Foreignness as an Asset: European Carbon Regulation and the Relocation Threat among Multinational Firms

—SUPPLEMENTARY MATERIALS—

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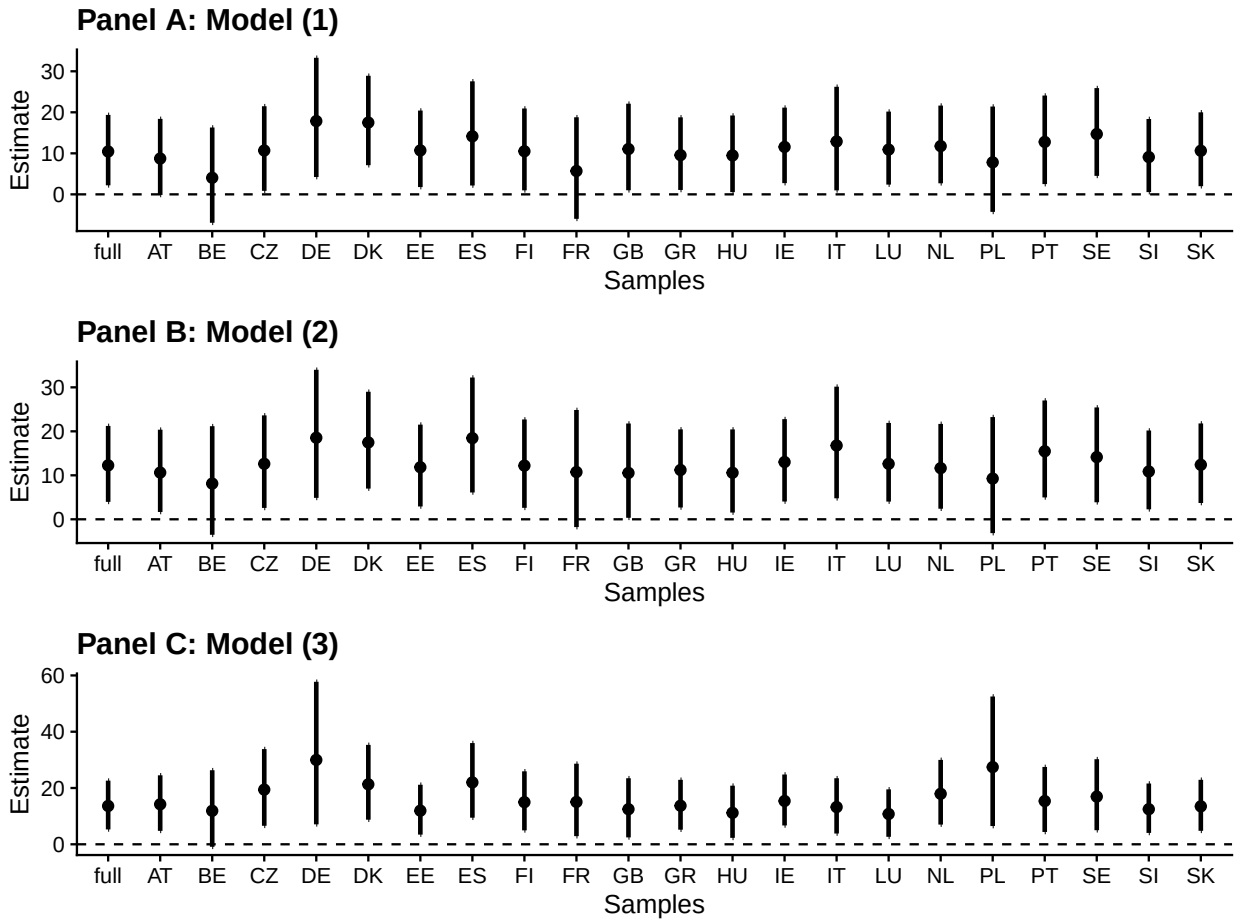
A Robustness Tests

This section presents results from two robustness tests. First, I show that results are robust to dropping firms country-by-country. Second, I use jackknife resampling to show that the estimates of the marginal effects and confidence bounds reported in the main text are, if anything, biased downwards.

For the first test, I replicate the main analysis but drop firms that operate in a given country from the data and re-estimate the main models for these smaller data sets. Figure A1 shows point estimates and 95% confidence intervals from these additional regressions when excluding firms that operate in the countries indicated along the x-axis, respectively. Panels A, B, and C show the estimates for Models (1), (2), and (3) from the results Table 2 in the main text. The first estimate always is the full sample estimate for reference. As can be seen, results are largely robust to exclusion of firms by country, especially in the more fully specified models. In Model (2), for instance, estimates are no longer statistically significantly once dropping firms from Belgium ($n = 1217$), France ($n = 929$), and Poland ($n = 958$), but this is likely driven by loss in statistical power as sample size reduces to about half in the latter two cases, while point estimates remain strong: 8.1% when dropping Belgium, 10.7% when dropping France, and 9.3% when dropping Poland. What is more reassuring is that for Model (3), which matches plants within firm on economic activity, all estimates except for when excluding Belgium (however, this is significant at the 10% level) are statistically significant and substantively strong.

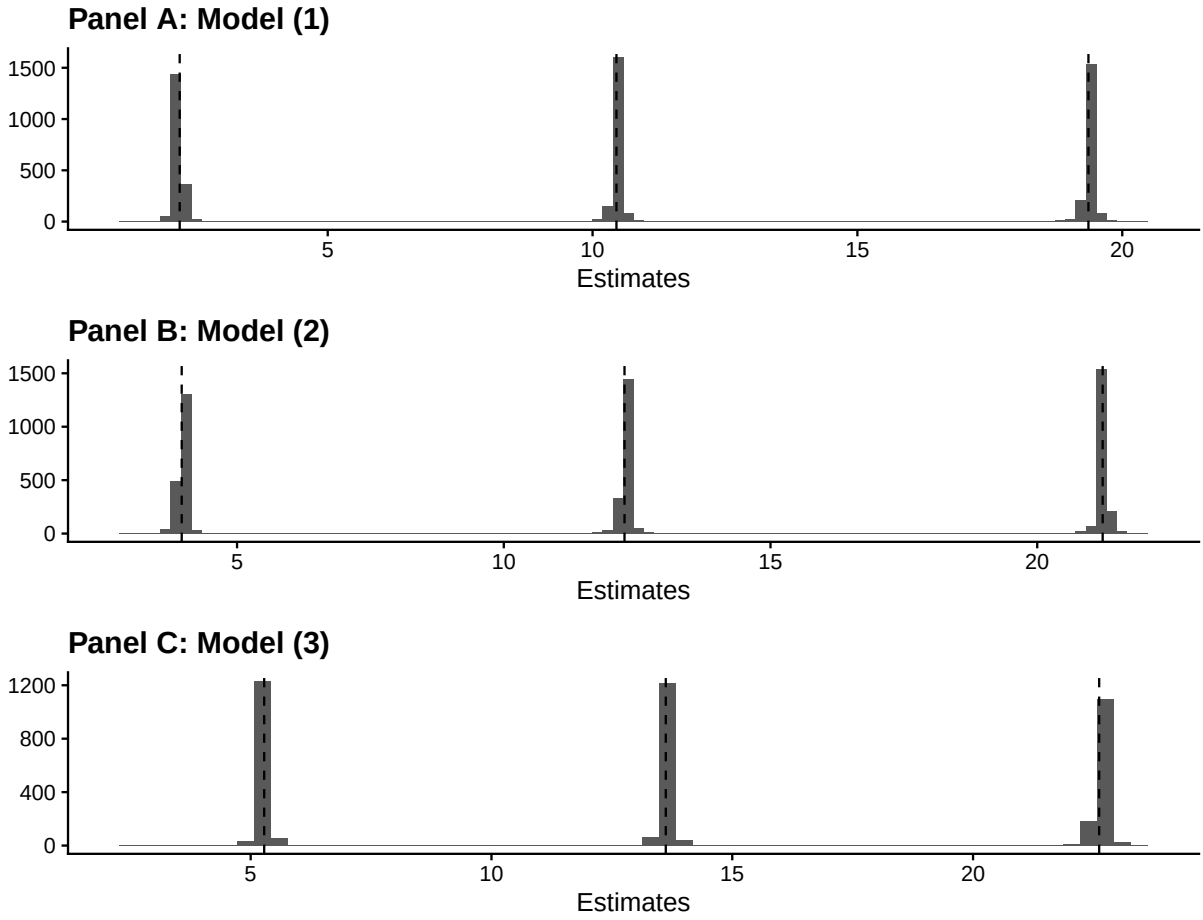
The second test presents results from jackknife resampling, which iteratively drops one observation at a time and re-estimates the models. Figure A2 shows histograms of the lower confidence bound, the central estimate, and the upper confidence bound from the resampled data. The dashed lines indicate the estimates reported in the main text. These are almost perfectly identical to the median of the histograms. The estimation results are hence robust to dropping individual observations one at a time.

FIGURE A1: Effect of foreign plant ownership on favorable regulation for full sample and when dropping firms by country



Note: Panels A, B, and C show marginal effect estimates and 95% confidence intervals for Models (1), (2), and (3), respectively, for the full sample and when dropping firms from the data that operate in the countries shown along the x-axis.

FIGURE A2: Effect of foreign plant ownership on favorable regulation with jackknife resampling



Note: Panels A, B, and C show histograms of the distribution of estimates for the lower confidence bound (left), the central estimate (middle), and the upper confidence bound (right) for Models (1), (2), and (3), respectively, when using jackknife resampling. The dashed lines indicate the values of the marginal effect and the 95% confidence interval bounds from the full data, which are consistently right at the median of the histogram of the jackknife sample.

B Count Models

Models in the main text are estimated with OLS after logging the dependent variable. Here, I re-estimate the same specifications using count models instead.

Poisson models

In a first instance, I estimate Poisson regression models even though the variance of the dependent variable (3.1 x 10^{13}) in the full data set is roughly seven orders of magnitude larger than the mean (1.7 x 10^{6}), suggesting over-dispersion. Table B1 shows average marginal effects and 95% confidence intervals for foreign plant ownership from Poisson models, estimated from R's `marginaleffects` package (Arel-Bundock, 2022). Standard errors are heteroskedasticity robust because they are known to be deflated in over-dispersed Poisson models (Cameron and Trivedi, 2005). Effects can be directly interpreted as increases in permit allocation as counts.

TABLE B1: Effect of foreign plant ownership on favorable regulation (Poisson models)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Excluding plants with zero allocation (same sample as in main text)			
Marginal effect	−58073	−20625	114862
95% CI	[−192306, 76161]	[−153720, 112470]	[−25671, 255396]
Countries	21	21	21
Sectors	—	9	9
Firms	159	159	123
Observations	1899	1899	1337
p-value (equidispersion test)	0.064	0.069	0.091
Including plants with zero allocation			
Marginal effect	−49672	−7593	109739
95% CI	[−175339, 75996]	[−133655, 118469]	[−21904, 241382]
Countries	21	21	21
Sectors	—	9	9
Firms	159	159	123
Observations	2000	2000	1431
p-value (equidispersion test)	0.060	0.064	0.090

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on allocated permits from Poisson models. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model and the p-value from an equidispersion test. Standard errors are heteroskedasticity robust.

Table B1 shows that results are qualitatively similar no matter whether models are estimated for samples that exclude (as in the main text) or include plants with zero permit allocations. Since only roughly 3%-5% of plants (101 in models (1)/(2) and 45 in model (3)) do not receive any permits, zero truncation is not a major concern statistically. Substantively, in the EU ETS, only trading accounts without any underlying carbon emissions from industrial activity, or plants that have ceased to operate or started up operations (and were scheduled to receive permits from the New Entrant Reserve) were allocated no permits at the start of the trading period. Including these plants into the sample adds noise to the data unnecessarily. For example, zero allocations for fully operational plants are not theoretically meaningful in the standard EU ETS allocation process, which my argument seeks to test empirically.

The results show that none of the models produces statistically significant effects. For models (1) and (2), estimated coefficients are negative, while model (3) produces results that are consistent in signature and about half the size of the models in the main text (estimated marginal effect of 114862 relative to a mean of 2085425 in the data used to run the regression model corresponds to an increase of permits of roughly 5.5%). However, equidispersion tests with a linear variance transformation function (what Cameron and Trivedi (2005) call "NB1") reject the assumption that the mean and variance of the permit allocation variable are identical, so negative binomial models are likely more appropriate than Poisson models.

Negative binomial models

Because of over-dispersion in the permit allocation data, I re-estimate the model specifications from the main text with negative binomial models. As with the Poisson models, effects can be directly interpreted as increases in permit allocation as counts. Marginal effects are again estimated from `R`'s `marginaleffects` package (Arel-Bundock, 2022) with robust standard errors. For faster convergence, I use the `glm.fit2` method from `R`'s `glm2` library for estimation (Marschner, 2011).

Table B2 shows that estimated effects are roughly between 200,000-300,000 permits (or 40,000-60,000 per year over the five-year trading period) that the average foreign-owned plant receives more than domestically-owned ones. When expressed as percentage increases relative to the mean permit allocation in the data used to estimate the models, the effects vary between 10.0%-14.4%, which is almost identical to the effect sizes estimated in the OLS models in the main text, which range from 10.5%-13.8%. This offers a high degree of confidence that the main results are not driven by the estimation method.

The bottom half of Table B2 demonstrates that average marginal effects become much larger when estimating negative binomial models for data that includes plants with zero permit allocations. As mentioned before, this adds noise to the estimation, but also offers some reassurance that dropping these plants, if anything, reduces estimated effects downwards, making it less likely for my proposed argument to find empirical support in the data.

While zero truncated Poisson models run into convergence issues, zero truncated negative binomial models (not reported) produce almost identical point estimates (up to at least the first three digits) relative to the non-truncated models.

TABLE B2: Effect of foreign plant ownership on favorable regulation (negative binomial models)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Excluding plants with zero allocation (same sample as in main text)			
Marginal effect	197075	240081	295898
95% CI	[−12546, 406697]	[36793, 443370]	[43596, 548199]
Effect in %	10.0%	12.2%	14.2%
Countries	21	21	21
Sectors	—	9	9
Firms	159	159	123
Observations	1899	1899	1337
Including plants with zero allocation			
Marginal effect	348299	400435	488674
95% CI	[37863, 658735]	[90569, 710301]	[50901, 926447]
Effect in %	18.7%	21.5%	25.0%
Countries	21	21	21
Sectors	—	9	9
Firms	159	159	123
Observations	2000	2000	1431

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on allocated permits from negative binomial models. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

C Clustered Standard Errors

Standard errors in the main models are estimated as heteroskedasticity robust standard errors. While the use of robust standard errors addresses concerns that the error variance is not constant conditional on covariates, robust standard errors do not account for the clustering in the data. Indeed, plants are for example nested in firms as well as countries and sectors. However, the main models do *not* present clustered standard errors by default as permit allocation is primarily guided by plant-level variables under the rules and regulations of the European Union Emissions Trading System (EU ETS) (Ellerman, Buchner, and Carraro, 2007).

TABLE C1: Effect of foreign plant ownership on favorable regulation

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	10.5%	12.3%	13.6%
95% confidence intervals from robust standard errors (main text)			
Robust	[2.2%, 19.4%]	[4.0%, 21.2%]	[5.3%, 22.6%]
95% confidence intervals from clustered standard errors			
Country	[2.4%, 19.1%]	[4.9%, 20.1%]	[3.5%, 24.7%]
Sector	[1.0%, 20.8%]	[4.2%, 21.0%]	[5.5%, 22.4%]
Firm	[−2.0%, 24.5%]	[1.1%, 24.7%]	[2.1%, 26.4%]
95% confidence intervals from two-way clustered standard errors			
Country-sector	[1.7%, 20.0%]	[4.8%, 20.2%]	[5.0%, 23.0%]
Country-firm	[0.2%, 21.8%]	[2.5%, 23.0%]	[4.7%, 23.3%]
Sector-firm	[−1.2%, 23.5%]	[1.1%, 24.7%]	[2.1%, 26.4%]
95% confidence intervals from three-way clustered standard errors			
Country-sector-firm	[0.3%, 21.7%]	[2.4%, 23.1%]	[4.7%, 23.3%]
Countries	21	21	21
Sectors	—	9	9
Firms	159	159	123
Observations	1899	1899	1337

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation for different types of clustered standard errors. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model.

To rule out that the way in which standard errors are calculated drives the results and conclusions in the main paper, Table C1 presents 95% confidence intervals when standard errors are clustered in different ways. Specifically, I present results from clustering at the country, sector, and firm-level together with results from two-way and three-way clustering. While confidence intervals become larger when estimating clustered standard errors, only Model (1) estimates become

insignificant in two cases when clustering at the firm-level and sector-firm level (results are still significant at $\alpha = 0.1$ confidence level). However, results remain strong and significant for all types of clustering for Model (2) with sector fixed effects and Model (3) of the matched sample. My main findings are hence not dependent on what type of standard errors are used.

D Additional Sector Fixed Effects Models

In the main model, sector fixed effects are defined based on economic activity codes from the EU ETS. This classification is useful as permit allocation rules were set up with these sectoral classifications in mind. Another way to categorize sectors is according to the official Statistical Classification of Economic Activities in the European Community, or NACE. NACE codes rely on a hierarchical classification at four levels. The top-level consists of 21 sectors classified by letters A-U, while lower levels consist of 2-digit, 3-digit, and 4-digit codes. A full list is available at https://ec.europa.eu/competition/mergers/cases/index/nace_all.html.

Since model (1) in the main text does not include sector fixed effects, I replicate only models (2) and (3) here, while using all four different levels of NACE classifications as sector fixed effects. As Table D1 shows, this means increasing the number of sector-level fixed effects considerably, ranging between 7-98 for model (2) and between 4-51 in model (3). The results remain robust across all models. For model (2), the marginal effect is between 10.2%-10.7% compared to 12.3% in the main text; for model (3), marginal effects range between 12.7%-14.1% and hence become a bit stronger compared to the 13.6% in the main text, especially for the models that use 4-digit level NACE codes.

The bottom part of Table D1 also shows estimation results when using country-sector fixed-effects, where sectors are defined according to all four hierarchies of NACE codes. These are obviously demanding models due to the large number of fixed effects (up to 375 for country-sector fixed effects alone). Despite this, the results remain strong, especially for NACE1 and NACE4 hierarchies. For the matched sample in model (3), all specifications are statistically significant at the 10%-level; models for country-sector fixed-effects where sectors are defined based on NACE1 and NACE4 codes are significant at the 5% level.

Overall, results are robust to the use of different types of sector-level fixed effects, which cautions against worries that particular sector definitions would drive the main findings.

TABLE D1: Effect of foreign plant ownership on favorable regulation (different sector-level FEs)

	Model (2)				Model (3)			
	NACE 1	NACE 2	NACE 3	NACE 4	NAC E	NACE 2	NACE 3	NACE 4
Sector-level fixed effects for different NACE codes								
Marginal effect	10.2%	10.6%	10.4%	10.7%	12.7%	12.8%	13.6%	14.1%
95% CI	[1.9%, 19.2%]	[2.5%, 19.3%]	[2.4%, 19.0%]	[2.4%, 19.6%]	[4.4%, 21.7%]	[4.5%, 21.8%]	[5.3%, 22.6%]	[5.8%, 23.2%]
Countries	21	21	21	21	21	21	21	21
Sectors	7	26	59	98	4	17	38	51
Firms	159	159	159	159	123	123	123	123
Observations	1896	1896	1896	1896	1337	1337	1337	1337
Country-sector fixed effects at different NACE codes								
Marginal effect	10.2%	6.0%	8.1%	15.0%	10.1%	8.8%	12.3%	17.3%
95% CI	[1.9%, 19.1%]	[−2.7%, 15.6%]	[−4.6%, 22.5%]	[1.1%, 30.9%]	[2.2%, 18.6%]	[−0.1%, 18.5%]	[−0.7%, 27.1%]	[0.8%, 36.5%]
Country-sector	56	172	297	375	47	142	213	250
Firms	159	159	159	159	123	123	123	123
Observations	1896	1896	1896	1896	1337	1337	1337	1337

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model specifications for models (2) and (3) are the same as in the main text, but with different sector-level fixed effects at all four levels for the NACE code industrial classification. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

E Main Results with Fixed Assets Control

The main results already use matching plants *within* firms on economic activity at the 4-digit NACE level to address concerns that plant-level differences in economic activity shape results. Since economic activities are also likely correlated with fixed assets, this matching approach also alleviates worries that plant-level differences in fixed assets drive the results rather than ownership structure.

As another robustness test, I construct an indirect measure to proxy for plant-level fixed assets in the absence of a direct measure. For this measure, I rely on data from the Bureau van Dijk's Amadeus database on firms' fixed assets (note that firm-level fixed assets are already absorbed by firm-level fixed effects, so including this variable is not useful to address the potential problem of heterogeneity in plant-level fixed assets) and weight this data by a plant's emissions. The weight is hence constructed as the share of a plant's CO_2 emissions relative to a firm's total emissions. I calculate the measure as follows:

$$\text{Fixed assets}_{\text{plant}} = \text{Fixed assets}_{\text{firm}} \times \frac{\text{Emissions}_{\text{plant}}}{\text{Emissions}_{\text{firm}}},$$

Data on firm-level fixed assets come from Bureau van Dijk's Amadeus database and are matched to plant owners through Bureau van Dijk firm identifiers for the year 2005. I use fixed assets data from 2005 for two reasons: first, it ensures that fixed assets are measured pre-treatment (the foreign ownership variable is based on 2006 ownership information); second, 2005 is the year before permit allocation decisions were made, which alleviates concerns about reverse causality. Emissions data are totals from the 2005-2007 pilot period to smoothen the impact of potential outlier years.

This measure comes with strengths and weaknesses. Its strength clearly is that it allows controlling for variation in plant-level fixed assets, which offers reassurance of the robustness of the main results (especially in addition to the maybe more convincing strategy of within-firm matching at the 4-digit NACE level). Its weakness, however, is its *assumption* that plant-level fixed assets are proportional to firm-level fixed assets, with a proportionality factor equal to the relative share of emissions. While the validity of the assumption can undoubtedly be questioned, it may very likely hold in some sectors, such as power generation, for instance, where larger facilities and hence larger fixed assets tend to translate into correspondingly larger emissions, especially when differences in efficiency across plants may not vary much within the same firm.

In any case, re-estimating the models from the main paper with the plant-level fixed assets control added provides a strong test as it controls for another potential confounder at the plant-level. Table E1 shows that sample sizes reduce by roughly a quarter, but results continue to be statistically significant for models (2) and (3) when sector-level fixed effects are included in the specification. Relative to the main text, marginal effects attenuate somewhat, but remain substantively strong. The plant-level fixed assets measure is negative as expected, but never attains standard levels of statistical significance.

TABLE E1: Effect of foreign plant ownership on favorable regulation

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	7.2%	9.0%	10.9%
95% CI	[−1.7%, 16.9%]	[0.1%, 18.7%]	[1.5%, 21.1%]
Countries	21	21	21
Sectors	—	8	8
Firms	122	122	95
Observations	1438	1438	1021

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls; *a measure for plant-level fixed assets is also included*. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

F Headquarters Operations

The argument presented in this paper is that domestically-owned plants (within the same firm) are less mobile than foreign-owned ones. This decreased mobility translates into less credible relocation threats and hence less preferential treatment in EU carbon regulation. One potential confounder could be that domestic operations would typically include company headquarters which may have much lower carbon emissions and hence a much lower demand for permits under the EU ETS. Headquarters house the executive management, legal and marketing teams, and administrative support, which are all much less carbon-intensive than industrial production.

While this concern is valid in theory, the EU ETS does only regulate industrial sites with substantial carbon emissions. By definition, this excludes headquarters from my analysis. Headquarters operations could only be included in my data in cases where the HQ is co-located with one of the company's production sites. In this case, carbon regulation targets emissions from industrial production, making it unlikely that headquarters operations confound my analysis. However, to rule this possibility out more systematically, I offer two additional tests:

First, I re-estimate the main models for only those plants which fall into the sectoral "Combustion" classification of the EU ETS. This analysis is useful because according to EU ETS rules and regulation, only plants with a total rated thermal input of at least 20MW from burning fuels come under regulation. For comparison, a heating system for a medium-sized residential accommodation has a thermal input of between 25-35kW. The 20MW threshold hence corresponds to a thermal input equal to residential heating from between 600-800 family homes. It is therefore unreasonable to assume that purely operational headquarters without any industrial activity would come across that threshold.

Re-estimating the main models (note that models (1) and (2) now become identical because sector fixed effects cannot be estimated for a single sector), I find statistically significant and substantively strong effects compared to the main models. The point estimates for model (1) are 18.5% [5.4%, 33.2%] (n=1182) and 11.90% [0.4%, 24.8%] (n=730) for model (3).

Second, I use address information from plants and plant owners to identify *potential* headquarters sites. Specifically, I code every plant a potential HQ site for which a plant is located in the same city as the plant owner and they share the same postcode. Consistent with the expectation that should only be few potential headquarters sites be regulated under the EU ETS, I can only identify 25 plants (less than 1%), owned by 15 firms, which might be HQ sites. Since excluding these sites risks biasing results because it selectively excludes domestically-owned plants (hence, making the estimate of within firm contrasts unreliable), I exclude domestically-owned *and* foreign-owned plants of those *firms* some of whose sites might be potential headquarters sites. (When excluding potential HQ plants—rather than firms—, results remain statistically significant and are as follows for the three models: 10.8% [2.0%, 20.3$], n=1766; 13.0% [4.1%, 22.6%], n=1766; and 9.7% [1.5%, 18.5%], n=1211.)

Excluding these plants from my analysis, the results in Table F1 show that point estimates are not only statistically significant across the board, but also become substantively larger. This offers some reassurance that the (in the EU ETS context very unlikely) inclusion of headquarters operations in the category of domestically-owned plants is not driving my results. If anything, excluding potential HQ sites makes my findings only stronger, even though the identification of

HQ sites without exact street information is somewhat speculative.

TABLE F1: Effect of foreign plant ownership on favorable regulation (without potential HQ sites)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	11.8%%	14.1%	20.3%
95% CI	[3.1%, 21.2%]	[5.4%, 23.5%]	[9.9%, 31.6%]
Countries	21	21	21
Sectors	—	9	9
Firms	144	144	119
Observations	1815	1815	1310

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

G Matching Analysis

This section presents descriptive information about covariate balance before and after matching together with tabular results from re-analyzing the main models on the matched data. Matching is implemented with the `MatchIt` package in `R` (Ho et al., 2011).

Table G1 shows that Mahalanobis matching (Rosenbaum, 2002) can help reduce covariate imbalance both in terms of standardized mean differences and the univariate imbalance measure $\mathcal{L}_1$ (Iacus, King, and Porro, 2012). These improvements in balance are achieved when matching on both covariates separately. Simultaneously matching on total allocation *and* total emission variables makes it difficult for the matching algorithm to achieve considerable balance improvements. This is the result of fairly balanced data already before matching due to the focus on multinational companies that are rather homogeneous in their allocation and emission profiles.

TABLE G1: Covariate balance before and after Mahalanobis matching

	Before matching	After matching	Balance improvement (percent)
Matching on total allocation (log) variable			
Standardized mean difference	-0.008	-0.001	83.6%
$\mathcal{L}_1$ measure	0.033	0.014	58.1%
Matching on total emissions (log) variable			
Standardized mean difference	-0.015	-0.004	73.8%
$\mathcal{L}_1$ measure	0.024	0.022	7.2%
Matching on both variables simultaneously			
Standardized mean difference (allocation)	-0.008	-0.007	4.8%
Standardized mean difference (emissions)	-0.015	-0.010	32.8%
$\mathcal{L}_1$ measure (allocation)	0.033	0.020	40.7%
$\mathcal{L}_1$ measure (emissions)	0.024	0.047	-95.4%

Note: The table reports standardized mean differences and univariate imbalance measure $\mathcal{L}_1$ before and after matching alongside balance improvements in percent. The sample size reduces from $n = 1899$ to $n = 1692$, or -11.0%.

Table G2 shows the estimation results for the matched data for three cases: for matching on the total permit allocation variable alone, which increases point estimates by 5% (first two models); for matching on the total emissions variable alone, which increases point estimates by 10% (middle two models); and for matching on both variables at the same time, for which point estimates are virtually identical to those from the main results (final two models).

TABLE G2: Effect of foreign plant ownership on favorable regulation (Mahalanobis matching)

	Matching on total allocation (log)		Matching on total emissions (log)		Matching on both variables	
	w/o sector FEs	full FEs	w/o sector FEs	full FEs	w/o sector FEs	full FEs
	(1)	(2)	(1)	(2)	(1)	(2)
Marginal effect	11.0%	13.4%	11.7%	14.0%	10.3%	11.8%
95% CI	[2.5%, 20.3%]	[4.8%, 22.7%]	[2.6%, 21.6%]	[4.8%, 24.0%]	[1.8%, 19.4%]	[3.3%, 21.0%]
Countries	21	21	21	21	21	21
Sectors	—	9	—	9	—	9
Firms	155	155	159	159	156	156
Observations	1692	1692	1692	1692	1692	1692

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

H Sectoral Mobility Placebo Tests

In the main paper, I argue that variation in plant-level ownership shapes how mobile a firm's operations are. While this mechanism relies on variation within the firm to identify estimated effects, differences in sector-level mobility can serve as an additional plausibility probe. Here, I offer two additional types of tests that support the general expectation of the main argument.

First, I re-estimate the main models for the subset of plants that are involved in power production, as measured by the 2-digit NACE code "35". Electric utilities are typically not very mobile because of the size of fixed assets and the need to be fairly close to their customer base (Edenington, Levinson, and Minier, 2005; Cole, Elliott, and Okubo, 2010). While foreign-owned plants should still be able to extract rents relative to their domestically-owned counterparts, the relative advantage should be attenuated as claims relating to relocation are less credible in less mobile sectors.

Indeed, Table H1 shows that the marginal effects, while still positive, decrease quite considerably in size by between 20%-31% relative to the point estimates in the main models. None of the estimates remain statistically significant at 10% levels. While this is to some extent driven by the reduction in sample size, these results are nonetheless at least indicative of the mechanism I propose.

TABLE H1: Effect of foreign plant ownership on favorable regulation (electricity sector)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	8.4%	8.4%	10.8%
95% CI	[−8.4%, 28.1%]	[−8.4%, 28.2%]	[−10.6%, 37.4%]
Countries	18	18	18
Sectors	—	4	2
Firms	54	54	19
Observations	710	710	494

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

Second, I take advantage of the European Commission's official "leakage list". This list records industries (at the 4-digit NACE level) that are deemed by the Commission to be particularly mobile. In keeping with my core argument, sectors that are included on this list should be able to make more credible relocation threat claims than those not on the list. As highlighted above, while my argument operates at the within firm level, differences between foreign-owned and domestically-owned plants in preferential regulation should be more pronounced in listed sectors than non-listed

ones. Notwithstanding limits in sample sizes, this logic offers another plausibility probe of the central logic of my argument.

The European Commission has been using a leakage list for its third trading period (2013-2020). The first such list was adopted in 2009 (Commission Decision C(2009) 10251), with (ad hoc) additions of sectors in 2011, 2012, and 2013. This first list covered the initial years of 2013/2014 in the third trading period, before an overhauled list has been adopted in 2014 to cover the 2015-2020 years (Commission Decision C(2014) 7809). The political rationale for the introduction of the leakage list was to ensure that sectors affected by carbon leakage (due to a greater ability to move operations and emissions abroad) would receive more permits for free. To cushion the impacts from carbon regulation on firms that face fierce international competition, the leakage list provisions allowed special protection to those sectors for which (i) the introduction of a EU ETS carbon price increased production cost (as a share of value added) of more than 5% *and* for which (ii) trade intensity with non-EU countries was higher than 10%.

For the re-analysis of my main models, I use the second leakage list—adopted in 2014 and valid for the 2015-2020 period—to identify mobile and less mobile sectors. This timing is useful as it almost certainly rules out the possibility that anticipated listings of particular sectors in 2014 could have affected permit allocation in 2006 for the second trading period (2008-2012), which I study. Hence, creating a leakage list inclusion dummy can serve as a valid measure of (politically perceived) mobility in the eyes of the European Commission.

TABLE H2: Effect of foreign plant ownership on favorable regulation (sectors not on leakage list)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	7.6%	8.0%	11.4%
95% CI	[−4.4%, 21.1%]	[−4.1, 21.6%]	[−3.6%, 28.6%]
Countries	19	19	18
Sectors	—	6	5
Firms	90	90	41
Observations	870	870	557

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

Tables H2 and H3 show the results for sectors included on the leakage list and those not included, respectively. Results for plants from listed sectors are largely comparable to those in the main models, expect for model (3), where effects become smaller. All models do produce statistically significant results although the sample size drops by almost one half. For sectors not listed on the leakage list, point estimates drop by at least a quarter and lose statistical significance (even

at the 10% level). While these weaker results may be driven by a loss in statistical power over a much smaller sample size, the combined results are suggestive that threats of relocation may be somewhat less credible in less mobile sectors. Importantly, since my argument draws on variation within the firm (rather than across sectors), these tests can only offer indirect evidence.

TABLE H3: Effect of foreign plant ownership on favorable regulation (sectors on leakage list)

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Marginal effect	11.5%	12.4%	9.2%
95% CI	[0.7%, 23.4%]	[1.7%, 24.2%]	[0.5%, 18.6%]
Countries	21	21	21
Sectors	—	9	9
Firms	127	127	87
Observations	1026	1026	780

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

I Exploratory Sectoral Analysis

Section H above shows that the estimated effects of foreign plant ownership become weaker in less mobile sectors, such as electricity production. As an additional sectoral analysis, I offer exploratory results of the main models here for the paper (NACE 2 code 17, $n = 182$), chemicals (NACE 2 code 20, $n = 243$), and non-metallic minerals (NACE 2 code 23, $n = 656$) industries. Together with plants from electricity production (NACE 2 code 35, $n = 1026$), these sectors jointly account for more than three fourths of all covered plants under the EU ETS.

As can be seen from Table I1, results for neither the paper nor chemical industries are statistically significant. While this is undoubtedly due to small sample sizes, point estimates in model (3) for the paper producing industry is similar in size to the ones from the main models, while those for the chemicals industry remain weaker. This is consistent with evidence that only 90% of plants (23 out of 243) in the sample of the chemicals industry are from sub-sectors included in the EU's leakage list, while this share is 95% for the paper industry (10 plants out of 182). Moreover, chemical production relies heavily on a skilled work force that may reduce the credibility of relocation threats further in these sectors.

For the non-metallic minerals sector, point estimates are statistically significant across all three models and range between 11.1%-14.8%—in fact, they are almost identical to the full sample results in the main paper. Interestingly, this sector includes sub-sectors, such as the manufacture of glass (NACE 2 code 23.1), the manufacture of clay building materials (NACE 2 code 23.3), and the production of cement (NACE 2 code 23.5), all of which are listed on the EU's leakage list. Excluding the residual category (NACE 2 code 23.99), only six plants out of 620 plants in the non-metallic minerals sector, or less than 1%, do *not* receive special regulatory protection over relocation concerns. Following the logic of my argument about credible relocation threats, we would expect strong effects among these plants. And, indeed, this is what I find, corroborating my central claim.

TABLE I1: Effect of foreign plant ownership on favorable regulation

	MNC sample		Matched MNC sample
	w/o sector FEs	full FEs	full FEs
	(1)	(2)	(3)
Paper industry (NACE 2 code 17)			
Marginal effect	4.1%	8.4%	14.2%
95% CI	[−47.2%, 105.3%]	[−45.8%, 116.9%]]	[−43.6%, 131.4%]
Countries	13	13	13
Sectors	—	2	2
Firms	22	22	18
Observations	132	132	119
Chemicals industry (NACE 2 code 20)			
Marginal effect	2.3%	0.8%	1.7%
95% CI	[−22.6%, 35.4%]	[−23.2%, 32.3%]	[−23.1%, 34.4%]
Countries	12	12	10
Sectors	—	4	2
Firms	30	30	15
Observations	129	129	61
Non-metallic minerals industry (NACE 2 code 23)			
Marginal effect	13.0%	14.8%	11.1%
95% CI	[4.2%, 22.6%]	[5.7%, 24.6%]	[3.1%, 19.9%]
Countries	21	21	21
Sectors	—	4	4
Firms	40	40	26
Observations	477	477	391

Note: Table shows marginal effects of foreign plant ownership and 95% confidence intervals (CI) on logged permit allocation. All models include the logged number of permits and emissions from the previous trading period as plant-level controls. Model (1) includes fixed effects (FE) at country and firm level; model (2) additionally includes sector FEs; model (3) includes the full set of fixed effects for a smaller sample that is exact matched on economic activity *within* firms on 4-digit NACE codes. The bottom part of the table includes information on the number of countries, sectors, firms, and total observations for each model. Standard errors are heteroskedasticity robust.

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