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Assessing the Effects of Climate Policy on Companies' Greenhouse Gas Emissions

Abstract

We study the effect of climate policy on companies' greenhouse gas emissions using emissions data for the headquarters and subsidiaries of the world's biggest manufacturing, energy, and utility companies. Our results suggest that financial incentives and legal requirements to audit energy use reduce companies' emissions, whereas support schemes aimed at promoting the combined generation of heat and power increased emissions of non-utility companies and feed-in tariffs aimed at increasing the use of renewable energy sources for electricity generation increase emissions of utility companies. We also find loans and subsidies for energy efficiency improvements to increase emissions in the short term. In addition, our results provide a solid foundation for researchers seeking consistent and comparable estimates on the mitigation effects of typical climate policy instruments in a cross-country setting.

JEL-Codes: H230, H320, Q420, Q480, Q540, Q580.

Keywords: climate policy evaluation, greenhouse gas emissions, cross-country micro panel data, companies, firms.

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1 Introduction

Growing concern over global warming has resulted in an increasing number of national policies designed to slow or halt climate change over the past two decades. Yet in the light of the fact that the climate is a global public good, there are concerns that these unilateral efforts are not sufficiently ambitious to effectively limiting greenhouse gas (GHG) emissions. Aside from the potential catastrophic consequences of climate change in the long run, ineffective policies can have a detrimental effect in the more immediate future because every policy implementation requires effort and resources that could have been put to better use. For this reason, it is important to assess the effectiveness of implemented climate policies so as to learn from past experiences and improve instruments found ineffective at reducing emissions.

Our study analyzes the effect of climate policy at the microeconomic level by examining companies' emissions. We assess several policy types simultaneously to obtain a direct comparison of the measures. Employing a cross-country panel approach enables us to identify effective climate policies. Consequently, our research fills an important gap in the process of formulating policy recommendations for the choice and sensible combination of climate policy instruments.

Our first contribution is the novel combination of analyzing company-level emissions and multiple climate policy instruments in a cross-country panel setting. Previous research has addressed only two of these dimensions, typically focusing on either a single instrument or a single country. As a result, they lack cross-instrument or cross-country consistency and comparability of the estimates, which is essential for evaluating multi-instrument combinations in multi-country settings. This type of setting is of particular interest for specific target groups such as integrated assessment modelers or transdisciplinary policy projects employing multi-agent based firm modelling, whose requirements motivated our research. Thus, the second contribution of our work is to provide a foundation for further research on paths for national climate policies in a global context.

We use company-level emissions data collected within surveys conducted by the Carbon Disclosure Project (CDP) and policy measures collected in the Policies and Measures Database of the International Energy Agency. The policies analyzed consist of financial incentives to increase the use of renewable energy sources in electricity generation, the use of combined heat and power generation technologies (CHP), and energy efficiency improvement measures. Our analysis focuses on the largest global manufacturing, energy, and utility companies and their operations in 39 OECD and BRICS countries. The final sample covers emissions by about 4,700 subsidiary-year pairs for the period 2007–2012. Total emissions in the sample comprised 23% of the total emissions of OECD and BRICS countries in 2007.[1]

The assessment is based on econometric regressions, where companies' emissions are explained by a set of variables indicating the number of a certain policy measure introduced in the respective country. Moreover, in order to separate business-as-usual emissions from the policy effect, companies' economic activity is considered by including their revenues as a control variable. Other characteristics, including company size, are also considered as determinants of emissions. By first differentiating the equations, we also control for time invariant observed characteristics (e.g. industry sector, and home country) as well as time invariant unobserved heterogeneity. However, the voluntary nature of emissions disclosures to CDP raises concerns about the representativeness of the data. If companies self-select into disclosure and non-disclosure based on the level of their emissions, the sample will be biased, as will the results. We therefore test and correct for sample selection in various ways, including a two-step procedure largely following Semykina and Wooldridge (2010). The results suggest that the issue of self-selection is not very problematic in our sample.

The rest of this paper is organized as follows. Section 2 reviews the literature on the effectiveness of general environmental regulation and specific climate policy measures at the industry or company level. Emissions, policies, and other company and country data used for the analysis, as well as their sources and descriptive statics, are described in Section 3. Section 4 introduces the model for identifying the effect of climate policy on companies' emissions, and includes a discussion of endogeneity-related econometric issues and how they are addressed in this study. Results of the regressions analysis are presented in Section 5. Section 6 contains concluding remarks and suggests several possible extensions of the analysis.

2 Related Literature

To the best of our knowledge, no study has yet compared the effectiveness of different climate policy measures using company-level data from several countries. The literature related to our study tends to investigate just one of the aspects, whereas our approach examines its international scope, company-level emissions, and how these are linked to

[1]Own calculations based on WRI (2016), CDP waves 2008–2013, and UNFCCC (2016)

different types of climate policy.

In the past, scholars have engaged in ex-post analyses of specific climate policies (e.g. Haug et al.'s 2010 analysis of studies evaluating different policies; Abrell et al., 2011; Martin et al., 2014). The effects of the Climate Change Levy (CCL) and Climate Change Agreements (CCA) in the UK, for example, have been scrutinized in studies by Ekins and Etheridge (2006) and, more recently, by Martin et al. (2014). Using panel data in relation to the economic characteristics of plants and detailed information on their energy use, Martin et al. (2014) found the CCL to have reduced energy consumption and energy intensity of manufacturing plants in the UK for the period 2001–2004.

Another strand of the related literature investigates the effects of environmental regulation (as a conglomerate of single measures) on pollutant emissions. While Cole et al.'s (2005) analysis for the UK was performed at industry level, Féres and Reynaud (2012) studied the response of plants' emissions in the Brazilian state of São Paulo, with both of them finding a negative effect of regulation on emissions. Similarly, Cheng et al. (2017) and Zhao et al. (2015) assessed the effects of environmental regulation in China, distinguishing between command-and-control policies, market-based instruments, and (in the case of Zhao et al. (2015)) government subsidies. Using province-level data, the former study found that command-and-control regulation reduces emissions, while the latter did not identify any effect of this type of policy using plant-level data. It is a different picture for market-based instruments. Cheng et al. (2017) established a weak impact on emissions reductions, whereas Zhao et al.'s (2015) results revealed a positive effect on emissions reductions.

Although it is important to analyze single measures in order to improve policies, approaches that compare policy instruments in different nations provide information on whether the lessons learned can be applied in other countries and on which types of policy are generally more effective. Although Press (2007) highlighted the usefulness of such an international assessment for policy-makers, it remains rare in the literature. Harrington et al. (2004) took a step in this direction by providing 12 detailed case studies assessing, among other things, the effectiveness as well as the static and the dynamic efficiency of command-and-control versus economic incentive instruments to tackle environmental problems. Analysis of the case studies did not allow the authors to clearly identify the comparative effectiveness of these instruments. The experience of Harrington et al. (2004) illustrates the difficulties in comparing case studies. Although a case study analysis would appear to be a promising method of assessing policies in different countries, the results of the comparison may be far from unambiguous. In this paper, we employ an econometric approach capable of simultaneously assessing different policy types and control for relevant country and company characteristics, enabling us to single out the effect of each policy type on corporate emissions, while allowing comparability across policies.

3 Data

3.1 Description

3.1.1 Emissions and Participation Data

It is vitally important when investigating the effects of national climate policy on corporate emissions that companies provide a country break-down of their GHG emissions and not only the company's global total. Emission figures of companies at the country level for the period from 2003 to 2012 were obtained from the Carbon Disclosure Project (CDP).[2] Emissions, expressed as metric tons of CO2-equivalent (CO2e), consist of so-called scope-1 emissions, that is, direct emissions from sources that are controlled or owned by the company (Greenhouse Gas Protocol, 2014) and that are predominantly attributed to the combustion of fossil fuels. Scope-1 emissions do not include indirect emissions from the generation of purchased or acquired electricity, steam, heat or cooling consumed by the reporting company. The time period of the analysis was selected on the basis of the availability and quality of emissions data. Thus, since there is a great deal of information missing from the CDP waves of 2003 to 2007, only post-2008 waves were included in the analysis.

CDP's datasets also provide information on the industry sector, the company's country of incorporation, the company's International Security Identification Number (ISIN), and the CDP's account numbers. The latter were used to map CDP data across years, since responses to each CDP wave are in separate workbooks. Since account numbers were not available in the pre-2010 workbooks, company names were used to match companies to account numbers from later CDP waves.

[2]CDP is a not-for-profit organization that collects information provided voluntarily on corporate emissions, energy use, and attitudes toward climate change from the largest companies in the world as well as from the largest companies in selected regions or countries. Table A.1 in Annex I shows, as an example, the number of companies per country and region that were asked to report on climate change via CDP in 2013.

In the data preparation process, a number of assumptions were made in order to allow comparability of the data. First, as some companies' reporting periods do not always coincide with calendar years, it was necessary to decide on a rule for assigning their emissions to a specific year. It makes sense to assign emissions to the year that coincides closest with the actual emissions period. For instance, emissions that were reported for the period between August 1 of year t and July 31 of year t+1 were assigned to calendar year t+1.

CDP questionnaires allow the reporting of emissions for more than one year, which has two consequences for data availability and completeness. On the one hand, even if companies do not report emissions for one year, for example, due to a lack of information, they are still able to do so in a future CDP wave when information becomes available. On the other hand, it was noticed that companies reported emissions for the same year in different CDP waves, indicating that companies corrected their calculations as more information became available to them. After merging all CDP waves, this phenomenon resulted in "duplicate" observations with respect to the company, country, and year. Assuming that the more recently disclosed information was correct, any older observations were eliminated from the dataset.

There were three issues with CDP data that might have an impact on the analysis. First, the voluntary nature of CDP surveys raises the concern that companies might self-select into disclosure and non-disclosure, depending on the level of their emissions. The consequence for this study would be that the sample on which the analysis is based would not be representative, leading to a biased analysis. To control for self-selection, it is necessary that the same information set is available for respondents and non-respondents, with the exception of emissions. Thus, CDP, at our request, provided an additional dataset containing basic information (name, identification number, and sector) for all companies invited to participate in their surveys and the response status of each (i.e. either participated or not).

Second, the group of companies asked to report their emissions was not chosen randomly, but based on company size. This could be another source of selection bias, although in this case it would be generated by the sampling methodology and not by the companies' decisions. Fortunately, this potential problem was easily addressed by including the variable on which selection is based as an explanatory variable in the model, as will be shown in Section 4.1.

Third, the fact that emissions at the country level were obtained by asking companies to provide a country breakdown of their total global emissions indicates that disclosure decisions were not made in the individual countries where emissions were released but, for example, at the company's headquarters. This could affect the estimation, since in the process of correcting for self-selection, companies reporting emissions for several countries will be more heavily weighted than those reporting for only one country or those not disclosing at all. Thus, disclosing companies are more heavily weighted than non-disclosing ones, since the latter show up only once per year and the former several times, depending on the number of emitting units for which the companies are reporting. To eliminate this bias, we used data from Bureau van Dijk's Orbis dataset indicating the number of subsidiaries a company has in each country. Since the sample only consists of large and stock-listed companies, the typical ownership structure is complex and the spectrum of industries in which each of the ultimate parent companies is involved can be wide. A pre-analysis performed in collaboration with Bureau van Dijk resulted in the inclusion of only those subsidiaries for which the company in our initial dataset is a majority owner. Moreover, only subsidiaries whose two-digit NACE code coincided with the two-digit NACE code of the parent company were used for the analysis. Ownership relations as of the end of 2012 were assumed for the entire sample period.

3.1.2 Policy Measures

Data on policy measures implemented in different countries were from three databases of the International Energy Agency (IEA, 2015a): the Addressing Climate Change Database, the IEA/IRENA Global Renewable Energy Policies and Measures Database, and the Energy Efficiency Database. The policies were sorted by goal and similarity of the policy types. Table 1 provides a description of the types of policy in the different groups.

For every year and country, the final dataset contains the cumulative sum of policy measures of every type implemented in 39 OECD and BRICS countries since 1970. Although it is clear that specific design and implementation details are important determinants of a policy's effectiveness, this count variable approach, together with a dummy variable approach, is one of the few means available for achieving comparability across countries given the current scarcity of data. In the empirical analysis, various possibilities of aggregating, averaging, or employing decay functions for policies were tested; the results remain robust. Thus, we used the most basic approach as its interpretation is straight forward and consistent with the derivation of the estimation equation. During the data collection process, it was assumed that a type of policy was not implemented in a certain country if for that country none of the databases consulted listed a policy

Table 1: Policy Variables

Category	Target	Description
RES loans and subsidies	Increase the use of renewable energy sources for electricity generation	Loans at reduced or market interest rates, grants, subsidies, and tax relief
RES feed-in tariffs	Increase the use of renewable energy sources for electricity generation	Feed-in tariffs
CHP	Expansion of combined generation of heat and power	Grants, subsidies, and loans
Energy audits	Auditing the energy use of companies	Financial incentives or legal requirements
EE loans and subsidies	Increasing energy efficiency	Loans at reduced or market interest rates, grants, subsidies, and tax relief

Notes: Own compilation based on IEA Policies and Measures Databases.

measure that could be assigned to that category. Although this was a plausible assumption, there remains the possibility that a policy measure existed but was not listed in the databases, especially in countries for which data availability was poor.[3]

3.1.3 Additional Company and Country Data

Revenue data was available only for the companies that responded to the CDP survey (i.e. this information was not available for companies that chose not to participate). However, to control for self-selection, revenue data were needed for non-respondents and the Thomson Reuters' Thomson.One Banker dataset was used to this end. Since some companies' fiscal years differ from calendar years, revenue data were assigned to a calendar year using the same rule as for emissions data. Thus, revenues of companies whose fiscal year ended between August 1 of year t and July 31 of year t+1 were assigned to calendar year t. Market capitalization figures were retrieved as of December 31 of the year before each CDP wave.

Because companies, and also the Thomson.One Banker dataset, report financial data in the respective country's currency, these figures were converted to USD using the official

[3]Belgium, Brazil, Chile, Slovenia, and Iceland are countries for which data availability seems to be poor.

exchange rates calculated as an annual average and reported by the World Bank in its World Development Indicators dataset (World Bank, 2014). The resulting revenues and market capitalization figures are expressed in million USD. To obtain real figures and to be consistent in terms of basis year and currency, revenues and market capitalization data were deflated using the GDP deflator of the U.S. Bureau of Economic Analysis with 2009 as base year (US BEA, 2013).

Ideally, revenue information should correspond to the company's activity in each country, allowing the calculation of emission intensities for each emitting unit, that is, how many tons of CO2e per USD revenue they emit. However, only figures for the entire company were available and so a weighting procedure was implemented to proxy for specific country revenues. The weighting factor for each company-country pair was calculated by dividing the number of subsidiaries a company has in each country by that company's total number of subsidiaries. Subsequently, the company's worldwide revenue was multiplied by the corresponding company-country weighting factor. This assumption is strong and various alternative specifications that are possible with the available data were tested. Fortunately, results are robust also in comparison to a small subsample with full revenue information.

Other data needed to control and correct for potential self-selection were extracted from Thomson Reuters' ASSET4 Environmental, Social and Corporate Governance (ASSET4 ESG) Dataset. ASSET4 gathers publicly available information from corporate social responsibility reports, company websites, annual reports, and NGOs on over 250 performance indicators (Thomson Reuters, 2012). The extracted variable indicates whether a company monitors the protection of human rights in its facilities or those of its suppliers.

Data on industry electricity prices and prices for emissions certificates of the European Union Emissions Trading System (EU ETS), used in the sensitivity analysis, were obtained from IEA (2010 and 2015b) and the ICE ECX platform, respectively. Information on subsidiaries' participation in the EU Emissions Trading System (EU ETS) was obtained by matching the ISIN numbers and subsidiary countries with the dataset resulting from the Ownership Links and Enhanced EUTL Dataset Project (Jaraite et al., 2013). This dataset identifies the ultimate owners of the installations covered by the EU ETS.

3.1.4 Matching Process and Resulting Sample

Emissions, financial data, and ASSET4 indicators were merged using CDP account numbers and years. Subsequently, policy and other country-specific data were matched to company data by country and year. For expositional reasons, the combination of country of emissions and company will be referred to as a subsidiary below.

Since financial and ASSET4 data were not available for all observations, the initial sample of over 100,000 observations was reduced to a final balanced sample of about 34,000 observations. More details on the data are provided below.

3.2 Descriptive Statistics

Summary statistics are set out in Table 2. The *Subsidiary level* panel reveals that the average subsidiary in the sample had a yearly revenue of one billion USD and emitted around 1.3 Mt CO2e a year. Disclosing emissions is the dependent variable in the first-stage regression of the selection-correction procedure and takes the value 1 whenever country emissions were disclosed in two consecutive years. Its mean tells us that out of 34,045 observations, we have the CO2e emissions levels for 14% of the subsidiary-years in the final sample, corresponding to 4,788 observations. Moreover, there is significant variation across all policy variables.

The *Corporate level* panel of Table 2 shows descriptive statistics for the whole corporation. The revenues of the average company in our sample amounted to around 15 billion USD and its market capitalization value was 14.4 billion USD. The statistic for the human rights monitoring variable indicates that 21% of the corporations in the sample monitored human rights on their premises and, as we can observe after additional calculations, 32% of the total number of observations were subsidiaries to these companies. In addition, significant variation is observed for each variable in Table 2.

Since sample selection was assumed, it was interesting to see whether disclosing firms differed significantly from non-disclosing firms. This analysis took place at the corporation level because the decision to report emissions to CDP is most probably made at corporate headquarters. Sample statistics of company data were drawn for both groups, making sure only one observation per year and per corporation entered the calculation. These are presented in the *Corporate level* panel of Table 3. Disclosing firms were on average 1.5 times as large and generate 1.5 times the revenue of their counterparts. Thirty-

Table 2: Descriptive Statistics

	Mean	Std.Dev	Min	Max
Subsidiary level:				
Disclosing emissions	0.14	0.35	0	1
Metric tons CO2e	1,337,436.39	6,726,845.33	.7	156,300,000
Weighted revenues, million USD	1,118.39	4,483.90	.0036	179,271
Policy variables:				
RES loans and subsidies	15.45	11.07	0	41
RES feed-in tariffs	2.03	2.31	0	9
CHP	1.06	1.57	0	6
EE loans and subsidies	4.87	7.74	0	28
Energy Audits	0.25	0.57	0	2
Corporate level:				
Revenues, million USD	15,317.23	27,361.92	.021	266,998
Market capitalization, million USD	14,408.64	26,166.60	.0003	475,892
Human Rights Monitoring	0.21	0.41	0	1
Observations	34045			
Uncensored Observations	4788			

Notes: Summary statistics for the Corporate level panel were calculated considering one observation per company and year, corresponding to a total of 1,049 company-year pairs.

seven percent of the disclosing companies monitored human rights protection on their premises; only 15% of the non-disclosing companies did so. Additionally, two-group mean comparison tests were applied to the revenue, market capitalization, and human rights monitoring variables. With a p-value below 0.001, the results indicate that in all three cases the hypothesis that the averages for the disclosing and non-disclosing group are equal can be rejected. Thus, firms with higher revenues, those that are larger, and those that monitor human rights are more likely to report their emissions. Moreover, the mean comparison test applied to weighted revenues (see *Subsidiary level* panel of Table 3) indicates that subsidiaries for which emissions were disclosed by their parent company were larger in terms of revenue than subsidiaries for which no emissions data were available.

Figure 1 illustrates the disclosure behavior of companies registered in selected countries. Most of the subsidiary-years in the sample were attributable to companies registered in the USA, followed by German and Japanese companies. Moreover, companies from these countries comprised around 50% of the disclosing company-year pairs. The figure also shows how in all cases the number of censored subsidiary-year pairs was much higher than the number of pairs for which emissions were disclosed.

Table 3: Disclosing vs. Non-disclosing Companies

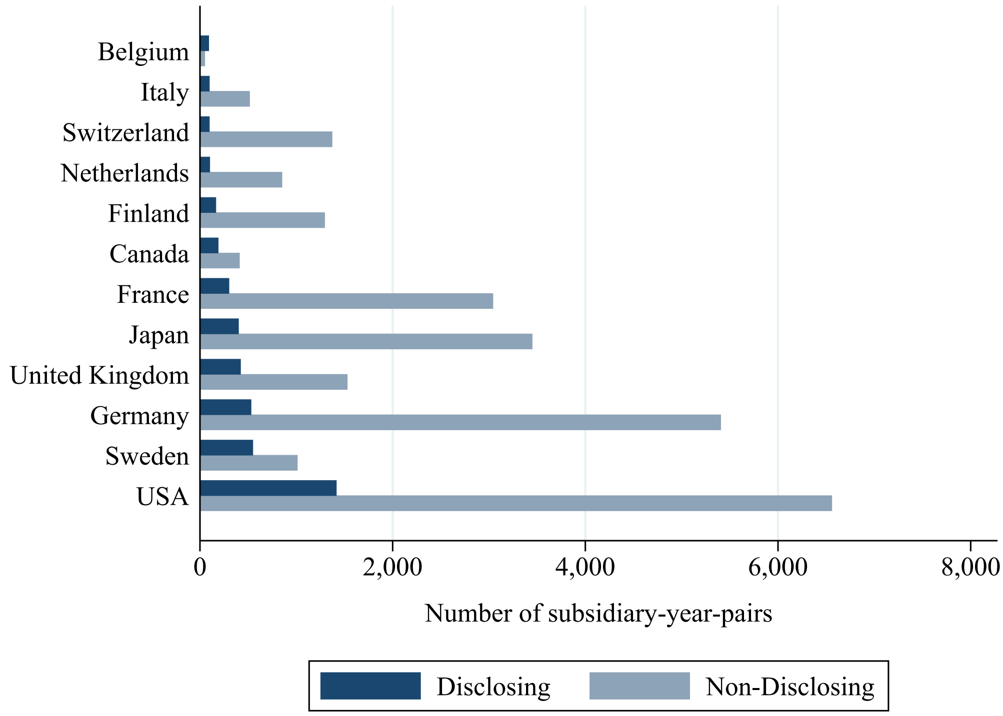
	Not disclosing	Disclosing	Difference
Subsidiary level:			
Weighted revenues, million USD	956	2,112	1,156***
	[4,146]	[6,066]	(70)
Corporate level:			
Revenues, million USD	13,252	20,525	7,273***
	[26,023]	[29,865]	(1,038)
Market capitalization, million USD	12,545	19,108	6,563***
	[26,475]	[24,770]	(993)
Human Rights Monitoring	.15	.37	.22***
	[.36]	[.48]	(.015)
Observations	2,413	957	3,370

Notes: The Mean Diff. column reports the significance levels of a two-group mean comparison test with unequal variances, *** p<0.01, ** p<0.05, * p<0.1. Standard deviation in brackets, standard error in parentheses. Statistics for the *Corporate level* panel were calculated considering one observation per company and year.

Figure 2 allows a closer look at the disclosing companies and their emissions in each country. Out of the 6,400 Mt CO2e released by the companies in the sample between 2007 and 2012, emissions of close to 1,800 Mt CO2e occurred in the USA, over 900 Mt in Germany, and around 500 Mt in both the UK, Canada and Japan. Although it is tempting to make sweeping statements as to how dirty or clean companies are in different countries, there are two reasons that prevent us from doing so. On the one hand, the number of emitting units differs dramatically. While in the USA GHG were released by about 640 subsidiary-year pairs, in Brazil 186 observations were responsible for the 70 Mt emitted in that country during the sample period. On the other hand, we do not know how a company's production is distributed among subsidiaries, and it is therefore not possible to calculate emission intensity figures.

Figure 2 also shows emissions released in each country and emissions that can be attributed to companies incorporated in the same country. For instance, German companies emitted around 1,500 Mt CO2e across all OECD and BRICS countries —as indicated by the dark blue bar— while emissions amounting to 900 Mt CO2e were released in Germany by subsidiaries of companies incorporated in Germany or any other country. The difference between the two bars for each country might be viewed as a kind of emissions balance: for example, German, French, and Italian companies emitted more in OECD and BRICS countries than was emitted in their territories, while the opposite holds for the USA, the UK, and Spain. However, we should bear in mind the general reporting behavior of companies by country of incorporation (Figure 1) —Germany and France are

Figure 1: Disclosing and non-disclosing company-year pairs by country of incorporation

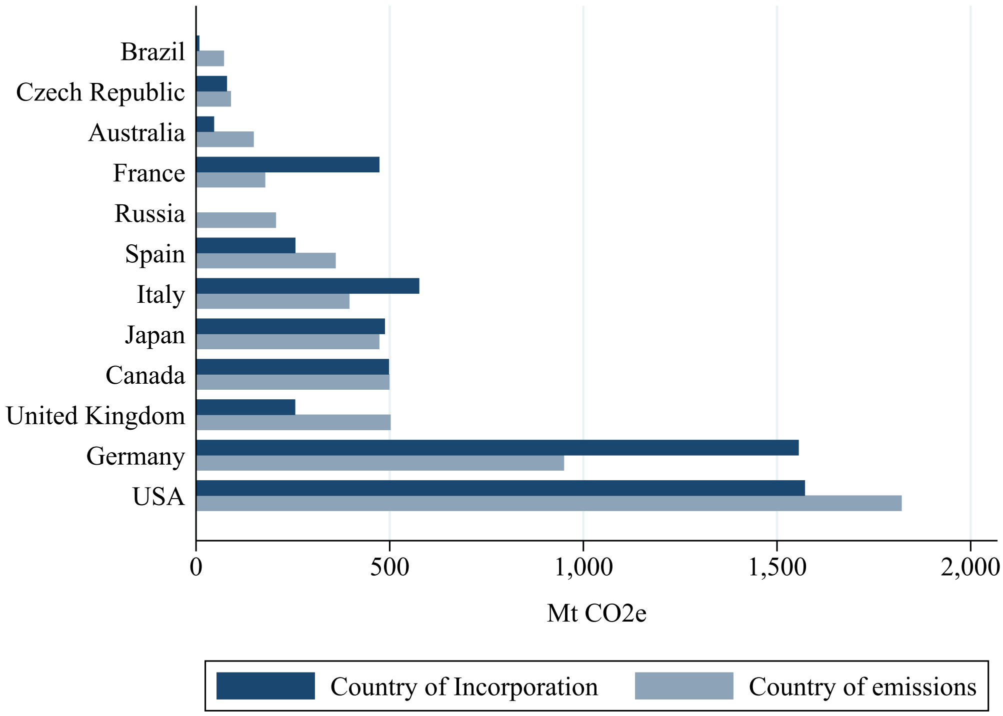


Notes: The countries shown in the figure were selected according to the number of disclosing subsidiaries. Own calculations based on CDP waves 2008–2013.

among the countries with the largest number of reporting companies, which means that the emissions balance interpretation of Figure 2 should be made with some caution.

To gain insight into the development of emissions and revenues, total figures per year were calculated by adding up reported emissions across subsidiaries on the one hand, and revenue figures across reporting companies on the other. Figure 3 plots these totals. There is an overall upward trend in total revenues, with an acceleration in 2011 followed by a slight decrease between 2011 and 2012. In contrast, total emissions initially decrease and then start increasing in 2011. This pattern of acceleration of total emissions is likely due to the increased number of companies for which emissions data is available as the end of the sample period approaches. The figure is informative in the sense that it provides insight into the overall development of emissions and revenues of companies in the sample, but it can be misleading as the number of disclosing firms varies every year. Total revenues and emissions were thus divided by the number of emitting units to calculate the averages and avoid confusing a larger number of reporting companies with increases in emissions or revenues. The resulting plot, presented in Figure 4, shows continuously declining average emissions until 2010, followed by a slight increase, while

Figure 2: Total emissions by country of emissions and country of incorporation (selected countries)

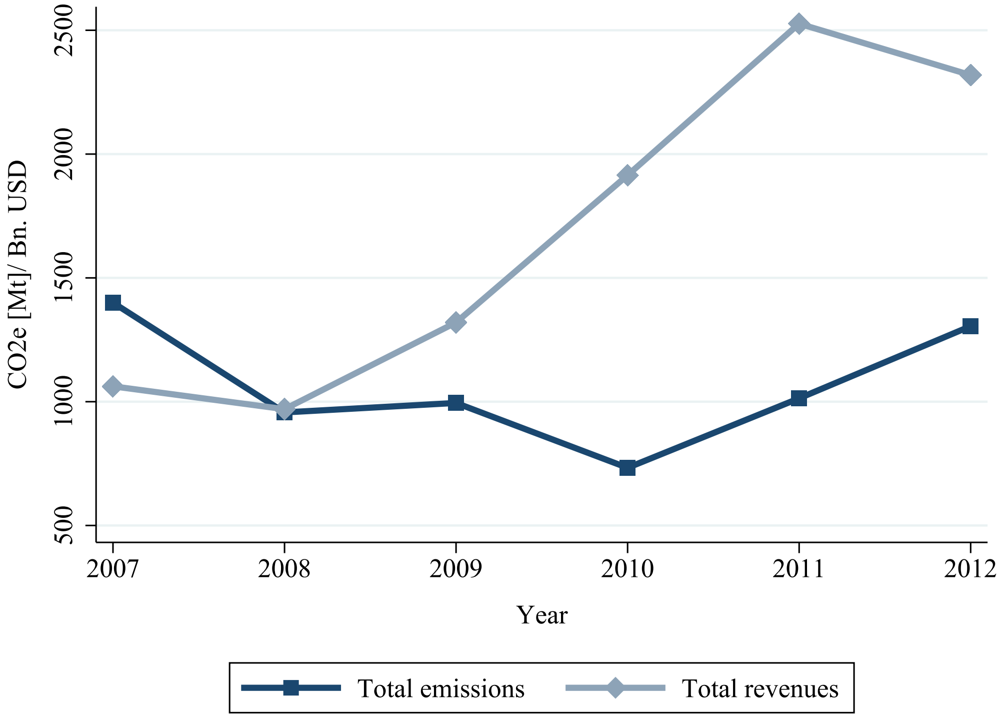


Notes: The countries shown in the figure were selected according to the level of emissions released by companies located in their territory. Own calculations based on CDP waves 2008–2013.

average revenue remains constant, except for the year 2009, during which companies experienced a fall in revenue, probably due to the outbreak of the financial crisis in 2008 and its expansion to the real economy.

The different trends observed for average emissions and revenue during the sample period point to a decoupling of these two outcomes of production and indicate that the observed emissions reductions cannot be attributed solely to deceleration of the economy. Whether this apparent decoupling is the result of climate policy will be analyzed in the following section.

Figure 3: Development of revenue and emissions (2007–2012)



Notes: Total revenue was calculated using weighted revenue figures. Own calculations based on CDP waves 2008–2013, Thomson.One Banker, and Orbis.

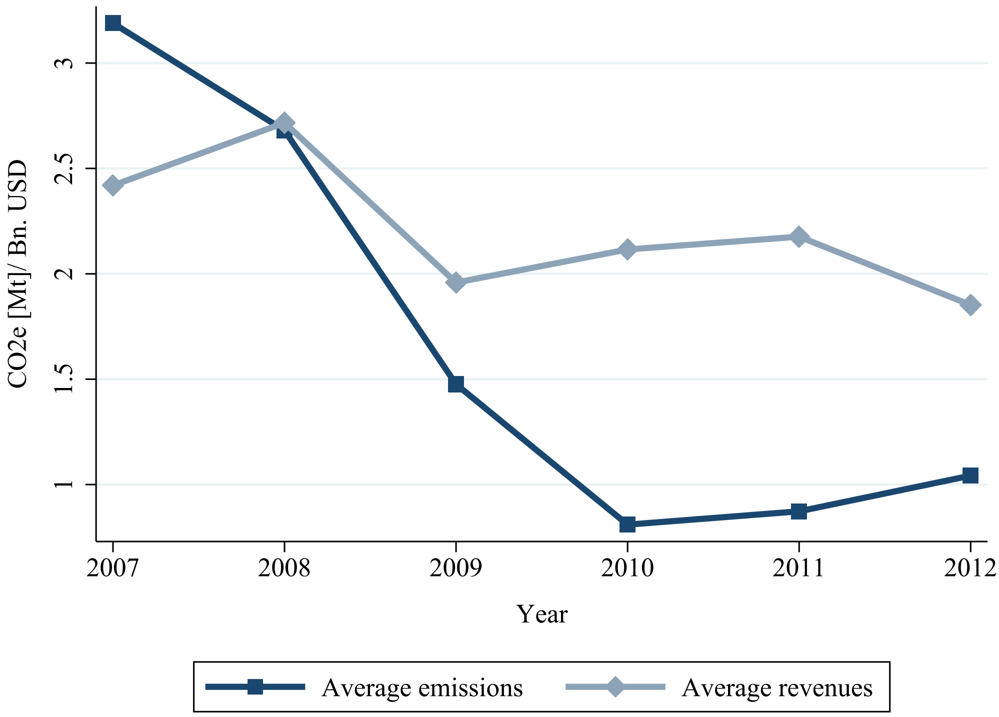
4 Model and Methods

4.1 Explaining Emissions

Analysis of the effectiveness of climate policy on companies' emissions involves much more than simply noting upward or downward trends in emissions; it requires the consideration of factors that might explain this development in the absence of regulation. For example, changes in production level are one of the most obvious reasons for changes in emissions and, indeed, have been found by other authors to be a significant predictor of emissions (Abrell et al., 2011). In general, an expansion of production is accompanied by higher emission levels, and vice versa. Therefore, to control for changes in production level, changes in companies' revenues are included as an explanatory variable.

Company size is also found to be an important determinant of emissions, possibly because larger companies have better access to environmentally efficient technology (Blackman, 2010; Féres and Reynaud, 2012). In this study, market capitalization figures are used as a proxy for company size. Another reason for taking market capitalization into

Figure 4: Development of average revenue and emissions (2007–2012)



Notes: Average revenue were calculated using weighted revenue figures. Own calculations based on CDP waves 2008–2013, Thomson.One Banker, and Orbis.

consideration is that CDP uses this figure as a criterion for participation in its surveys; hence including it in the model as an exogenous explanatory variable prevents selection generated by sampling methodology from becoming an issue. This means that, arguably, we are dealing with exogenous sample selection, which does not affect the estimation (Wooldridge, 2009).

We could consider the direct and indirect effect of informal regulation on pollution, which is shown in some studies to be non-negligible (Cole et al., 2005; Féres and Reynaud, 2012). However, community pressure on both polluters and regulators is likely to be limited in the special case of GHG, as the local effect of emission by companies located in a specific area is so small that it is hardly perceivable by the community. In fact, Cole et al. (2005) found that informal regulation has very little influence on CO2 emissions; thus this type of regulation is not considered in the present analysis.

The relationship between changes in emissions and the above-discussed determinant factors can be expressed as:

$$ln(CO2_{it}) = \boldsymbol{\beta_p}\mathbf{POL_{ct}} + \beta_r ln(REV_{it}) + \beta_m ln(MC_{it}) + \mu^E_{it} \quad (1)$$

where $CO2_{it}$ is GHG emissions of emitting unit i in year t, REV_{it} represents deflated revenues, and MC_it is deflated market capitalization. $\mathbf{POL_{ct}}$ is a vector of variables capturing the different policy measures in country c with which firms are confronted, that is, the variables of interest. Each policy variable counts the number of measures implemented in the period from 1970 to the respective year t. The error term is represented by μ^E_{it}.

Equation 1 represents the relationship of interest, yet estimating it with ordinary least squares (OLS) could lead to biased estimates due to three potential sources of endogeneity: measurement error, unobserved heterogeneity, and self-selection. Each aspect is discussed below.

First, it seems likely that at least some of the companies do not report their real emissions, either because they do not have complete information or because, for various reasons, they deliberately choose to exaggerate or underreport. For example, they might report inflated emission figures if they expect climate policies based on past emissions to be implemented in the near term. This would be the case for an emissions trading system that allocates allowances based on companies' historical emissions, so that over-reporting emissions would grant companies access to more allowances in the future. However, this is unlikely to be the chief consideration when disclosing emissions to CDP, simply because it is not an official data source on which regulation is based. On the other hand, underreporting would make companies appear cleaner, not only to communities and customers, but also to investors. Since the expected implementation of certain policy measures might affect the profit prospects of the companies concerned, investors should, in theory, consider a company's emissions level in their risk assessments and be less interested in "dirty" companies. Thus, it seems more reasonable that measurement error would go in the direction of companies underreporting their emissions, with the consequence for the estimation being that the effect of climate policy appears to be smaller than it actually is, that is, measurement error will cause attenuation bias.

The second potential source of bias, the one arising from unobserved heterogeneity, is addressed by analyzing the first differences of the logarithms of emissions, revenue, and market capitalization. This goes beyond controlling for firm characteristics and takes account of unobserved subsidiary effects. Finally, we include a full set of year dummies, which is particularly important considering that the period of analysis includes the turbulent years following the 2008 financial crisis.

The third source of endogeneity arises from the fact that our emissions data are taken from a survey in which many companies did not participate, and some of those that did participate did not provide information on their emissions, resulting in a non-random sample. As this issue is the main methodological challenge for the present study, the following subsection is dedicated to analyzing the selection problem and discussing the measures taken to address it.

With respect to the policy variables, an important implication of the fact that the measures of the *RES loans and subsidies*, or *RES Feed-in tariffs* types are aimed at increasing the use of renewable energy sources (RES) for electricity generation is that presumably they more strongly influence the emitting behavior of companies in the *Utilities* sector than of manufacturing companies. A similar consideration applies to grants, loans, and subsidies for combined heat and power (*chp*). Since *chp*-type policies target electricity and heat generation, their effect on utilities' GHG emissions is expected to differ from their effect on other sectors' emissions. To take these factors into consideration, the above-mentioned policy variables enters the analysis interacting with the dummy variable identifying utility companies.

Thus the policy vector in Equation 1 should be:

$$\mathbf{POL_{ct}} = \begin{pmatrix} reslosu_{ct} \\ ut_{it} \times reslosu_{ct} \\ resfit_{ct} \\ ut_{it} \times resfit_{ct} \\ chp_{ct} \\ ut_{it} \times chp_{ct} \\ eelosu_{ct} \\ indaud_{ct} \end{pmatrix}$$

where $reslosu_{ct}$, $resfit_{ct}$, chp_{ct}, $indaud_{ct}$, and $eelosu_{ct}$ represent the policies described in Table 1 and ut_{it} is the dummy variable identifying companies in the utilities sector.

Thus, the relationship of interest expressed by Equation 1 becomes:

$$\Delta ln(CO2_{it}) = \boldsymbol{\beta_p \Delta POL_{ct}} + \beta_r \Delta ln(REV_{it}) + \beta_m \Delta ln(MC_{it}) + \beta_t \Delta \xi_t + \upsilon_{it}^E \tag{2}$$

where ξ_t represents the unobserved year effects.

4.2 Controlling for Self-Selection

The self-selection problem arises because data on a key variable are missing as a result of the outcome of another variable, namely disclosure (Wooldridge, 2002). If firms made their disclosure decision randomly, there would be no reason for concern. However, it could be that companies base their disclosure decision on their actual level of emissions. For example, cleaner companies might be proud to disclose their emissions information, whereas dirtier companies might wish to keep this information private. If this is indeed the case, the sample of reported emissions is downward biased. There are also good reasons to believe that companies active in some specific sectors or incorporated in a given country are more prone to disclose their emissions. For instance, companies active in a sector that is subject to regulation requiring the reporting of emissions may be more likely to disclose their emissions in the survey because they have already compiled the figures. Thus, the outcome of the disclosure decision is likely to be related to other regressors and to the dependent variable, which means that ignoring the issue could create an omitted variable bias, as pointed out by Heckman (1979).

Therefore, to control for the selection problem, a two-step procedure is applied, which involves the estimation of two sets of equations:

$$disc_{it} = \alpha_h HR_{it} + \boldsymbol{\alpha_z Z_{ict}} + \boldsymbol{\alpha_m \bar{Z}_{ict}} + \upsilon_{it}^D \tag{3}$$

$$\Delta ln(CO2_{it}) = \boldsymbol{\beta_p \Delta POL_{ct}} + \beta_r \Delta ln(REV_{it}) + \beta_m \Delta ln(MC_{it}) + \beta_t \Delta \xi_t + \beta_l \Delta \hat{\lambda}_{it} + \upsilon_{it}^E \tag{4}$$

In Equation 3 $\mathbf{Z_{ict}}$ is a vector containing the explanatory variables in Equation 1. We follow Semykina and Wooldridge (2010) in controlling for time invariant unobserved heterogeneity in the selection equation by including the time averages of the exogenous variables, $\bar{Z}_{it}$, and estimating Equation 3 for each year t using probit. $\hat{\lambda}_{it}$, the inverse Mills ratio, is obtained using the estimates from Equation 3, and included in Equation 4 as an additional regressor that allows controlling for self-selection in the equation of interest.

This procedure requires the inclusion of an instrument in the first step. One important condition is that the instrument must be related to disclosure but not to emissions, either directly or indirectly through unobservable variables contained in the error term v_{it}^{E}. Our instrument is a measure of the company's engagement in monitoring human rights (HR). Since monitoring is a prerequisite to disclosure, HR provides us with valuable information on a company's overall commitment to monitor and report on aspects beyond the financial sphere. Therefore, it is a relevant variable for explaining a company's willingness to disclose GHG emissions. The validity of HR as an instrument is motivated by the fact that monitoring human rights has no relationship to GHG emissions, since it represents a social rather than an environmental concern. Nevertheless, it could be the case that companies that care about the environment also care about social aspects, and vice versa. Thus, companies that monitor the protection of human rights on their premises would also tend to have lower emissions levels. The main factor that gives us confidence about the validity of the instrument is that HR is measured at the corporate level while emissions are measured at the subsidiary level, generating some distance and therefore independence between human rights monitoring decisions and decisions concerning emissions behavior. Nonetheless, this does not affect the connection between HR and emissions disclosure since they are both measured at the corporate, that is, at the headquarters, level. There is no appropriate way of testing the exclusion restriction, but we can, and did, check whether there is a significant correlation between human rights monitoring and emissions. No significant correlation was found; thus, we can rule out an obvious violation of the restriction.

5 Data Analysis

5.1 Estimation Results

Table 4 sets out the estimation results. The results in Columns (1) and (2) correspond to a model estimated on the subsample of emitting units for which emissions figures are available, ignoring the possibility of selection bias. The first column presents the result of an OLS estimation, without considering any of the endogeneity concerns raised in Section

4.1, while the second correspond to the estimation results for Equation 2. Specification (3) presents the results of the second step of the selection correction procedure, estimated in first differences.

Table 4: Regression Results OLS, FD and Selection Correction

	(1) OLS	(2) FD	(3) Selection cor. FD
RES loans and subsidies	−0.002	−0.007	−0.006
	(0.010)	(0.006)	(0.006)
UtilityxRES loans and subsidies	0.015	−0.004	−0.009
	(0.042)	(0.014)	(0.014)
RES feed-in tariffs	−0.048	−0.006	−0.002
	(0.050)	(0.012)	(0.013)
UtilityxRES feed-in tariffs	−0.091	0.057**	0.057**
	(0.137)	(0.028)	(0.028)
CHP	0.175***	0.039**	0.040**
	(0.053)	(0.015)	(0.016)
UtilityxCHP	−0.136	−0.007	−0.019
	(0.276)	(0.032)	(0.037)
EE loans and subsidies	0.014	0.037**	0.036*
	(0.010)	(0.018)	(0.020)
Energy Audits	−0.115	−0.069***	−0.064***
	(0.116)	(0.022)	(0.023)
Lambda			0.095*
			(0.053)
Year FE	No	Yes	Yes
Observations	6556	4349	4307
R^2	0.914	0.017	0.019

Notes: All regressions include revenue and market capitalization. Robust standard errors clustered by country. ***/**/* indicate significance at the 1%/5%/10% level.

Comparing Specifications (2) and (3), we see that the significance and magnitude of the coefficients are maintained irrespective of the estimation method. An important observation from Specification (3) is that the coefficient of the parameter *Lambda* is statistically significant at the 10% level, giving some indication of the presence of self-selection.[4] Although not reported here, the results for the disclosure equations are not

[4]We also perform the selection correction procedure using bootstrapping in order to take into account that lambda is an estimated parameter and, therefore, its standard error needs to be adjusted. In that

surprising. They show that human rights monitoring is in fact a relevant predictor of disclosure, since we see highly significant coefficient estimates. Moreover, we see that, all else being equal, companies that monitor human rights on their premises are more likely to disclose their country-wide emissions. The results also indicate that the probability of disclosure is higher for companies with higher market capitalization, which is in line with the findings by Prado-Lorenzo et al. (2009).

Since the results from Specifications (2) and (3) are very similar, the rest of the analysis deals with the results of the first-differences specification (Column (2) of Table 4). Among the results for the policy measures of interest we find that financial incentives and legal requirements for energy auditing have a highly significant negative effect on emissions, so that an additional policy measure of this type reduces emissions by about 7%. One straightforward mechanism that could drive these results is that, after auditing their energy use, companies realize the cost savings potential of efficiency improvements, and thus implement new emission-reducing measures.

Moreover, the results indicate that the effect of feed-in tariffs aimed at increasing the use of renewable energy sources for electricity generation have a different effect on utilities' emissions than on other companies' emissions. If we perform the regression on the subpanel of utility companies, we find that, overall, this policy type increases utilities' emissions by 8.9% on average and that this effect is statistically significant. Although this finding might be surprising at first, it can be explained considering the technology portfolio of traditional utility companies and observations from the German electricity market, where CO2 emissions per generated kilowatt hour increased between 2010 and 2012, according to the German Federal Environmental Office (Umweltbundesamt, 2015). The mechanism driving this result can be explained in the following way. Since cleaner, more expensive fossil fuel power stations are placed at the bottom of the merit order, an increased generation from RES (which are financed by feed-in tariffs and either have preferential entry into the electricity network or are placed at the top of the merit order due to their low marginal costs) crowds out cleaner fossil fuel power stations from the wholesale market. As a result, generation by traditional utility companies is now dirtier on average. The use of the German example as an explanation might cause the reader to think that the results are specific to Germany, and yet running the regression without subsidiaries located in that country generates the same results. This result shows that well-intentioned policies can lead to unintended outcomes, at least in the short run, by inducing behavioral changes in market actors. A theoretical motivation for this effect is

case, the standard error increases only by about 0.004 points, which does not have any implications for the statistical significance of *Lambda*.

provided by Böhringer and Rosendhal (2010).

Support schemes for CHP have a positive effect on the emissions of non-utility companies, while they do not seem to have any effect on the emissions of utility companies, as shown by the interacted coefficient. The results can be seen as an indication that the introduction of CHP support schemes leads to an increase of about 4% in the emissions of companies in other sectors. A plausible mechanism causing this result is that the support scheme incentivizes companies that are not in the utilities sector to engage in power and heat generation as self-suppliers instead of purchasing it. While this "new product" increases companies' emissions, it is not sold and is therefore not reflected in their revenues. Even though this increases scope-1 emissions, on which the econometric analysis is based in the respective company, the global effect on emissions is ambiguous since indirect scope-2 emissions are reduced due to a decline in purchased electricity.

The coefficient estimates for energy efficiency improvement measures are positive, suggesting a rebound effect beyond 100%, and thus an increase of emissions. Sounders (2000) coined the term "backfire" for this special case of the rebound effect and the result is consistent with previous studies, e.g the empirical analysis of energy efficiency improvements of Brännlund et al. (2007) for Swedish households and Mizobuchi (2008) for Japanese households. Puzzling at first sight, Mizobuchi (2008) shed light on the mechanism behind this observation. The rebound effect can be decomposed in a direct and an indirect rebound effect. The former manifests itself as energy efficiency improvements for a specific energy service causing reductions in the effective price of that service and consequently leading to an increase in its consumption and therefore in emissions. That is, the initial negative effect on energy consumption and emissions would then be partially offset by the effect of the reduced effective price (Brännlund et al., 2007; Sorrell and Dimitropoulos, 2008). The indirect rebound effect results from an income effect. The lower effective price for the energy service sets income free that is spent for the use of other inputs or in other production processes, and thus increase emissions. Brännlund et al.'s (2007) result showing a rebound effect of over 100% was contested by Mizobuchi (2008), who founds that the magnitude of the rebound effect is reduced from 115% to 27% when the capital costs for energy efficient appliances are considered in the estimation. More energy efficient appliances are generally more costly than the inefficient ones. Thus, the additional income resulting from savings on energy service expenditures due to the energy efficiency improvement is partially offset by the expenditures for the additional capital. This reduces the indirect rebound effect and consequently the total rebound effect. Since the policy measure analyzed in this paper typically aim at reducing or eliminating additional capital costs for energy efficiency improvements, it comes as no surprise that this distortion in the capital costs results in the undesired effect. By effectively generating additional income for the companies, the indirect rebound effect is strengthened and total emissions might increase. In a comparable analysis, Mizobuchi (2008) shows that reducing the additional capital cost to zero increases his estimated rebound effect to 117%.

No effect on emissions was detected with regard to the remaining policy measure, that is, loans and subsidies aimed at increasing the use of renewable energy sources for electricity generation. A potential source of statistical insignificance of the coefficient of some policies might be the time lag between the implementation of a policy and companies using the support schemes offered. Accordingly, we extend the analysis by also including policies implemented two and three years prior to the measurement of emissions as presented in Columns (2) and (3) of Table 5. The first column contains the results presented in column (2) of Table 4 to facilitate comparison. We observe that the results for the policies implemented in $t-1$ (as in our baseline specification) remain stable as we include additional lags. This is reassuring because we can be confident that, by performing the analysis as in Column (1), we do not capture the effects of policies implemented in the past. We learn from the extension as presented in Column (2) that, in the case of CHP, emissions decrease again after an initial increase following the implementation of this type of policy. A possible interpretation of this result is that the effect of companies engaging in self-supply dominates in the first two years immediately after the implementation of a CHP support scheme. In the third year, the impact of efficiency gains of CHP (compared to separate heat and power generation) is more prevalent.

Table 5: Extended Time Pattern of Policy Effects

	(1) FD	(2) FD	(3) FD
RES loans and subsidies t-1	−0.007	−0.003	−0.009
RES loans and subsidies t-2		0.004	0.005
RES loans and subsidies t-3			−0.003
UtilityxRES loans and subsidies t-1	−0.004	0.001	0.003
UtilityxRES loans and subsidies t-2		−0.027	−0.023*
UtilityxRES loans and subsidies t-3			0.018
RES feed-in tariffs t-1	−0.006	−0.006	−0.003
RES feed-in tariffs t-2		0.001	−0.001
RES feed-in tariffs t-3			0.013
UtilityxRES feed-in tariffs t-1	0.057**	0.044*	0.061**
UtilityxRES feed-in tariffs t-2		0.047	0.081**
UtilityxRES feed-in tariffs t-3			−0.117
CHP t-1	0.039**	0.060***	0.083***
CHP t-2		−0.045*	−0.084**
CHP t-3			0.002
UtilityxCHP t-1	−0.007	−0.009	−0.034
UtilityxCHP t-2		0.027	0.020
UtilityxCHP t-3			−0.124*
EE loans and subsidies t-1	0.037**	0.039*	0.031
EE loans and subsidies t-2		−0.007	−0.003
EE loans and subsidies t-3			−0.009
Energy Audits t-1	−0.069***	−0.067**	−0.067**
Energy Audits t-2		−0.034	−0.040
Energy Audits t-3			0.085*
Year FE	Yes	Yes	Yes
Observations	4349	4349	4349
R^2	0.017	0.019	0.020

Notes: All regressions include revenue and market capitalization. Robust standard errors clustered by country. ***/**/* indicate significance at the 1%/5%/10% level.

5.2 Sensitivity Analysis

By analyzing the sensitivity of the estimated coefficients to specification changes and to the exclusion of specific countries and other groups of observations, we rule out a wide set of possible sources of bias. The first set of results is summarized in Table 6, where Column (1) is identical to Column (2) in Table 4. Table 6 shows the results we obtain when each policy type is analyzed separately. Coefficient estimates and their statistical significance remain unchanged, except for *EE loans and subsidies*.

Cap-and-trade schemes should have a negative impact on emission levels, as long as the caps have been set wisely. Therefore, although we do not analyze the performance of emission trading systems, we run additional regressions, where we include the annual average of the price for emissions allowances of the EU ETS. Since future contracts represent over 80% of all EUA transactions (Kossoy and Guigon, 2012), we rely on the price of this type of contract for the analysis. For subsidiaries that are not covered by the system, including those in non-EU ETS countries, the price for emissions permits is assumed to be zero. Moreover, New Zealand had to be excluded from the analysis because, although the country has an ETS in force, we do not have any data on emission permit prices. This time too, as reported in columns (2) and (3) of Table 7 we determine no differences in the results.

Table 6: Sensitivity Analysis - Single Policies

	(1) FD	(2) FD	(3) FD	(4) FD	(5) FD	(6) FD
RES loans and subsidies	−0.007	0.003				
	(0.006)	(0.005)				
UtilityxRES loans and subsidies	−0.004	0.001				
	(0.014)	(0.015)				
RES feed-in tariffs	−0.006		−0.004			
	(0.012)		(0.012)			
UtilityxRES feed-in tariffs	0.057**		0.056**			
	(0.028)		(0.026)			
CHP	0.039**			0.042**		
	(0.015)			(0.020)		
UtilityxCHP	−0.007			−0.011		
	(0.032)			(0.034)		
EE loans and subsidies	0.037**				0.025*	
	(0.018)				(0.014)	
Energy Audits	−0.069***					−0.050**
	(0.022)					(0.020)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4349	4349	4349	4349	4349	4349
R^2	0.017	0.015	0.016	0.016	0.016	0.016

Notes: All regressions include revenue and market capitalization. Robust standard errors clustered by country. ***/**/* indicate significance at the 1%/5%/10% level.

Table 7 also shows the results of including industrial electricity prices as an explanatory variable. The motivation behind this test is the concern that companies engage in CHP generation as a response to higher electricity prices rather than to the support schemes analyzed here. The number of observations is reduced by more than 25%, since we only have electricity prices for OECD countries, and even then, we are missing data for some countries and years. The results indicate that our *CHP* variable does not pick up the effect of electricity prices. However, the coefficient for *Energy Audits* declines in magnitude and loses its statistical significance. In a further analysis, we run our baseline regression for the set of countries for which we have data on electricity prices and determine the same changes for the *Energy Audits* variable: a drop in the coefficient and no statistical significance. We can therefore interpret these changes as the result of dramatic changes in the sample composition rather than the *Energy Audits* variable capturing the effects of electricity price changes.

Additional robustness tests consist of excluding different groups of observations. For example, we run several regressions omitting one country at a time and find only minor changes in the significance levels and magnitudes of the coefficients. Alternatively, we trim the dataset based on different thresholds but, again, coefficient magnitudes and significance remain stable.[5] We also conduct the entire analysis, including all robustness tests, for the sub-group of OECD countries. We do not observe any significant differences in the magnitudes of coefficients or significance levels, except for the different trimming options for which the results seem to be more stable for OECD countries than for the entire sample. Finally, the observation that data availability in some countries seems poor challenges the assumption that a policy measure was considered not to be in place in a country if none of the datasets consulted listed the measure for that country. We therefore exclude the five countries that presumably have the poorest data availability (Belgium, Brazil, Chile, Slovenia, and Iceland) to verify that they do not distort the results. The findings do not differ significantly from those in our baseline regression.

[5] In the baseline, we trim the data at the 1.5 and 98.5-percentile of emissions changes. The cutoff levels were chosen to only eliminate obvious and implausible outliers

Table 7: Sensitivity Analysis - EUA and Electricity Prices

	(1) FD	(2) FD	(3) Selection cor. FD	(4) FD	(5) Selection cor. FD
RES loans and subsidies	−0.007	−0.008	−0.006	0.004	0.002
	(0.006)	(0.006)	(0.006)	(0.009)	(0.014)
UtilityxRES loans and subsidies	−0.004	−0.004	−0.007	0.014	−0.016
	(0.014)	(0.014)	(0.014)	(0.026)	(0.044)
RES feed-in tariffs	−0.006	−0.007	−0.003	−0.012	−0.014
	(0.012)	(0.012)	(0.013)	(0.015)	(0.012)
UtilityxRES feed-in tariffs	0.057**	0.055*	0.055*	0.068**	0.074**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.035)
CHP	0.039**	0.038**	0.039**	0.116***	0.115**
	(0.015)	(0.015)	(0.015)	(0.023)	(0.046)
UtilityxCHP	−0.007	−0.007	−0.018	−0.017	0.018
	(0.032)	(0.032)	(0.036)	(0.110)	(0.173)
EE loans and subsidies	0.037**	0.038**	0.036*	0.028	0.029
	(0.018)	(0.018)	(0.020)	(0.026)	(0.031)
Energy Audits	−0.069***	−0.069***	−0.065***	−0.037	−0.010
	(0.022)	(0.022)	(0.023)	(0.031)	(0.035)
EUA price		0.012	−0.004		
		(0.027)	(0.030)		
Lambda			0.087*		0.149**
			(0.049)		(0.068)
Ind. electricity price					0.267**
					(0.126)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4349	4305	4263	3072	2850
R^2	0.017	0.018	0.019	0.020	0.022

Notes: All regressions include revenue and market capitalization. Robust standard errors clustered by country. ***/**/* indicate significance at the 1%/5%/10% level.

6 Conclusions

This paper studied the effect of climate policy on companies' GHG emissions using emissions data for the headquarters and subsidiaries of the world's biggest companies. In our empirical analysis, we found that four out of the five policy types investigated have a significant influence on companies' GHG emissions: feed-in-tariffs aimed at increasing the use of RES for electricity generation, grants and subsidies for CHP, loans and subsidies aimed at increasing energy efficiency and financial incentives or legal requirements requiring the auditing of a company's energy use. The findings were not sensitive to several changes in the model specification.

With respect to the direction of the impact, our results suggest that financial incentives and legal requirements for auditing companies' energy use reduce their emissions. In the case of support schemes for CHP generation, the estimations point to an increase in emissions by companies in non-utility sectors, possibly because these companies now have an incentive to engage in the production of electricity and heat for their own use, increasing their emissions. This effect is reversed in the third year after implementation of the policies. Feed-in tariffs aiming at increasing the use of renewable energy sources for electricity generation also seem to increase utilities' emissions. We explain this effect as the consequence of renewable energy sources crowding out cleaner fossil fuel power stations from the wholesale electricity market, which results in traditional utility companies' generation now being dirtier on average. With regard to policies aimed at increasing energy efficiency, we found weak evidence that they increase emissions in companies, yet the effect vanished when we included more lags of the policy variable. This might be an indication of an initial rebound effect, something worth analyzing more closely.

There are numerous possibilities for extending this analysis, especially considering that, to the best of our knowledge, no other similar studies have been conducted. An invaluable project would involve overcoming data issues. Exerting effort towards collecting a more detailed compilation of climate policy measures implemented (e.g. listing the amount of funding dedicated to each measure) and towards obtaining figures indicating the share of the companies' production taking place in each country would make a more reliable analysis possible.

These data improvements would additionally permit the study of other interesting research questions, such as the assessment of carbon leakage occurring through the investment channel. This phenomenon occurs when climate policy provokes the relocation of production away from countries with a strict climate policy to countries where climate policy is laxer, undermining the effects of policy measures implemented in the former countries (Babiker, 2005; Felder and Rutherford, 1993; Reinaud, 2008).

This study has shed some light on climate policy effects at the micro level. We hope that more research along these lines will be conducted, in addition to research that improves the availability and quality of data, providing a solid foundation for climate policy evaluation.

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Appendix

Table 1: Policy Variables

	Region/sector	Based on	Index used
800 of the largest	Global	market cap.	FTSE All-World Developed—Large Cap
800 of the largest and mid-sized	Emerging markets	market cap.	S&P/IFCI Large/Mid Emerging Market Index
725 of the largest	UK	market cap.	FTSE All-Share and FTSE Fledgling Index
500 of the largest	Global	market cap.	Global 500
500 of the largest	Japan	market cap.	
500 of the largest	USA	market cap.	S&P 500
300 of the largest	Europe	market cap.	FTSEurofirst 300 Eurozone
260 of the largest	Nordic	market cap.	
250 of the largest	France	market cap.	SBF 250
250 of the largest	Germany & Austria	market cap.	
250 of the largest	Korea	market cap.	
250 of the largest	Electric utilities globally	market cap.	
200 of the largest	Australia	market cap.	ASX 200
50 of the largest	New Zealand	market cap.	NZX 50
200 of the largest	Canada	market cap.	
200 of the largest	India	market cap.	BSE 200
180 of the largest	Issuing bonds	market cap.	S&P CDS U.S. Investment Grade Index and Markit iBoxx USD Liquid Investment Grade Index
170 of the largest	Asia ex-Japan, India, China, and Korea	market cap.	Asia ex-JICK
150 of the largest	Netherlands, Belgium, and Luxemburg	market cap.	
125 of the largest	Spain and Portugal	market cap.	
100 of the largest	Brazil	market cap.	BM&FBOVESPA IBrX100
100 of the largest	Central & Eastern Europe market cap.		
100 of the largest	China	market cap.	
100 of the largest	Italy	market cap.	
80 of the largest	Latin America	market cap.	
100 of the largest	South Africa	market cap.	FTSE/JSE 100
100 of the largest	Switzerland	market cap.	SPI Large & MidCap SOCI
100 of the largest	Transport sector globally	market cap.	
100 of the largest	Turkey	market cap.	ISE 100
50 of the largest	Russia	market cap.	RTS Index
30 of the largest	Ireland	market cap.	

Notes: CDP (2013)