \cdot (CZ * AF_{12}) + \cdots + \beta_{7_{ES}} \cdot (ES * AF_{12})$$

The OLS results for the change in revenues between 2012 and 2011 are shown in Table 4, which only includes variables that are important to the null hypothesis. In part A of section V, I found that without considering country-specific effects of emission constraints, the OLS results do not suggest that emission constraints have a significant impact on the change in firm-level revenues or on the change in the number of employees between 2012 and 2011. Table 4 demonstrates that by including the country dummy variables and interaction terms between country dummy variables and the allocation factor, we do not see a sizable increase in the goodness of fit of the OLS model for the change in revenues ($R^2 = 0.5577$ in Table A.6.3 in *Appendix 4* compared to $R^2 = 0.5614$ in Table 4). The inclusion also does not alter the significance levels of the allocation factor coefficient in the OLS model for the change in revenues.

TABLE 4—OLS RESULTS FOR THE CHANGE IN REVENUES WITH COUNTRY DUMMY VARIABLES AND INTERACTION TERMS

Revenues 2012−2011 (Mio. Euro)	Coefficients	Standard Error	P > | t |
Allocation Factor 2012	42.81534	57.35557	0.456
Bulgaria (BG)	237.3113*	142.7303	0.097
Czech Republic (CZ)	138.6365	155.1673	0.372
Finland (FI)	95.25259	146.6658	0.516
France (FR)	−24.64451	266.6732	0.926
Italy (IT)	217.9252	154.8126	0.160
Spain (ES)	119.5672	155.7544	0.443
BG × Allocation Factor 2012	−70.96541	50.85093	0.163
CZ × Allocation Factor 2012	−35.6735	63.28425	0.573
FI × Allocation Factor 2012	−44.43677	62.89205	0.480
FR × Allocation Factor 2012	−26.95588	96.63534	0.780
IT × Allocation Factor 2012	−70.66818	65.44207	0.280
ES × Allocation Factor 2012	−25.63118	61.41302	0.677
Constant term	−166.3211	167.6768	0.322

Note: 1) Heteroscedasticity-consistent standard errors are used. 2) * p < 0.10, ** p < 0.05, *** p < 0.01. 3) $R^2 = 0.9094$.

By setting a specific country dummy variable to a value of one and the remaining country dummy variables to zero in equation (7) (for example, set BG to one, and CZ, FI, FR, IT, and ES to zero) I derive equation (10). For simplicity, I only retain variables that are crucial to the analysis, including the allocation factor and the country dummy variables. After excluding extraneous variables, I obtain equation (11).

$$(10)\quad or_{12-11} = \beta_1 \cdot AF_{12} + \beta_2^T \cdot OR + \beta_3^T \cdot L + \beta_4 \cdot ne_{11-10} + \beta_5^T \cdot D + \beta_{6_{BG}} + \beta_{7_{BG}} \cdot AF_{12} + \varepsilon$$

$$(11)\quad \widehat{or_{12-11}} = \widehat{\beta_1} \cdot AF_{12} + \widehat{\beta_{6_{BG}}} + \widehat{\beta_{7_{BG}}} \cdot AF_{12} + C = \left(\widehat{\beta_{6_{BG}}} + C\right) + \left(\widehat{\beta_1} + \widehat{\beta_{7_{BG}}}\right) \cdot AF_{12}$$

Therefore, to test whether there are differences in regression functions across different groups, I only need to test the null hypothesis that $\widehat{\beta_6^T} = \vec{0}$ and $\widehat{\beta_7^T} = \vec{0}$. The former tests the differences in terms of intercept of different functions and the latter tests the differences in terms of the slope.

As a result, I utilize the F-tests to examine whether we can reject or sustain the null hypothesis $\widehat{\beta_6^T} = \vec{0}$ or $\widehat{\beta_7^T} = \vec{0}$. An F-test for $\widehat{\beta_6^T} = \vec{0}$ reveals that the F-statistic is 1.08 and the p-value is 0.3722, which is not significant even at the 0.10 level. An additional F-test for $\widehat{\beta_7^T} = \vec{0}$ similarly demonstrates that the F-statistic is 0.93 and the p-value is 0.4736, which is also not significant even at the 0.10 level. Both F-tests suggest that the null hypotheses $\widehat{\beta_6^T} = \vec{0}$ and $\widehat{\beta_7^T} = \vec{0}$ cannot be rejected, indicating that there are no significant differences in regression functions across firms in different countries. The regression functions do not significantly differ in the intercept (as suggested by $\widehat{\beta_6^T} = \vec{0}$) nor in the slope (as suggested by $\widehat{\beta_7^T} = \vec{0}$).

The F-tests suggest that regression functions do not differ across countries. However, it is still interesting to plot these regression functions. Equation (11) shows that by setting one country dummy variable to one and the rest to zero, we generate $\widehat{or_{12-11}} = \left(\widehat{\beta_{6_{BG}}} + C\right) + \left(\widehat{\beta_1} + \widehat{\beta_{7_{BG}}}\right) \cdot AF_{12}$. Utilizing the coefficients obtained in the regression shown in Table 4, I plot the regression functions (excluding extraneous variables) for the seven countries in the sample, as shown in Figure 6. The plot visualizes the effects of emission constraints on the change in firms' revenues between 2012 and 2011, although the effects are not significant as indicated by the regression coefficients and their p-values. Figure 6 visually suggests that the regression functions for different countries indeed have different intercepts and slopes. If a regression function has an upward slope, we can generally expect the firms in the country represented by the regression function to benefit from less strict emission constraints (as measured by a larger allocation factor). On the other hand, if a regression function has a downward slope, then firms in the country represented by the regression function—contrary to intuitions—actually benefit from tighter emission constraints in general.

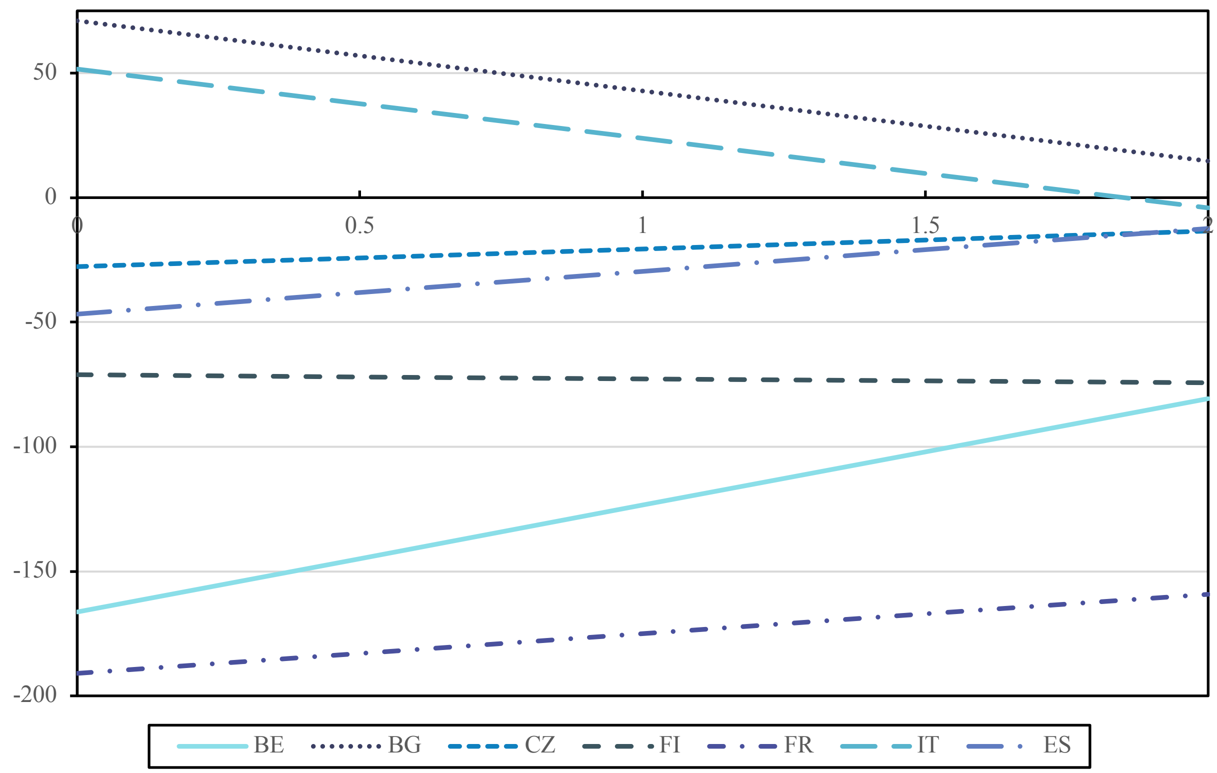

FIGURE 6. DIFFERENCES IN THE EFFECT OF EMISSION CONSTRAINTS ON THE CHANGE IN REVENUES BETWEEN 2012 AND 2011
HORIZONTAL AXIS: ALLOCATION FACTOR | **VERTICAL AXIS**: CHANGE IN REVENUES BETWEEN 2012 AND 2011
(SOURCE: EU COMMUNITY TRANSACTION LOG, ORBIS; REGRESSION RESULTS IN TABLE 4)

VI. Using Machine Learning Techniques to Determine Allocation Factors

The field of machine learning has been growing in recent years. However, the application of machine learning in economics is rather limited and there are key differences in the approaches taken by economists and by machine learning practitioners. As noted by Susan Athey (2017), in economics researchers pick a model based on economic principles and test it once. This approach is drastically different from that of machine learning, for which the focus is how well a model predicts future data instead of merely trying to fit the current data. The emphasis on predicting instead of fitting determines that instead of testing a model once, there will be "tuning" based on an existing model such that the modified version can have a better predictive power.

Athey (2017) also notes that for the empirical work of economics, economists largely have a primary interest in estimating causal effects. That is, economists are more interested in constructing an unbiased estimate of a causal parameter of interest. This approach (also the focus of previous sections) is often not compatible with the goal of accurately predicting outcomes, which is the primary focus of machine learning practitioners.

Despite its limited use and the differences in the two approaches, the applications of machine learning to policy problems in economics are not uncommon. Kleinberg et al. (2015) consider the applications of machine learning in medicine and the criminal justice system. For example, they present a case in which they predict the life expectancy of patients seeking hip or knee replacement using existing data. Because the benefits of joint replacement take time, it only makes sense for someone who will live for many more years after hip or knee replacement to receive the operation. Otherwise, the operation will constitute a waste of money and unnecessary pain for recipients.

A classification model using machine learning techniques also has practical significance in the context of the EU ETS. An important mechanism of the EU ETS is allowance allocation. How many allowances should we allocate to a specific company? If a firm is allocated far more allowances than its actual emissions, then emission reductions are unlikely to be achieved. On the other hand, if the emission constraints are too stringent, it is possible that the firm will be overly negatively impacted by the EU ETS. In earlier sections of this paper, I have discussed how emission constraints impact firms in EU countries. In this section I explore how to construct a model that is capable of categorizing firms, with great confidence, into two groups: those that have increasing profitability in 2012 and those with decreasing or constant profits in 2012. With the revenue data available, it is relatively easy to determine which firms belong to which group and as-sign a (positive or negative) label to each of them. In machine learning, this problem belongs to what is called supervised learning: each example (in this case, a firm) is a pair of input data (features such as emission constraints, country dummy variables, sectoral dummy variables, etc.) and a desired label (positive or negative). We must first separate the dataset into three parts: a training set, a validation set, and a held-out set for testing. We want to increase the goodness of fit for the model on the training set. But a higher goodness of fit for the training set does not necessarily lead to a better predictive power for the validation and testing sets. As a result, the validation set is needed to avoid overfitting. The general goal is a model that can have excellent predictive power on both the training and the validation set. The held-out set for testing is to calculate the error rate after we have chosen a model based on the training and the validation set. After we have trained the model, it can be applied to the case of a new firm entering the EU ETS. Based on the "trained" model, we can input a range of allocation factors with other features and predict the associated label of any firm with a given allocation factor.[5] The classification model has the ability to assist policymakers in determining ideal allowances allocated to firms so that the EU ETS can achieve emission reductions while firms maintain their relative economic competitiveness and performance.

VII. Conclusions, Limitations, and Future Research Directions

Building on Anger and Oberndorfer (2008), this paper documents the relative allocation of allowances in the EU ETS, and empirically assesses whether the relative abundance of allowances has an impact on firms' performances and employment levels in 2012, the last year of the second trading period. I verify that in 2005 the EU ETS overall was in a net long position, which was

[5] I compare the performance score of multiple machine learning algorithms, including support vector machines (SVM), boosting, decision trees, random forests, and neural networks. See https://github.com/ricardowang/carbon_emissions.

especially evident in Lithuania. On the other hand, countries such as the United Kingdom and Ireland have an allocation factor of less than one in this year. This indicates that the UK and Ireland received less freely allocated allowances than their verified emissions. My calculations also provide an overview of the relationship between the allowance allocation and emissions for an extended period. I find that most countries have a decreasing trend in allocation factor during the period 2005–2008 and have an increasing trend in allocation factor during the period 2008–2012 due to the reduction of emissions, which is potentially an outcome of a reduction in economic activities as a result of the financial crisis. I also note that in 2013, all eight countries studied exhibit a steep drop in allocation factor. After 2013, the allocation factors of those countries remain at a relatively low level (less than 1 for almost all countries in every year). The steep drop and the subsequent low levels of allocation factors are a result of auctioning becoming the default mechanism for allowance allocation.

The central question examined in this paper is whether emission constraints, as measured by the allocation factor, have an impact on the competitiveness and employment of EU firms. Competitiveness is measured by the change in firms' operating revenues between 2012 and 2011. Employment is calculated by the change in a firm’s number of employees between 2012 and 2011. The regression analysis suggests that emission constraints have a significant impact on German firms’ competitiveness in 2012. The impact is positive: when controlling for other factors, a German firm with a higher level of surplus allowances, tends to have a larger gain in operating revenues in 2012. On the other hand, I do not find evidence that emission constraints have any significant impact on German firms’ employment levels in 2012.

Using economic and emissions data of a wider sample of countries for an extended period, I also perform a comparative analysis to examine whether emission constraints have a similar impact on firms in seven selected EU countries. Although the OLS results do not suggest any significant effects of emission constraints on the change in firm-level revenues or employment in 2012, the 2SLS finds that such effects do exist, i.e., firms in those countries tend to be more competitive and have an increase in employment in 2012 when facing less strict emission constraints. Furthermore, the impact of emission constraints does not seem to differ for firms across different countries, as indicated by the OLS results. However, in theory, countries may be either positively, negatively, or even neutrally impacted by emission constraints.

There are several limitations in this paper that I would like to acknowledge. First, the regression results are based on a limited sample. Due to missing entries in both the emissions data and firm-level economic data, I had to exclude a sizable number of companies from my analysis. The missing data therefore result in a substantial loss of power in my analysis. I excluded firms with more than one missing value or with one missing value that cannot be imputed. This approach is sometimes justified because of the substantive reasonableness to loosely claim missing at random. However, this may not necessarily be the case. It is hard to verify whether the missing data, e.g. in emissions and economic data, is completely representative of the entire sample. If the assumption of missing at random is specious, it can corrupt the accuracy of the regression results.

Second, the economic indicators in my analysis only include firms' operating revenues and number of employees. As mentioned in earlier sections, the measurement of firms' competitiveness and employment using firms operating revenues and number of employees as proxies might not be completely accurate. For example, variables such as net profit margin, returns on investment (ROI), and market share can all be used to measure firm competitiveness. Furthermore, employment is also not just about the quantity, but also the quality of employees. It is possible that although the number of employees has remained constant or even increased in a year, the composition of the employees has changed such that low-income employees substitute for high-income employees or the average salary decreases. Moreover, the regression analyses did not take into account the change in operating revenues and employment when there were mergers and acquisitions. The financial data for companies in the Orbis database are based upon the filings that the companies submit to their local registry or publish in their annual report if they are public. In general, if the parent files any “consolidated” financials, then the next year’s financial data will include the new subsidiaries’ financials in them, not if they only file “unconsolidated” financials. Although it is likely that a negligible number of firms underwent mergers and acquisitions during this period of time, it is important to reconsider their effects because the validity of the regression results relies on the correctness of the data for changes in revenues and employment.

Nevertheless, this study provides insights into potential directions for future research that may circumvent the limitations mentioned above. First, instead of relying exclusively on the Orbis database, future researchers can collect economic data from other databases. If the problem of missing data persists, appropriate imputing methods other than single imputations could be utilized to counter the loss of power. Second, the economic analysis can be extended to firms in all countries in the EU ETS. It might also be of interest to researchers to incorporate more economic variables. As mentioned in section I, most empirical literature focusing on the EU ETS tests the Porter hypothesis, but without attempting to assess the impact of the EU ETS on innovations. Future research can therefore design appropriate methods to fill the void in this regard. Finally, future research may focus on emissions-intensive sectors to estimate upper-bound effects in particular. This can also be accomplished by selecting firms with the most binding emission constraints.

APPENDIX

A.1. The EU Community Transaction Log

According to the official website of the EU ETS[6], EU ETS created a centralized EU registry after 2009, known as the Union Registry, to record critical transactional data of 31 participating countries in the EU ETS. The EU Community Transaction Log (EUTL) checks, records, and authorized transactions between accounts in the Union Registry. Firms that are regulated by the EU ETS have to open an Operator Holding Account and register its annual emissions data in the EUTL. For the purpose of my regression analysis, I extracted information including firm name, the main address line, city name, allocated allowances from 2005 to present, verified emissions from 2005 to present, etc. The extracting process was smoothed by data scraping. Detailed Python code used for scraping was uploaded to the project GitHub repository for replication.

[6] https://ec.europa.eu/clima/policies/ets/registry_en

A.2. The Orbis Database by Bureau van Dijk

The Orbis database contains information on over 200 million companies worldwide. The Orbis database and the Amadeus database are both products of Bureau van Dijk, but the latter has a regional focus (mostly European companies). After obtaining emissions data from the EUTL, I utilized the batch search function in the Orbis database to automatically download firm-level economic data, including firm name, address, city name, the operating revenues of firms from 2008 to 2017 in Mio. Euro, number of employees of firms from 2008 to 2017, and the NACE Rev.2 Core Code. After obtaining the firm-level economic data, I manually compared the firm name, the city name, and the address line of each observation in the file containing emission data and the corresponding file downloaded from the Orbis database. For every match, I made sure that the firm names in two files are consistent. The consistency problem may arise because the EUTL and the Orbis database record firm names differently. For example, Gesellschaft mit beschränkter Haftung and GmbH are often used interchangeably, Aktiengesellschaft and AG are often used interchangeably, three letter-diacritic combinations Ä/ä, Ö/ö, and Ü/ü are often replaced with A/a, OE/oe, and UE/ue respectively in the Orbis database, ss often substitutes the ligature ß in the Orbis database, etc. I then proceeded to merge two files based on firm names. Because one firm could have multiple installations in the EUTL, I collapsed multiple installations from the same firm into one observation before merging.

TABLE A.3.1— SECTORAL DISTRIBUTION OF SAMPLE GERMAN FIRMS BASED ON NACE REV.2 CORE CODE

Sector	Frequency: no. sample firms (%)
Mining	8 (2.57)
Paper & Pulp	29 (9.32)
Chemicals	20 (6.43)
Metal	18 (5.79)
Other manufacturing	79 (25.40)
Electricity	94 (30.23)
Gas & Steam	30 (9.65)
Others	33 (10.61)
Total	311 (100)

TABLE A.3.2— SECTORAL DISTRIBUTION OF SAMPLE SELECTED FIRMS BASED ON NACE REV.2 CORE CODE

Sector	Frequency: no. sample firms (%)
Mining	14 (1.52)
Paper & Pulp	114 (12.36)
Chemicals	106 (11.50)
Metal	49 (5.31)
Other manufacturing	413 (44.79)
Electricity	99 (10.74)
Gas & Steam	59 (6.40)
Others	68 (7.38)
Total	922 (100)

A.3. NACE Rev.2 Core Code and Sectoral Classification

According to Eurostat[7], a major revision of NACE was launched, and the NACE Rev. 2 has been used to refer to economic activities as from January 1 2008 onwards. Statistical classification of economic activities using NACE Rev.2 can be found on Eurostat.[8] Based on its classification, I divided 311 German firms as well as 922 sample EU firms into eight sectors. Table A.3.1 and Table A.3.2 show the sectoral indicator, number of firms, and percentage of total sample

[7] http://ec.europa.eu/eurostat/web/nace-rev2

[8] http://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_NOM_DTL&StrNom=NACE_REV2

firms in each sector. For each sector, I created a sectoral dummy variable that was given a value 1 for a company in the sector and a value 0 for a company not in the sector.

For the sample of German firms, the sectoral dummy variables include dummy variables for "mining" (2.57% of the sample firms; NACE Rev. 2 Code between 0500 and 0999), "paper & pulp" (9.32% of the sample firms; NACE Rev. 2 Code between 1700 and 1899), "chemicals" (6.43% of the sample firms; NACE Rev. 2 Code between 2000 and 2199), "metal" (5.79% of the sample firms; NACE Rev. 2 Code between 2400 and 2599), "other manufacturing" (25.40% of the sample firms; Any other NACE Rev. 2 Code between 1000 and 3399 except for the manufacturing of paper & pulp, chemicals, and metal), "electricity" (30.23% of the sample firms; NACE Rev. 2 Code between 3500 and 3519), "gas & steam" (9.65% of the sample firms; NACE Rev. 2 Code between 3520 and 3999), and "others" (10.61% of the sample firms; any NACE Rev. 2 Code except those above).

Similarly, the percentage of total sample firms in each sector for the sample of firms in selected EU countries can be found in Table A.3.2.

A.4. Descriptive Statistics

TABLE A.4.1—DESCRIPTIVE STATISTICS OF SAMPLE GERMAN FIRMS

				Quantiles				
Variable	No. obs.	Mean	Std. dev.	Min	25 %ile	Median	75 %ile	Max
Allocation factor 2012	311	1.49	0.72	0.30	1.08	1.26	1.64	4.97
Allowances allocated 2012	311	5.6e+05	2.4e+06	2060.00	19148.00	57158.00	2.7e+05	3.8e+07
Verified emissions 2012	311	5.8e+05	3.8e+06	753.00	13517.00	41953.00	1.7e+05	6.4e+07
Revenues 2012−2011	311	188.60	2119.76	−6934.00	−7.00	3.00	17.00	33928.00
Revenues 2011−2010	311	329.23	2253.24	−1465.00	−3.00	4.00	33.00	33949.00
Revenues 2010−2009	311	358.40	2030.34	−1082.00	−2.00	5.00	41.00	21919.00
Revenues 2009−2008	311	−270.56	1534.43	−1.7e+04	−43.00	−4.00	3.00	892.00
Revenues 2012	311	2781.25	14990.10	7.00	72.00	193.00	594.00	2.0e+05
Revenues 2011	311	2592.65	13291.94	7.00	68.00	208.00	596.00	1.7e+05
Revenues 2010	311	2263.43	11219.74	7.00	66.00	188.00	519.00	1.3e+05
Revenues 2009	311	1905.03	9221.34	8.00	61.00	177.00	511.00	1.1e+05
Revenues 2008	311	2175.59	10529.07	7.00	63.00	184.00	563.00	1.2e+05
No. employees 2012−2011	311	105.46	3243.85	−3.0e+04	−7.00	1.00	12.00	47807.00
No. employees 2011−2010	311	459.02	5955.91	−911.00	−6.00	2.00	15.00	1.0e+05
No. employees 2010−2009	311	186.52	1976.83	−1408.00	−11.00	0.00	9.00	30881.00
No. employees 2009−2008	311	−135.03	1388.60	−1.7e+04	−14.00	−1.00	8.00	7855.00
No. employees 2012	311	6105.45	39334.77	2.00	122.00	412.00	1072.00	5.5e+05
No. employees 2011	311	5999.99	37799.93	2.00	123.00	412.00	1109.00	5.0e+05
No. employees 2010	311	5540.98	32782.65	2.00	120.00	407.00	1106.00	4.0e+05
No. employees 2009	311	5354.46	31086.50	2.00	119.00	411.00	1082.00	3.7e+05
No. employees 2008	311	5489.49	31921.39	2.00	110.00	406.00	1079.00	3.7e+05

Note: Revenue data are given in Mio. Euro.

TABLE A.4.2—DESCRIPTIVE STATISTICS OF SAMPLE FIRMS IN SELECTED COUNTRIES

				Quantiles				
Variable	No. obs.	Mean	Std. dev.	Min	25 %ile	Median	75 %ile	Max
Allocation factor 2012	922	1.70	1.02	0.27	1.06	1.36	1.93	5.95
Allowances allocated 2012	922	4.0e+05	1.7e+06	13.00	14219.00	35220.50	1.3e+05	3.0e+07
Verified emissions 2012	922	3.6e+05	1.9e+06	5.00	8644.00	24314.00	1.0e+05	3.8e+07
Revenues 2012−2011	922	19.04	890.47	−8762.00	−5.00	0.00	6.00	22753.00
Revenues 2011−2010	922	64.11	606.07	−1.0e+04	0.00	3.00	22.00	9137.00
Revenues 2010−2009	922	102.41	673.16	−1019.00	0.00	3.00	24.00	15134.00
Revenues 2009−2008	922	−113.44	1467.91	−2.5e+04	−32.00	−5.00	0.00	30762.00
Revenues 2012	922	973.75	5903.58	0.00	18.00	78.50	258.00	1.3e+05
Revenues 2011	922	954.72	5536.03	0.00	17.00	79.00	263.00	1.1e+05
Revenues 2010	922	890.61	5328.28	0.00	16.00	72.50	245.00	99479.00
Revenues 2009	922	788.20	4828.07	0.00	15.00	64.00	220.00	84345.00
Revenues 2008	922	901.64	5218.08	0.00	16.00	73.00	264.00	1.1e+05
No. employees 2012−2011	922	−34.02	558.56	−1.5e+04	−6.00	0.00	2.00	4319.00
No. employees 2011−2010	922	6.89	548.76	−4821.00	−6.00	0.00	5.00	10000.00
No. employees 2010−2009	922	1.22	437.40	−4021.00	−10.00	0.00	2.00	8535.00
No. employees 2009−2008	922	−2.19	1522.67	−8531.00	−14.00	−1.00	1.00	43515.00
No. employees 2012	922	1963.07	15645.46	1.00	53.00	188.00	681.00	3.6e+05
No. employees 2011	922	1997.09	16052.36	1.00	55.00	190.00	689.00	3.7e+05
No. employees 2010	922	1990.21	15905.38	1.00	53.00	189.00	684.00	3.6e+05
No. employees 2009	922	1988.98	15748.25	1.00	53.00	191.50	695.00	3.5e+05
No. employees 2008	922	1991.18	15029.97	1.00	55.00	196.50	732.00	3.5e+05

Note: Revenue data are given in Mio. Euro.

A.5. Correlation Tables

TABLE A.5.1— CORRELATION TABLE FOR SAMPLE GERMAN FIRMS

	AF_12	OR 12−11	OR 11−10	OR 10−09	OR 09−08	OR10	NE 12−11	NE 11−10	NE 10−09	NE 09−08	NE10	Mining	P & P	Chemi-cal	Metal	Manu_other	Electric-ity	G & S
AF_12	1																	
OR12−11	−0.0184	1																
OR11−10	−0.0369	0.895^{***}	1															
OR10−09	−0.0577	0.687^{***}	0.879^{***}	1														
OR09−08	0.0620	-0.41^{***}	-0.66^{***}	-0.88^{***}	1													
OR10	−0.0636	0.735^{***}	0.904^{***}	0.987^{***}	-0.84^{***}	1												
NE12−11	−0.0336	0.902^{***}	0.723^{***}	0.444^{***}	-0.180^{**}	0.498^{***}	1											
NE11−10	−0.0588	0.883^{***}	0.889^{***}	0.716^{***}	-0.44^{***}	0.758^{***}	0.738^{***}	1										
NE10−09	−0.0688	0.748^{***}	0.842^{***}	0.738^{***}	-0.49^{***}	0.764^{***}	0.553^{***}	0.943^{***}	1									
NE09−08	0.0168	-0.178^{**}	-0.19^{***}	-0.44^{***}	0.485^{***}	-0.45^{***}	0.134^{*}	-0.20^{***}	-0.23^{***}	1								
NE10	−0.0614	0.663^{***}	0.831^{***}	0.912^{***}	-0.75^{***}	0.932^{***}	0.373^{***}	0.816^{***}	0.866^{***}	-0.57^{***}	1							
Mining	−0.0880	−0.0110	0.0102	0.00204	0.00204	−0.0098	−0.0046	−0.0079	−0.0145	0.0198	−0.0213	1						
P & P	0.0487	−0.0307	−0.0468	−0.0525	0.0531	−0.0587	−0.0120	−0.0253	−0.0307	0.0357	−0.0493	−0.0521	1					
Chemical	0.0191	−0.0223	0.0359	0.0751	−0.0708	0.0722	−0.0085	−0.0133	0.0500	0.0551	0.0606	−0.0426	−0.0841	1				
Metal	−0.0431	−0.0289	−0.0202	−0.0188	−0.0081	−0.0296	−0.0094	−0.0184	−0.0278	0.00452	−0.0266	−0.0403	−0.0795	−0.0650	1			
O_manu	-0.136^{*}	0.133^{*}	0.159^{**}	0.166^{**}	-0.179^{**}	0.188^{***}	0.0594	0.129^{*}	0.118^{*}	-0.182^{**}	0.192^{***}	−0.0948	-0.19^{***}	-0.153^{**}	-0.145^{*}	1		
Electricity	0.105	−0.0385	−0.0665	−0.0980	0.109	−0.0902	−0.0246	−0.0525	−0.0626	0.0715	−0.0967	−0.107	-0.21^{***}	-0.173^{**}	-0.163^{**}	-0.38^{***}	1	
G & S	−0.0423	−0.0302	−0.0606	−0.0365	0.0685	−0.0554	−0.0100	−0.0255	−0.0180	0.0286	−0.0525	−0.0531	−0.105	−0.0857	−0.0810	-0.19^{***}	-0.22^{***}	1

Note: 1) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
2) AF: allocation factor; OR: operating revenue; OR X−Y: operating revenue of year X minus operating revenue of year Y; NE: number of employees; NE X−Y: number of employees of year X minus number of employees of year Y; P & P: pulp & paper; Manu_other: other manufacturing; G & S: gas & steam.
3) 311 Observations. Pearson's correlation coefficients for the respective pairs are given in the table.

TABLE A.5.2— CORRELATION TABLE FOR SAMPLE FIRMS IN SELECTED EU COUNTRIES

	AF_12	OR 12−11	OR 11−10	OR 10−09	OR 09−08	OR10	NE 12−11	NE 11−10	NE 10−09	NE 09−08	NE10	Mining	P & P	Chemi-cal	Metal	Manu_ot her	Electric-ity	G & S
AF_12	1																	
OR12−11	−0.0343	1																
OR11−10	−0.0508	0.670***	1															
OR10−09	−0.0427	0.610***	0.734***	1														
OR09−08	0.0371	−0.68***	−0.93***	−0.69***	1													
OR10	−0.0333	0.283***	0.293***	0.771***	−0.20***	1												
NE12−11	−0.0165	0.281***	0.418***	−0.0781*	−0.54***	−0.60***	1											
NE11−10	0.0144	0.0126	0.330***	0.121***	−0.28***	0.0247	0.0887**	1										
NE10−09	−0.0018	0.128***	−0.071*	0.0166	0.159***	0.162***	−0.26***	0.274***	1									
NE09−08	0.0175	−0.27***	−0.56***	−0.0785*	0.700***	0.414***	−0.77***	−0.35***	0.171***	1								
NE10	0.00465	−0.0710*	−0.0690*	0.269***	0.219***	0.728***	−0.75***	0.252***	0.371***	0.509***	1							
Mining	0.00212	0.223***	0.124***	0.185***	−0.14***	0.150***	−0.0131	−0.0275	0.0240	−0.0081	0.0364	1						
P & P	−0.0782*	−0.0110	−0.0263	−0.0362	0.0148	−0.0412	0.0104	−0.0034	−0.0316	−0.0156	−0.0286	−0.0466	1					
Chemical	−0.0818*	0.00873	−0.0127	0.0164	−0.0021	−0.0147	0.0347	0.0398	−0.0348	−0.0088	−0.0217	−0.0448	−0.14***	1				
Metal	0.0138	−0.0160	0.0114	0.0165	−0.0305	−0.0132	0.00710	−0.0007	0.0297	0.00150	−0.0090	−0.0294	−0.089**	−0.085**	1			
O_manu	0.158***	−0.0296	0.0227	−0.0172	−0.0091	−0.0222	0.0279	−0.0257	−0.0259	−0.0268	−0.0368	−0.11***	−0.34***	−0.33***	−0.21***	1		
Electricity	−0.15***	0.00553	0.00789	−0.0030	0.00142	−0.0058	0.0145	−0.0163	0.00171	0.00413	−0.0261	−0.0431	−0.13***	−0.13***	−0.0822*	−0.31***	1	
G & S	0.0120	−0.0276	−0.0606	−0.0372	0.0205	−0.0393	0.0163	−0.0048	−0.0028	0.00144	−0.0272	−0.0325	−0.098**	−0.094**	−0.0619	−0.24***	−0.091**	1

Note: 1) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2) AF: allocation factor; OR: operating revenue; OR X−Y: operating revenue of year X minus operating revenue of year Y; NE: number of employees; NE X−Y: number of employees of year X minus number of employees of year Y; P & P: pulp & paper; Manu_other: other manufacturing; G & S: gas & steam.

3) 922 Observations. Pearson's correlation coefficients for the respective pairs are given in the table.

A.6. Detailed Regression Results

TABLE A.6.1—REGRESSION RESULTS ON CHANGE IN REVENUES BETWEEN 2012 AND 2011 FOR GERMAN FIRMS

Dep. var.	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)
Allocation factor 2012	103.40** (45.43)	109.18 (68.34)	34211.78*** (2535.79)	34002.63*** (2342.50)
Revenues 2011−2010 (Mio. Euro)	0.18 (0.35)	–	−1.29*** (0.16)	−1.27*** (0.15)
Revenues 2010−2009 (Mio. Euro)	−0.50 (0.36)	–	−0.25*** (0.09)	−0.25** (0.13)
Revenues 2009−2008 (Mio. Euro)	0.16 (0.14)	–	0.00 (0.11)	–
Revenues 2010 (Mio. Euro)	0.25** (0.10)	0.17*** (0.05)	−1.02*** (0.08)	−1.01*** (0.08)
No. employees 2010	−0.06*** (0.02)	−0.07*** (0.02)	0.22*** (0.02)	0.21*** (0.02)
No. employees 2011−2010	0.29*** (0.09)	0.37*** (0.05)	0.41*** (0.03)	0.41*** (0.02)
Mining	−112.32 (156.07)	–	−25.84 (28.82)	–
Paper & Pulp	3.77 (41.18)	–	4.80 (16.21)	–
Chemicals	−148.07 (281.70)	–	119.40 (83.17)	–
Metal	−7.78 (62.60)	–	36.79 (23.64)	–
Other manufactur-ing	71.63 (68.72)	–	−17.91 (24.29)	–
Electricity	−38.14 (60.07)	–	−45.51** (22.32)	−51.26*** (19.12)
Gas & Steam	36.28 (58.11)	–	−6.71 (26.56)	–
Constant term	−189.38** (79.47)	−165.12* (99.04)	−5.99 (15.96)	−0.27 (12.06)
No. obs.	311	311	311	311
R^2	0.9158	0.9024	0.9904	0.9902
F-test (p-val.)	0.0000	0.0000	0.0000	0.0000
F-test on excl. exp. var. (p-val.)	–	0.1311	–	0.1276

Note: 1) Std. errors are in brackets. Heteroscedasticity-consistent standard errors are used. 2) * p < 0.10, ** p < 0.05, *** p < 0.01.

TABLE A.6.2—REGRESSION RESULTS ON CHANGE IN EMPLOYMENT BETWEEN 2012 AND 2011 FOR GERMAN FIRMS

Dep. var.	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS
	No. employees 2012−2011	No. employees 2012−2011	No. employees 2012−2011	No. employees 2012−2011
Allocation factor 2012	31.08 (51.15)	33.02 (57.18)	15769.79 (15908.02)	3807.41 (3171.27)
No. employees 2011−2010	0.91*** (0.15)	0.72*** (0.09)	0.94*** (0.15)	0.30** (0.15)
No. employees 2010−2009	−0.27 (0.59)	–	−0.34 (0.51)	–
No. employees 2009−2008	−0.41 (0.30)	–	−0.13 (0.43)	–
No. employees 2010	−0.21*** (0.07)	−0.18*** (0.05)	−0.06 (0.16)	–
Revenues 2010 (Mio. Euro)	0.39*** (0.13)	0.34*** (0.10)	−0.17 (0.56)	–
Revenues 2011−2010 (Mio. Euro)	−0.20 (0.29)	–	−0.98 (0.93)	–
Mining	−396.78 (378.59)	–	−295.31 (315.77)	–
Paper & Pulp	2.53 (76.32)	–	2.28 (76.22)	–
Chemicals	805.23* (455.52)	435.36 (477.27)	756.49* (398.29)	−236.16 (373.06)
Metal	−16.14 (88.26)	–	49.06 (116.12)	–
Other manufacturing	8.32 (132.11)	–	−2.27 (127.94)	–
Electricity	−130.45 (92.03)	–	−139.12 (94.78)	–
Gas & Steam	−89.50 (129.98)	–	−94.21 (128.89)	–
Constant term	−28.77 (122.12)	−83.51 (103.07)	12.42 (78.95)	−201.20 (182.89)
No. obs.	311	311	311	311
R^2	0.9081	0.8841	0.9108	0.5980
F-test (p-val.)	0.0000	0.0000	0.0000	0.0000
F-test on excl. exp. var. (p-val.)	–	0.2689	–	0.0086

Note: 1) Std. errors are in brackets. Heteroscedasticity-consistent standard errors are used. 2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.6.3—REGRESSION RESULTS ON CHANGE IN REVENUES BETWEEN 2012 AND 2011 FOR SELECTED FIRMS

Dep. var.	(9) OLS	(10) OLS	(11) 2SLS	(12) 2SLS
	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)	Revenues 2012−2011 (Mio. Euro)
Allocation factor 2012	2.76 (7.56)	−8.00 (9.23)	35723.31*** (117.72)	35704.36*** (356.58)
Revenues 2011−2010 (Mio. Euro)	0.23 (0.64)	–	−1.00*** (0.01)	−1.00*** (0.02)
Revenues 2010−2009 (Mio. Euro)	0.61** (0.27)	0.78* (0.45)	−0.01 (0.01)	–
Revenues 2009−2008 (Mio. Euro)	−0.25 (0.25)	–	0.05*** (0.00)	0.05*** (0.01)
Revenues 2010 (Mio. Euro)	−0.07 (0.08)	–	−0.97*** (0.00)	−0.97*** (0.01)
No. employees 2010	0.01 (0.02)	–	−0.25*** (0.00)	−0.25*** (0.00)
No. employees 2011−2010	−0.43 (0.33)	–	−0.24*** (0.00)	−0.24*** (0.03)
Mining	709.48* (418.14)	825.50 (513.68)	10.34 (17.82)	–
Paper & Pulp	−12.90 (47.46)	–	0.14 (9.14)	–
Chemicals	3.65 (62.79)	–	−11.72 (9.30)	–
Metal	−182.39*** (66.32)	−88.14 (55.61)	7.76 (11.18)	–
Other manufacturing	−63.15 (59.12)	–	−4.28 (7.84)	–
Electricity	−10.45 (49.92)	–	−6.30 (9.40)	–
Gas & Steam	25.34 (51.33)	–	−3.52 (10.59)	–
Constant term	−30.09 (58.78)	−54.99 (40.82)	1.40 (7.31)	−2.28 (1.56)
No. obs.	922	922	922	922
R^2	0.5577	0.3851	0.9957	0.9957
F-test (*p*-val.)	0.0000	0.0000	0.0000	0.0000
F-test on excl. exp. var. (*p*-val.)	–	0.0000	–	0.5867

Note: 1) Std. errors are in brackets. Heteroscedasticity-consistent standard errors are used. 2) * p < 0.10, ** p < 0.05, *** p < 0.01.

TABLE A.6.4—REGRESSION RESULTS ON CHANGE IN EMPLOYMENT BETWEEN 2012 AND 2011 FOR SELECTED FIRMS

Dep. var.	(13) OLS	(14) OLS	(15) 2SLS	(16) 2SLS
	No. employees 2012−2011	No. employees 2012−2011	No. employees 2012−2011	No. employees 2012−2011
Allocation factor 2012	−0.52 (5.94)	−2.51 (5.86)	3899.77*** (1264.69)	4789.31*** (1192.70)
No. employees 2011−2010	−0.05 (0.13)	–	−0.03 (0.14)	–
No. employees 2010−2009	−0.01 (0.09)	–	−0.07 (0.09)	–
No. employees 2009−2008	−0.09** (0.04)	−0.09** (0.04)	−0.09** (0.04)	−0.11*** (0.04)
No. employees 2010	−0.01* (0.00)	−0.01*** (0.00)	−0.04*** (0.01)	−0.04*** (0.01)
Revenues 2010 (Mio. Euro)	−0.04*** (0.01)	−0.04*** (0.01)	−0.15*** (0.04)	−0.17*** (0.04)
Revenues 2011−2010 (Mio. Euro)	0.37*** (0.09)	0.35*** (0.08)	0.13 (0.10)	–
Mining	54.08 (61.66)	–	−29.15 (46.85)	–
Paper & Pulp	10.11 (42.49)	–	5.60 (40.96)	–
Chemicals	65.03 (48.83)	–	53.74 (46.73)	–
Metal	11.22 (42.59)	–	24.37 (40.85)	–
Other manufacturing	17.48 (41.07)	–	22.11 (39.64)	–
Electricity	25.75 (39.93)	–	27.84 (37.29)	–
Gas & Steam	30.29 (37.63)	–	23.83 (36.10)	–
Constant term	−21.19 (39.93)	6.13 (14.23)	−16.50 (35.71)	8.98 (7.60)
No. obs.	922	922	922	922
R^2	0.8116	0.8092	0.8243	0.8166
F-test (*p*-val.)	0.0000	0.0000	0.0000	0.0000
F-test on excl. exp. var. (*p*-val.)	–	0.7076	–	0.3437

Note: 1) Std. errors are in brackets. Heteroscedasticity-consistent standard errors are used. 2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

REFERENCES

Abrell, Jan, Anta Ndoye Faye, and Georg Zachmann. 2011 Assessing the impact of the EU ETS using firm level data. No. 2011/08. Bruegel working paper.

Ambec, Stefan, et al. 2013. "The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness?." Review of environmental economics and policy 7.1: 2-22.

Anger, Niels, and Ulrich Oberndorfer. 2008. "Firm performance and employment in the EU emissions trading scheme: An empirical assessment for Germany." Energy policy 36.1: 12-22.

Athey, Susan. "The Impact of Machine Learning on Economics." Economics of Artificial Intelligence. University of Chicago Press, 2017.

Balassa, Bela A. 1962. Recent developments in the competitiveness of American industry and prospects for the future. Vol. 12. Yale University Press, 1962.

Böhringer, Christoph, et al. 2005. "Assessing emission regulation in Europe: an interactive simulation approach." The Energy Journal: 1-21.

Brown, Lucas Merrill, Alex Hanafi, and Annie Petsonk. 2012. "The EU Emissions Trading System: Results and Lessons Learned." Environmental Defense Fund.

Directive, Linking. 2004. "Directive 2004/101/EC of the European Parliament and of the Council of 27 October 2004 amending Directive 2003/87/EC establishing a scheme for greenhouse gas emission allowance trading within the Community, in respect of the Kyoto Protocol's project mechanisms." Official Journal of the European Union, L 338.18 (2004): 13-11.

Demailly, Damien, and Philippe Quirion. 2006. "CO2 abatement, competitiveness and leakage in the European cement industry under the EU ETS: grandfathering versus output-based allocation." Climate Policy 6.1: 93-113.

Demailly, Damien, and Philippe Quirion. 2008. "European Emission Trading Scheme and competitiveness: A case study on the iron and steel industry." Energy Economics 30.4: 2009-2027.

EC Climate Action. 2017. "The EU emissions trading system (EU ETS)." Brussels: European Commission. https://ec.europa.eu/clima/policies/ets_en.

Ellerman, A. Denny, and Barbara K. Buchner. 2007. "The European Union emissions trading scheme: origins, allocation, and early results." Review of environmental economics and policy 1.1: 66-87.

Ellerman, A. Denny, Frank J. Convery, and Christian De Perthuis. 2010. Pricing carbon: the European Union emissions trading scheme. Cambridge University Press.

European Commission. 2009. "Report from the commission to the European Parliament and the Council Progress Towards achieving the Kyoto objectives." Commission staff working document. Accompanying the (required under article 5 of decision 280/2004/EC of the European Parliament and of the Council concerning a mechanism for monitoring community greenhouse gas emissions and for implementing the Kyoto Protocol) Bruxelles, 12, p.2009.

European Commission. 2017. "EU ETS handbook."

European Environmental Agency. 2017. "EU Emissions Trading System data viewer User manual and background note." https://www.eea.europa.eu/data-and-maps/dasboards/emissions-trading-viewer-1.

European Union. 2017. "EU Community Transaction Log." http://ec.europa.eu/environment/ets/.

Gabel, H. L., et al. 1998. "The International Yearbook of Environmental and Resource Economics 1998/1999.": 89.

Kennedy, Peter. 1994. "Innovation stochastique et coût de la réglementation environnementale." L'Actualité économique 70.2: 199-209.

Kettner, Claudia, et al. 2008. "Stringency and distribution in the EU Emissions Trading Scheme: first evidence." Climate Policy 8.1: 41-61.

Kleinberg, Jon, et al. 2015. "Prediction policy problems." American Economic Review 105.5 (2015): 491-95.

Neuhoff, Karsten, Kim Keats Martinez, and Misato Sato. 2006. "Allocation, incentives and distortions: the impact of EU ETS emissions allowance allocations to the electricity sector." Climate Policy 6.1: 73-91.

Porter, Michael E. 1991. "Towards a dynamic theory of strategy." Strategic management journal 12.S2 (1991): 95-117.

Porter, Michael E., and Claas Van der Linde. 1995. "Toward a new conception of the environment-competitiveness relationship." The journal of economic perspectives 9.4: 97-118.

Zhang, Yue-Jun, and Yi-Ming Wei. 2010. "An overview of current research on EU ETS: Evidence from its operating mechanism and economic effect." Applied Energy 87.6: 1804-1814.