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Abstract

This study examines how environmental stringency affects the location decision of foreign direct investments. We analyze a firm-level data set on German outbound FDI and innovate on previous studies by controlling for the mode of entry and applying the mixed-logit analysis. The results show that Greenfield projects react to environmental regulation in a strongly different way than M&As. We find robust support for pollution haven hypothesis for polluting Greenfields. M&A investments in low polluting industries, on the other hand, seem to be attracted by stricter environmental regulation. We introduce a new instrumental variable for environmental stringency and apply it to verify the results.

JEL-Code: F640, Q500, Q580.

Keywords: FDI, environmental stringency, mixed logit, entry mode, PHH.

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1. Introduction

The pollution haven hypothesis (PHH) posits that differences in environmental regulation cause the production of dirty goods to relocate from jurisdictions with stringent standards to more lenient locations. This relocation,if present, should be reflected in changes in the international trade patterns as well in foreign direct investment (FDI) flows from firms that flee highly regulated locations.

Theoretical foundations for the PHH were laid with the help of Heckscher-Ohlin model with pollution as a factor of production. Accordingly, in jurisdictions that provide a low cost of pollution the producers should make intensive use of this factor (Siebert [46], Pethig [41], Markusen et al. [38]).

The models built up at the outset of the PHH literature made rather strong and unequivocal statements about whether the production relocates in response to regulation. Some papers suggested that, given the free mobility across frontiers, even marginal differences in environmental stringencies may induce polluting industries to relocate entirely from high to less regulated economies (McGuire [39]). More recent studies point to the factors that could weaken the pollution haven effect, among others corruption and endogeneity of environmental policy as in Fredriksson et al. [19], small market sizes as in Dong et al. [15] and endogenous market structure as in Elliott and Zhou [16].

If true, the predictions of the PHH have important implications for environmental and trade policies. The carbon leakage and other effects implied by the PHH would render unilateral regulations futile. However, at least when it comes to the FDI channel, the theoretical predictions concerning firm location have gained only mixed empirical support on the macro and micro level.[2]

Notably, early studies like Bartik [6] and Levinson [29], which due to the dearth of international data worked mostly with U.S. new plant locations and performed a cross-section analysis of the aggregated data, were inconclusive about the effect of regulation on FDI flows. The latest studies have brought mixed results. While many studies find support for PHH (e.g. Hanna [21], Wagner and Timminis [50], Kellenberg [27], Xing and Kolstad [51], Chung [10]), a considerable share of the publications indicates a lacking

[2]For a recent study of the influence of environmental regulation on trade see Aichele and Felbermayr [3].

or small impact of the environmental regulation on the investment patterns (Javorcik and Wei [26], Dean [13], and Manderson and Kneller [37]). Some studies point at heterogeneous effects for different types of countries (developed vs. developing) as found by Kheder and Zugravu [28] or different types of investments (vertical vs. horizontal) as shown by Rezza [45]. Finally, Poelhekke and van der Ploeg [43] put forward the idea that in some industries a reputation for sustainable management and corporate social responsibility (CSR) may be more important than avoiding stringent environmental policy ("green haven effect"). Indeed, they were able to corroborate the hypothesis with the empirical finding that highly regulated countries attract FDI in machines, electrical and automotive sectors.

Brunnermeier and Levinson [8] and Dong et al.[15] provide reviews of the empirical publications and comment on the mixed results. A possible explanation for the inconclusive results could be the failure of the literature to sufficiently account for the heterogeneity of the investment which may dilute the effect. Indeed, heterogeneity has been identified as an important factor that makes finding evidence for the PHH difficult in trade studies (Levinson, Taylor [32]). Moreover, Hanna [21] points out that the studies which test on the macro level whether the effect of environmental stringency varies across industries with different pollution intensity could confuse industry specific trends in FDI like recessions or changes in consumers taste with regulation.

We avoid some of the potential problems by analyzing individual location choices. An additional advantage of microdata is that, unlike aggregate FDI flow model, it enables one to focus on individual firms, thus better representing location choices as an individual firms' profit maximization decision. It also allow analyses that are otherwise not possible, such as computing cross elasticities of choosing among alternatives.

Simply looking at individual observations may not be enough without controlling for sources of heterogeneity. It seems to us that distinguishing between the two modes of FDI - Greenfield investments and mergers and acquisitions may be crucial for the sensitivity of FDI towards environmental regulation.

The intuition is that Greenfield projects usually need to obey all the latest environmental requirements whereas M&As involve local firms that usually, due to grandfathering policies, remain unaffected by the latest rules and need to adhere to the older regulations only.

The so-called grandfathering of existing sources of pollution is a quintessential feature of the environmental regulation. Objects in operation at the time of the enactment of new regulatory requirements are usually exempted from these requirements or granted a long time for transformation due to the high cost of adjusting their operations and the need for minimizing the general investment uncertainty. One of the examples comes from the U.S. where under the 1970 amendments to the Clean Air Act, Congress decided to subject new sources of air pollution to stringent pollution control standards while grandfathering preexisting sources, leaving them free of federal regulation. In the course of time, some rules were implemented to regulate which expansions of a grandfathered plant subject it to the newest regulation. Nevertheless, the legislation favoured the object existing before 1970 (Nash and Revesz [40]).

The environmental regulation may also enhance profits of existing producers by restricting access to common property and thus creating a scarcity rent. In general, grandfathering regimes give a competitive advantage to the industries, firms, and regions where the preexisting plants are located. Some quantification of the 'new source bias' is provided by Levinson [30] based on state variation in toxic air pollution regulations in the U.S. and by Ackerman et al. [1] for coal-burning power plants.

Moreover, in the case of an M&A project, the acquisition price may already be a function of the regulation faced by the company as the purchaser of the existing plant is only willing to pay the present discounted value of future profits. This is in analogy to the taxation literature which states that in a high tax country a portion of the tax burden may be capitalized, reducing the acquisition price (Hebous, Ruf and Weichenrieder [23]). Huizinga et al. [25] find similarly that additional international taxation in form of non-resident dividend withholding taxes and home - country corporate income taxation is fully capitalized into takeover premiums implying that the incidence of this taxation is primarily on target-firm shareholders.

Particular regulations may be easier to comply when starting a firm from the scratch. However, we believe that the above listed reasons may overweight those costs and so we expect Greenfield projects to have a significantly higher sensitivity with respect to environmental requirements than M&A investments.

To the best of our knowledge, the distinction between the two modes of entry has not been taken care of in the literature on the effects of environmental regulation on FDI location. List and Co [34] could be seen as an exception here as they explicitly acknowledge the possible problems connected to the grandfathering rules. However, they do not compare the two investment modes but instead confine themselves to Greenfield investments for their estimations. They find evidence that environmental policies matter for multinational corporations' new plant location decisions.

The other problem that we see in the hitherto existing literature using the firm-level data is the potentially inappropriate econometric modeling. The conditional logit approach is by far the most popular one (with some notable exceptions of Poisson regressions, probit and nested logit estimation, e.g. by Dean et. al. [13], propensity score matching estimator model by List et. al. [35] and Millimet et. al. [36], panel data approach [12], difference-in-difference estimation by Chung [10] as well as nonparametric estimation by Henderson and Millimet [24]). The logit, conditional logit and independent probit approaches depend on the underlying independence of irrelevant alternatives (IIA) assumption. The IIA implies that if one alternative became unavailable, the probability of all other alternatives to be chosen would increase proportionally, which strongly restricts the extent to which countries are different substitutes from the point of view of a foreign investor. The nested logit approach overcomes to some extent the problem of rigid substitution patterns, it requires, however, the researcher to identify the nests which are open to subjectivity.

In general, the IIA assumption may be too restrictive, especially in situations where the number of alternatives in the choice set is large, such as in the model of country destination choice for the FDI. A Hausman-McFadden test that we conducted showed inconsistency of the German data with the IIA and made us turn to estimating a mixed logit model in addition to a usual conditional logit model.

Mixed logit (also known as random-parameters logit) generalizes standard logit by allowing taste variations among individuals. It enables one to control for the fact that companies may attach different weights to the location factors which in terms of the model involves replacing the β coefficients in the regression by β_i where the i index refers to the parent company-specific sensitivity towards the covariate. The econometric approach involves estimation of the so-called deep parameters that describe the moments of the distribution of parameters in the population (the number of those parameters depends on the functional form of the distribution function assumed).

Variance in the unobserved customer-specific parameters induces correlation over alternatives in the stochastic portion of utility. Consequently, mixed logit does not exhibit the restrictive substitution and forecasting patterns of standard conditional logit. Additionally, it allows efficient estimation when there are repeated choices by the same decision makers, as it is the case in our application (Revelt, Train [44]).

Our study analyzes additionally the economic significance of the findings by looking at the magnitudes of the marginal effects of environmental regulation.

The observation used are all FDIs that were undertaken from Germany in years 2005-2009. The data was obtained from Microdatabase Direct Investment (MiDi) gathered by the Deutsche Bundesbank in accordance with the provisions of the Foreign Trade and Payments Regulation. MiDi keeps a comprehensive account of all the FDIs where the balance sheet total of the foreign direct investment exceeds 3 million Euro and the obtained voting rights are 10% or more. The data contain industry characteristics of both the investing and the target company. Due to the reliability of the data we can exclude any measurement errors for the FDI choice variable. What is rare among FDI data sets, the German data differentiates between the modes of new entries allowing us to account for the investment heterogeneity discussed above.

Since MiDi contains confidential individual data reports, the use of the database is subject to restrictions; notably, the data may be used only at the premises of the Deutsche Bundesbank.

German investment behavior should be particularly relevant in the PHH context as Germany is one of the largest economies with 10% of the total world exports (Francis [18]) and a share of 5-8% in the world FDIs in the years considered according to UNCTAD data. Chung [10] criticizes utilization of data coming from developed countries in PHH studies on the ground that firms employing clean technologies in response to the domestic environmental regulations, which is usually the case in the industrialized countries, would have less incentive for outward migration. However, we believe that such claims in general do not invalidate the information coming from data on highly developed countries. Looking from Chung's perspective and knowing that Germany belongs to one of the environmentally most regulated economies, we could formulate our question as follows: given that they have green technologies at their disposal, do the firms nevertheless want to use the dirty technologies? Additionally, the approach we take - conditioning the results on firm's decision to go abroad without investigating who and why wants to perform FDI in the first place makes the critique even less germane to our study.

There exist already one study (Wagner and Timminis [50]) that explores German (manufacturing sector) investment decisions on the macro level and finds robust evidence for pollution haven effect for the chemical industry. We believe we can considerably enhance those results by working with individual projects, including more sectors in our analysis and differentiating between modes of entry.

Our main finding is that investors' preferences for environmental laxity depend strongly on both the mode of FDI and the pollution intensity of the sector. Environmental stringency is shown to reduce the probability of investing in a given country for projects in dirty industries with the deterrence effect being much more pronounced in the case of Greenfield projects. For clean investments of M&A type we find evidence that increased environmental requirements may boost the attractiveness of a given location.

The reminder of our paper is split into four parts. Section 2 describes our empirical approach and the data. Section 3 compares the estimation results in different setups to findings in the literature. We also provide some robustness checks, among others we instrument the environmental stringency. Section 4 analyses the economic importance of the findings while Section 5 provides concluding remarks.

2. Methodology and the Data

The theoretical framework of our model is derived from the standard location model for firms establishing a new affiliate in a host country. Like in Head and Mayer [22], we use the partial-equilibrium framework for the equation explaining the determinants of FDI decisions. The parent firms, after having made up their mind concerning the mode of the investment (Greenfield vs. M&A) as well as industry they want to invest in (decisions that we take as given) selects the country for the location of its investment. The only criterion applicable for the decision-making is the expected profit associated with different countries - the firm settles its affiliate there where it expects the profits to be the highest possible.[3] For each investment they select one

[3] Our empirical investigation does not control for reasons for which the firms perform FDI instead of exporting in the first place. We also support no insights into how firms choose the mode of entry and the industry to invest in, even though those desicions may somehow relate to environmental regulations as well. This shortcoming is due to the structure of the data - it contains information on the foreign direct investment only. Similar limitations were met, among others, by Delbecque et.al. [14].

of the 70 countries.[4] The set of potential locations has been determined by the availability of the environmental stringency index and other covariates.[5]

The profit associated with a given location $i = 1, 2 \ldots 70$ for a company making an investment j is a function of country and investment characteristics and gives rise to following probability function of FDI in a given location:

$$Prob(FDI_{ij} = 1) = f(envI_i, Greenfield_j, industry_j, x_{ij}), \qquad (1)$$

where f is some function appropriate for the chosen econometric model, $envI_i$ measures the degree of environmental stringency of the host economy, $Greenfield_j$ is a dummy variable that captures the mode of investment, $industry_j$ describes the qualities of the industry in which the firm is investing and x_{ij} is a vector containing the remaining control variables.

The variable of key interest for our study is the degree of environmental stringency of the host economy. It was a contentious issue in the literature how to compare and capture the level of regulation. Lately, though, more and more publications have used the Stringency of Environmental Regulation Index from the Executive Opinion Survey published annually by the World Economic Forum (WEF). The index reflects the perception of Partner Institutes of the Forum (recognized research institutes, universities, business organizations, and in some cases survey consultancies) of the environmental policy run by different countries.[6] The values of the index range between 1 and 7, where 1 marks lax regulatory standard and 7 indicates a country among the world's most stringent. We employ the policy stringency index in our regressions and interact it with the Environmental Policy Enforcement Index (also from the World Economic Forum) as it was done in Kellenberg [27] and rescale it down by factor 10. A thus-created environmental index may take on values between 0.1 and 4.9. We multiply the policy stringency and enforcement indicators as they are highly correlated and a separate inclusion of both may lead to multicollinearity. Second, we expect a strong

[4] For years 2005-2006 they choose between 69 countries due to the unavailability of data for Saudi Arabia.

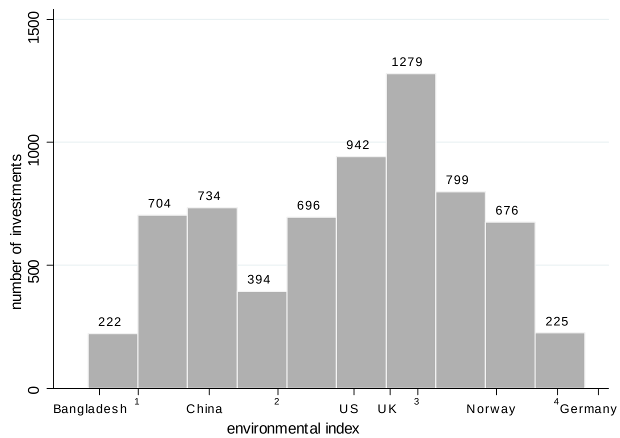
[5] With the resulting collection of countries we cover 94,5% of the investments undertaken by German investors. Some 400 entries had to be dropped, investment in the Cayman Islands constituted there a major group (86 investments).

In the robustness analysis we work additionally with the FDI data for 2009-20011. For those years we manage to gather the covariates for around 120 countries, thus covering around 98,5% of the investments performed.

[6] The merits of using the WEF data are discussed thoroughly by Kellenberg [27].

complementarity between the stringency of rules and the intensity of enforcement that should best be captured by interacting the indexes. Figure 1 plots the number of conducted FDIs against the values of environmental index.

Figure 1: The relationship between the number of investments performed by German firms and environmental regulation of the host countries



Note: As reference the 2009 environmental index of some countries was plotted on the horizontal axis.

Intuitively, highly polluting sectors are more likely to be affected by the regulation than clean ones. Additionally, as we have argued, we expect the investment profits of companies entering the market in form of M&A to be less influenced by the environmental requirements. To account for those effects, we include in our model the interaction of environmental stringency variable with the dummy for the Greenfield investment ($Greenfield_j$) and a variable describing pollution intensity of the sector ($industry_j$). Consequently, the coefficients associated with environmental stringency reflect the effect of the regulation *per se* as well as its influence on the composition of the FDIs flowing into a country.

The $industry_j$ variable was assigned one of the three values: H (high polluting), M (medium polluting) or L (low polluting) depending the sector in which the FDI took place. The assignment of sectors to pollution levels was conducted for manufacturing industries using the German data on the relative pollution abatements costs and the relative green investments completed in 2009 (data taken from Statistisches Bundesamt [47]). To make sure that the data do not reflect some preference of German authorities for particular sectors or lobbying efforts but rather the differences in pollution intensity we cross-checked the resulting classification against computations obtained from the analog U.S. data and found no important differences (U.S. Census Bureau, [49]). For services, the classification relies on the data gathered by Levinson [31]. The classification of the industries is presented in table 9 (in the appendix).

We created dummy variables for each of the manifestations of the industry variable $(lowP, medP, highP)$ and interacted them with dummies for the entry mode $(Greenf, M\&A)$ so that the complete regression estimated reads:

$$\begin{aligned} Prob(FDI_{ij}=1) = \ & f(\alpha + \gamma x_{ij} + \beta_1 envI_i \\ & + \beta_2 envI_i \cdot Greenf_j \cdot lowP_j \\ & + \beta_3 envI_i \cdot Greenf_j \cdot medP_j \\ & + \beta_4 envI_i \cdot Greenf_j \cdot highP_j \\ & + \beta_5 envI_i \cdot M\&A_j \cdot medP_j \\ & + \beta_6 envI_i \cdot M\&A_j \cdot highP_j), \end{aligned}$$

Such a setup allows for nonlinear changes in sensitivity to environmental regulation when altering the pollution footprint of the investment. Individual components of the interaction - industry and entry mode as well as the interactions between them are excluded from the regression as they are unidentified in that framework. Consequently, the β_1 coefficient is to be interpreted as the effect of environmental regulation on the probability of investment for the M&A projects in clean sectors.

As the mixed logit choice probability does not have closed form formulation, simulations need to be performed for the estimations. To assure reasonably low simulation error in the estimated parameters 300 Halton draws were used. Train [48] discusses the efficiency of Halton draws compared to random draws and, among others, concludes that with random draws, the simulation variance decreases at a rate of approximately $1/R$, where R is the number of draws whereas with the Halton draws, the rate of decrease is faster: doubling the number of draws decreases the simulation variance by a factor of about three.

The resource dependent industries, transportation, mining and agriculture were excluded from the study as we expect the locational characteristics to dominate strongly in these areas and lead to a very different hierarchy among the drivers of FDI decisions. We analyzed some 6500 new cross-border projects, out of which 37.5% took the form of Greenfield investments. We disregarded expansions of already existing investments. Most of the analyzed projects were conducted in the low polluting industries (73%), geographically they concentrated in Europe (63%) and the Americas (20%). Expanding the data for it to fit the logit and mixed-logit structure gives in total around 459 000 observations.

The observed location decisions are made by 1892 different companies. On average, a firm in our sample performs 3,5 different investments, with five firms performing over 100 investments. 1071 firms were observed only once in their choice.

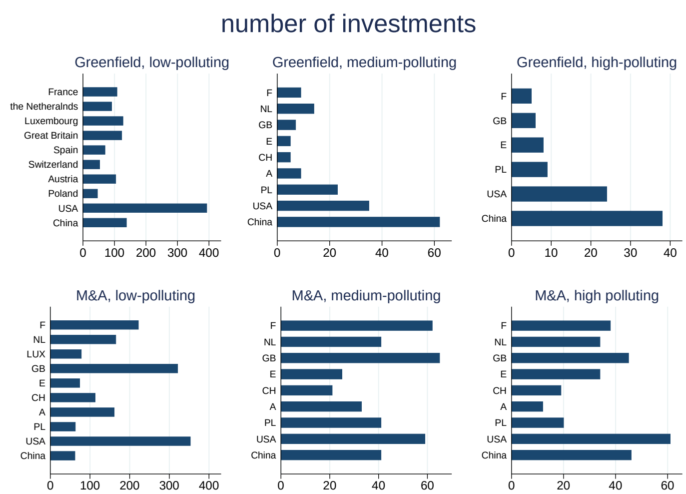


Figure 2: Structure of investments flowing into major host economies.

The distribution of different types of investments between the most important host countries is shown in figure 2. The visual analysis of the figure already seems to reveal some interesting patterns. For instance, while China receives only a small share of clean projects, it is a major host for dirty investments, especially of Greenfield type.

The remaining explanatory variables employed in the main model are typical for the location decision literature: logarithm of GDP per capita (gdp), logarithm of population ($population$), logarithm of the distance to Germany ($distance$), The Heritage Foundation index of corruption freedom

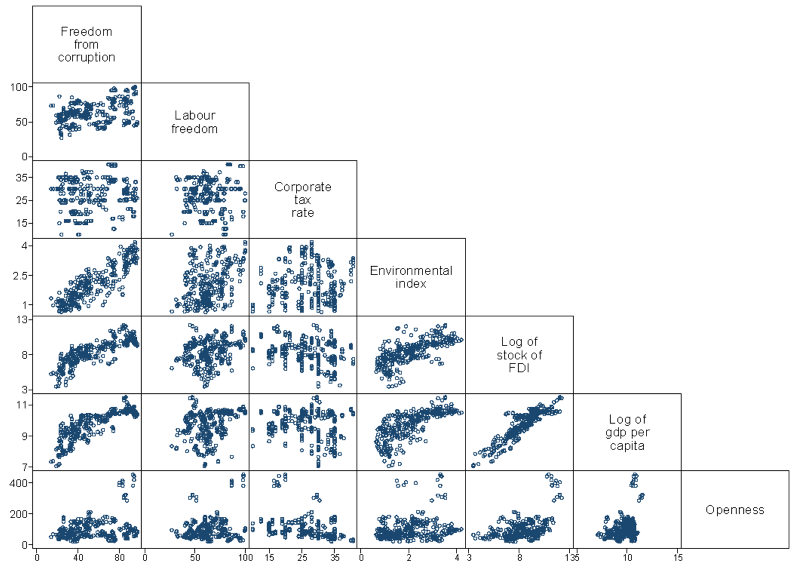


Figure 3: Correlation in the main control variables.

(*corruption fr*) and labor freedom (*labor fr*), the statutory corporate tax rate (*ctax*) and openness (*openness*) measured as ratio of summed imports and exports over the country's GDP. *FDIstock* is measuring the value of the stock of the inward FDIs for a given country (data taken from UNCTAD) and its purpose is to proxy the factor endowments and the agglomeration effects as in Wagner and Timminis [50]. In some specifications we control also for the country fixed effects.

The correlation between major variables is shown in figure 3. The descriptive statistics for the variables are given in table 1 together with information about the data sources.

Importantly, we run the regressions with various other explanatory variables as well. The variables that are included in our preferred regressions presented here were selected on the basis of significance across empirical models or their prevalence in the literature. It should be emphasized that the coefficients of interest (i.e. those reflecting the effects of environmental stringency) proved robust in terms of sign and significance when including (or excluding) additional variables.

For the mixed logit estimations, we assume the coefficients to be inde-

Table 1: Descriptive statistics of the explanatory variables

Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**Source**
Environmental index	1,99	0,93	.416	4,20	WEF
Corporate tax	26,88	7,10	10,00	40,70	Hebous et al. 2011
Openness	99,53	72,50	19,88	453,43	Penn Tables
Freedom from corruption	52,68	16,06	14,00	97,00	Heritage Foundation
Labour freedom	62,97	16,06	14,00	97,00	Heritage Foundation
Log of FDI stock	8,13	1,84	3,44	12,22	UNCTAD
Log of population	9,86	1,64	5,69	11,50	Penn Tables
Log of GDP per capita	9,59	0,96	7,07	11,51	Penn Tables
Log of distance	8,00	1,20	5,15	9,84	CEPII
HDI	0,77	0,12	0,43	0,94	UN
FDI restrictiveness	0,07	0,16	0,00	1,00	OECD

pendently normally distributed.[7]

3. Empirical results

3.1. Estimations

The results are presented in table 2. Since we assume that the coefficients are normally distributed in the population of firms we first report the mean of the coefficients. Stars attached to these coefficients imply whether firms' sensitivity towards a covariate is, on average, different from zero. Secondly, we report the variances of the sensitivity in the population (given in brackets). The variances may be starred as well, indicating whether there is heterogeneity in the population. Insignificant variance implies that every firm reacts in the same way towards a given covariate.

To visualize how using mixed logit affects our prediction compared to the most popular models used in the literature, we report their results in table 3. The structure of that table is analogue to 2 with b representing the linear probability model (LPM), c logit and d conditional logit.

[7] This does not restrict the flexibility of the model in the sense of departure from IIA.

The basic setup (Ia) uses the environmental index ($envI$), but ignores any possible interactions between the environmental regulation and investment characteristics assuming the same sensitivity pattern for all firms. In this simple framework the investors seem to have very mixed attitude towards environmental regime but are on average negligent of it with most of the other coefficients staying in accordance with standard predictions. The insignificance of the corruption freedom ($corruption\ fr$) variable is in contrast to some literature, among others to findings of Fredriksson et. al. [19] Kheder, Zugravu [28] and Kneller, Manderson [37]. Presumably this is due to the fact that our environmental index, part of which derives from the enforcement of the regulation, is correlated with the corruption level of the country just as log of FDI stock is ($FDIstock$). This can be seen in the correlation pattern between the variables shown in figure 3.

In a next step we interacted the environmental stringency index with pollution intensity of the sector (setup IIa, terms $medP\#envI$ and $highP\#envI$) which is the typical specification in the FDI-PHH literature. We notice that sharpened environmental requirements increase the probability of attracting FDI in low polluting industries and reduces the probability for middle and high polluting industries. The coefficients of interest still exhibit significant heterogeneity. The $envI$ coefficient has significantly increased compared to Ia specification, nevertheless, for some 33% of low polluting investments negative weight is placed on the regulatory stringency.

Table 2: Estimation results - mixed logit.

Variable	**Coefficient** (Ia)	**Coefficient** (IIa)	**Coefficient** (IIIa)
envI	.0067	.1645***	.226***
	(.434)***	(.4769)***	(.0016)
ctax	-.0278***	-.0234***	-.0251***
	(.0823)***	(.0797)***	(.0787)***
Greenf # ctax	.007	.0033	.0113**
	(.0508)***	(.099)	(.0405)***
population	.8259***	.8092***	.8697***
	(.4354)***	(.4554)***	(.4508)***
gdp	1.0864***	.9355***	1.089***
	(.5358)***	(.1373)***	(.409)***
openness	-.0003	-.0015***	-.0004
	(.0034)***	(.0038)***	(.0038)***
distance	-.4754***	-.5413***	-.5003***
	(.4545)***	(.4453)***	(.4365)***
corruption fr	.0014	-.0007	-.001
	(.0231)***	(.0274)***	(.0265)***
labor fr	-.0014	-.0014	.00
	(.0206)***	(.0235)***	(.022)***
FDIstock	.174***	.1996***	.1883***
	(.0263)	(.0992)***	(.0949)***
M&A # medP # envI	-	-	-.455***
			(.3494)***
M&A # highP # envI	-	-	-.3079***
			(.5589)***
Greenf #l owP # envI	-	-	-.2298***
			(.7463)***
Greenf # medP # envI	-	-	-.9616***
			(.375)*
Greenf # highP # envI	-	-	-1.0354***
			(.1896)
medP # envI	-	-.5592***	-
		(.3112)***	-
highP # envI	-	-.418***	-
		(.2793)***	-
Log likelihood	-22006	-21904	-21871

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Clustered standard errors at the investing company's level were used. Number of observations: 459267. Number of Halton draws: 300. Coefficients are assumed to be independently normally distributed.

Table 3: Estimation results for linear probability model, logit and conditional logit.

	(Ib)	**(IIb)**	**(IIIb)**	**(Ic)**	**(IIc)**	**(IIIc)**	**(Id)**	**(IId)**	**(IIId)**
	linear	**linear**	**linear**	**logit**	**logit**	**logit**	**cond. logit**	**cond. logit**	**cond. logit**
envI	-.0062***	-.0059***	-.0049***	.014	.0274	.1106**	.0131	.1347**	.2267***
ctax	.0003***	.0003***	.0003***	-.01**	-.0098**	-.0168***	-.019***	-.0184***	-.0207***
Greenf # ctax	.00	.00	.0002***	.0008	.0003	.0191***	.0131*	.012*	.018**
population	.009***	.009***	.009***	.8011***	.8011***	.8021***	.7975***	.8001***	.8017***
gdp	.008***	.008***	.008***	.9285***	.9279***	.9337***	.9533***	.9614***	.9711***
openness	-.00	-.00	-.00	.0021***	.0021***	.0021***	.0021***	.0021***	.0021***
dist	-.0073***	-.0073***	-.0073***	-.3969***	-.3968***	-.3972***	-.3795***	-.3769***	-.3762***
corruption fr	.0003***	.0003***	.0003***	.0014	.0014	.0014	.0005	.0003	.0002
labor fr	.0001***	.0001***	.0001***	.0028	.0028	.0027	.0018	.0017	.0017
FDI stock	.0007	.0007**	.0007	.1172***	.1173***	.117***	.1233***	.1274***	.1286***
M&A # medP # envI	-	-	-.0007***	-	-	-.031***	-	-	-.38***
M&A # highP # envI	-	-	-.0009***	-	-	-.0504***	-	-	-.4239***
Greenf # lowP # envI	-	-	-.0026***	-	-	-.2259***	-	-	-.228***
Greenf # medP # envI	-	-	-.0041***	-	-	-.3125***	-	-	-.9675***
Greenf # highP # envI	-	-	-.0042***	-	-	-.3177***	-	-	-.9596***
medP # envI	-	-.0009***	-	-	-.0433***	-	-	-.4563***	-
highP # envI	-	-.0009***	-	-	-.0529***	-	-	-.4399***	-
(pseudo) R2	.0205	.0205	.0207	.1349	.1351	.1363	.1642	.1675	.1696
Log-likelihood				-29897	-29888	-29848	-23407	-23312	-23253

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Clustered standard errors at the investing company level were used. Number of observations: 459267.

Interestingly, the positive and significant coefficient of $envI$ in IIa suggests that more stringent environmental regulation may increase the attractiveness of a given location in case of low polluting firms. This may be due to the "green effect" reported by Poelhekke and van der Ploeg [43]: some firms that put much weight on the sustainable management image and on corporate social responsibility may want to avoid settling in low regulated regions to prevent potential reputation losses. As their expenses for obeying the regulation are probably low (they are in the low polluting sector) this image boosting does not come at a high cost. There could also be competition for input factors between various sectors. High regulatory standards put the polluters at a competitive disadvantage and may potentially deter them from the market. That, in turn, means for low polluters less competition for inputs, such as land and labour force.

The final specification ($IIIa$) uses interactions between mode of entry and pollution intensity to gauge the effect of environmental stringency. The results suggest that investors' perception of the environmental policy is strongly dependent not only on how polluting the investment sector is, but also on the mode of investment, and the difference is significant. Just by looking at the gap in magnitudes of coefficients of interest for Greenfield investments as compared to M&A (e.g. $Greenf\#highP\#envI$ vs. $M\&A\#highP\#envI$) one may assume that the two investment types exhibit structurally different sensitivity towards the environmental regulation. For the medium polluting and high polluting industries the interaction coefficients for the Greenfield investments were 2-3 times higher in absolute terms but pointing in the same direction (negative). At the same time the respective sensitivity of the clean M&A projects was positive.

Introducing the interaction terms leads to the standard deviation of the environmental index coefficient $envI$ becoming insignificant. It means that we are thereby able to capture an important part of the heterogeneity in the tastes. Likewise, the standard deviation of the $Greenf\#highP\#envI$ coefficient is statistically insignificant meaning that all pollution intensive Greenfield investments respond in a similar, negative manner to environmental regulation.

Considerable variability in tastes can still be observed for the Greenfield projects in clean industries. As for mergers in highly polluting sectors, around 30% of the firms exhibit positive value of the coefficient, which corroborates our intuition that M&A are very different from Greenfields when it comes to pollution regulation. There are probably other firm and sector characteristics that drive up the variability of sensitivity towards environmental regulation, like the extent of grandfathering, technology used and R&D spending but that could not be controlled for as our information on parent characteristics is limited.

The magnitudes of the estimated standard deviations relative to the estimated means are important for some other variables as well. For example, the very pronounced heterogeneity in the responses towards taxation (37.5% of the companies having a positive *ctax* coefficient) seems to mirror how differently the profits of various companies are affected by the corporate tax rates and point towards individual issues like tax holidays or possibilities of transfer pricing which are not observed by the researcher. Note that the standard logit model conceals this effect: its slightly negative coefficient for the corporate tax variable would be interpreted as companies shunning high-taxation countries whereas in reality the picture may be more complicated.

The results from the "traditional" regressions reported in the table 3 are congruent to a great extent with the findings from the mixed logit model[8]. When comparing the coefficients from conditional logit and random-parameters logit, we notice that most of them are even of similar magnitudes. The major differences appear for coefficients with relatively high estimated standard deviations. Furthermore, openness loses its significance in the mixed logit model. However, based on the likelihood-ratio tests, the likelihood values of all the mixed logit models are statistically different from their conditional logit counterparts. In other words, allowing the parameters to vary across individual decision makers significantly improves the fit of the model.

In all the estimated models the coefficients for medium polluting and heavy polluting industries are not statistically different from each other. This could be due to some underlying threshold of pollution footprint above which the firms become concerned about the regulation. It could be also that our classification of industries into different polluting categories had some measurement problems.

[8] An exception is the linear probability model that always predicts negative and significant (at 1 or 5% level) sign of of *envI*. The interaction terms in LPM exhibit monotonicity similar to that obtained in other models. However, when observation spam is increased to 2011, LPM yields the implausible result that GDP has negative effect on FDI and that population does not influence the location decision. In general, we deem LPM inferior to other models used in the paper and present its results for completeness only.

To ensure that the above described monotonicity in environmental coefficients is not just some artifact of using interaction terms in nonlinear models, we investigated the marginal effects and were able to confirm our statements. The details of this approach are described in section 3.2.

3.2. Marginal Effects

The effect the regulation exerts on different types of investments is easily recognizable with the linear model where the deterrence effect clearly increases with the pollution intensity and rises correspondingly for Greenfield FDIs. However, with the nonlinear probability models the interpretation of the coefficients and their comparison is potentially deceptive. We should also stress the problem of assessing the significance of interaction effects in such models pointed out by Ai and Norton [2]. Therefore, to be able to draw precise conclusions on the impact of the pollution prevention on the investment decision, we simulate the marginal effects of environmental stringency - the change in the probability of choosing a particular country when the environmental stringency increases for that country (and remains unchanged in all the other locations). We calculate marginal effects for individuals, average marginal effects (AME) and average conditional marginal effects (CME) of environmental regulation, where CME is defined to be the AME within a certain group of investments (e.g., CME Greenf. medium is the average marginal effect for the Greenfield investments in medium polluting sectors).

The results for all the econometric models used are shown in table 4. All industries but the clean ones are on average negatively affected by the regulation and the difference in responsiveness of medium polluting investments as compared to the dirty ones is a rather tenuous one. However, the policy impact is much more pronounced for the Greenfield investments. The clean M&A projects are allured by the increased stringency, for clean Greenfields we observe no significant effects.

Evidence for the pollution haven effect is found in the form of the CME for Greenfield investments in medium and highly polluting sectors – a unit increase in the environmental index lowers the probability of investment by one percentage point. On the other hand, positive CME for M&A in clean sectors implies that such investments tend to be attracted to highly regulated locations. This may be due to the reasons we discussed before (the reputation for sustainable management and corporate social responsibility, competition for local input resources and deterrence effect of changes in environmental stringency on polluting sectors). However, once we differentiate between the modes of entry, a new dimension of the competitive advantage occurs. In the case when an existing firm is acquired the investor does not have to fear the instantaneous influence of increased environmental requirements on his operating processes due to the grandfathering rules. The changed regulation will, however, apply to all the companies freshly entering the market, driving the cost wedge between the new units and existing ones. As Gruenspecht [20] points out, that bias against new sources in regulation reduces investment in new facilities and lengthens the economic lifetime of old ones. This effect sustains the longer, the lower the rates of physical deterioration and technical obsolescence in the industry with grandfathering rules. Buchanan and Tullock [9] argue that whenever grandfathering encompasses some assignment of quotas to existing firms, excess profits may even result in the short term.

Allurement impact is especially visible for the low polluting industries as, we believe, for more pollution intensive sectors the fact that some adjustments need to be done to comply with the altered regulations in the long run prevails over the advantages.

This positive effect, albeit relatively small in magnitude, points to the fact that environmental policy has a bearing on the composition of inflowing FDI.

Imposing the sensitivity of the investments reaction to the environmental regulation to be the same for all the firms blurs the effect. This is reflected in the fact that the unconditional average marginal effect (AME) in the nonlinear models is insignificant.

Table 4: Marginal effects and conditional marginal effects of environmental stringency and their significance in different setups.

	AME	p>|t|	CME Greenf. low poll.	p>|t|	CME Greenf. medium poll.	p>|t|	CME Greenf. high poll.	p>|t|	CME M&A low poll.	p>|t|	CME M&A medium poll.	p>|t|	CME M&A high poll.	p>|t|
setup IIIa	.0001	.99	-.0001	0.924	-.0094	.00	-.0105	.00	.0029	.00	-.0029	.008	-.0014	.355
mixed logit	(.0008)		. (00105)		(.00151)		(.00211)		(.00084)		(.00108)		(.00151)	
setup IIIb	-.00615	.000	-.00752	.000	-.00903	.00	-.00909	.00	-.00492	.00	-.00564	.00	-.0058	.00
linear	(.0008)		(.00)		(.00)		(.00)		(.00)		(.00)		(.00)	
setup IIIc	.00019	.789	-.00163	.043	-.00233	.001	-.0024	.001	.00156	.049	.0001	.169	.00077	.302
logit	(.0007)		(.0008)		(.0007)		(.00071)		(.00079)		(.00746)		(.00075)	
setup IIId	.0002	.917	-.00002	.924	-.01036	.00	-.01024	.00	.00314	.156	-.00214	.294	-.00275	.226
cond.logit	(.00199)		(.00194)		(.00191)		(.00212)		(.00222)		(.00202)		(.00226)	

Note: Standard errors of the estimates are given in brackets. In case of logit and conditional logit models, the errors were calculated using the delta method, for the mixed logit they were bootstrapped using 229 repetitions.

The heterogeneity of responses in various groups is illustrated by figure 5 that plots individual marginal effects versus the probability of investment for mixed logit. Particularly salient is the wide spread in marginal efects of regulation for the Greenfield projects in the low polluting sectors. Figure 4 gives an overview on the different responsiveness of particular investment types in the conditional logit.[9] As we have acknowledged when looking at the coefficients, the effect that the environmental regulation exerts on heavy polluting projects is hardly discernible from that exerted on medium polluting investments.

3.3. Robustness checks

Our findings, especially the allurement effect for clean M&As, stay in contrast to most of the literature where it has been claimed that, as summarized by Kheder, Zugravu [28], "all industries have interest to avoid additional costs induced by stricter environmental regulation" as there are no totally "clean" industries.

Such statements were made mostly in publications which investigated the manufacturing sectors only. One could therefore expect our contradictory finding to be due to inclusion of services in our analysis, especially that the share of investment in services in the clean M&As in our sample is abve 80%. To check whether this is indeed the reason, we reestimated our models using manufacturing projects only. The *envI* coefficient remained positive and significant (.3317*** and .5088*** in logit and conditional logit correspondingly) and the significance level of the corresponding CME improves in conditional logit from 15.6% to 7% upon the exclusion of investments in services. This seems to reinforce that stricter environmental regulation may be a bait for certain types of FDI and that even if no "totally clean" sectors exist, the pollution environmental costs may be outweighed by the competitive aspects of pollution stringency.

[9] The graphs plot the individual marginal effects against the investment probability for the conditional logit specification. The values of the marginal effects are given by: $p(1-p)(\beta_{1i}+\beta_{di})$, where β_{di} is the coefficient assigned to the appropriate dummies. For the conditional logit case the coefficients are constant across individual firms ($\beta_{ji}=\beta_{ji}$ $\forall i$, $j=\{1,d\}$). Additionally, the estimated probabilities of investments are relatively low (the highest being 0.14), so the CMEs in the conditional logit seem to be linear functions of probability.

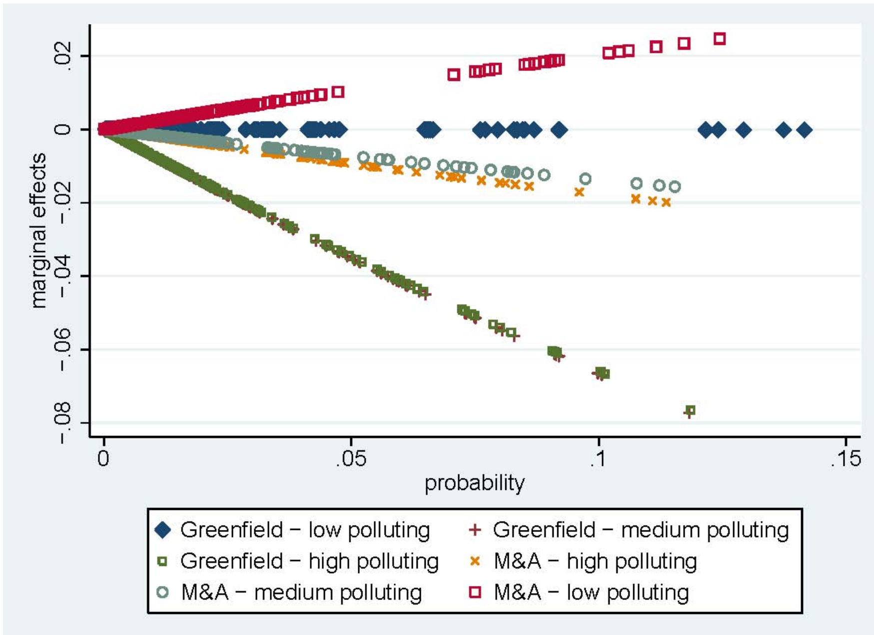


Figure 4: Individual marginal effects of environmental stringency in conditional logit setup.

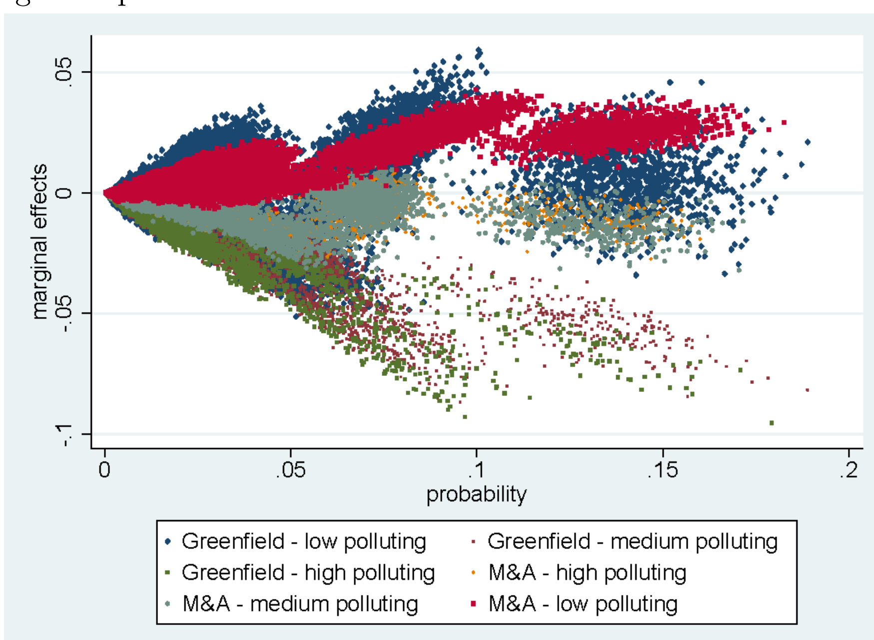


Figure 5: Individual marginal effects of environmental stringency in mixed logit setup.

To assure the robustness of our results we perform several additional estimations.

Firstly, we explicitly explore the panel character of the data with fixed effects logit model. We also investigate spatial effects in conditional logit model by introducing spatially weighted exogenous variables to cap the third country effects like in Baltagi et al. [5] but without allowing for spatial autocorrelation in the error term.[10] Countries used for weighting are the ones belonging to the same region where the region classification is taken from the World Bank.

In different specifications we employ various combinations of additional controls: continent dummies to (explicitly) mimic the nested choice structure, tariffs and number of documents necessary for imports/exports to proxy for trade costs of the host countries, index of FDI Restrictiveness Index prepared by OECD to proxy the investment costs, share of high-tech exports/ R&D in GDP, HDI/share of population with tertiary education to proxy for quality of labour force, exchange rates, GDP growth, exchange rate and inflation. We also check for "announcement effect" - the impact of the announced future environmental policies that we try to capture by adding variable lagged environmental index ($envI_{t-1}$).

The additional estimation results are available on request.[11]

In all the cases we observe some changes in the magnitudes of coefficients and their significance level. Nevertheless, the previously discussed economic insights concerning the responsiveness towards environmental policy remained (roughly) robust throughout the different specifications.

[10] Spatial autocorrelation would account for the transmission of shocks across host countries. Blonigen et al. [7] conclude, however, that the estimated relationships of traditional determinants of FDI are highly robust to the inclusion of terms to capture spatial interdependence. They also find little evidence of spatial errors in the data. Importantly, they emphasize that spatially-treated error structure is of secondary interest as it does not affect point estimates.

[11] Most of the robustness checks were performed for the LPM, logit and conditional logit only. The great computational power and long estimating time required rendered running mixed logit estimations for all the robustness checks infeasible. However, for all the regressions that we did perform with both mixed logit and its conditional logit counterpart, the estimates (and the conclusions concernig the environmental stringency) behaved similarly which gave us confidence in using the conditional logit for robustness testing.

3.4. Endogeneity issues

Starting with Cole et al. [11] the question of endogeneity of the environmental stringency has been permeating the FDI-PHH literature. Some studies, among others Cole [12] and Kellenberg [27], show that, once the endogeneity is accounted for, the deterrence effect of the environmental policy becomes much more pronounced implying a potential positive bias.

A coarse way to deal with that potential vice of our study could be inclusion of country level fixed effects. Table 5 presents the new coefficients on environmental stringency in the case of logit (IIIc) and conditional logit (IIId). Due to the short time dimension and the relatively small year to year changes in many policy variables, many of the coefficients lose significance.

The results give some (weak) evidence for no omitted variable bias for environmental stringency in our study but tells nothing about the potential reversed causality or measurement errors.

Table 5: Coefficient on environmental stringency for (IIIc) and (IIId) specifications when using country-fixed effects.

	(IIIc) **logit**	**(IIId)** **cond. logit**
envI	.1263	.1963**
M&A # medP # envI	-.0381***	-.3807***
M&A # highP # envI	-.0484***	-.4334***
Greenf # lowP # envI	-.2169***	-.2217***
Greenf # medP # envI	-.3111***	-.9766***
Greenf # highP # envI	-.3112***	-.9768***
(pseudo) R2	.1516	.1926
Log-likelihood	-29153	-22610

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Clustered standard errors at the investing company level were used.

In our second attempt to handle the endogeneity problem we employ a control function (CF) approach by using "external pressure on environmental regulation" (*ext_pressure*) as an instrument. We construct *ext_pressure* as a weighted average of the regulation level in the countries that import the goods produced by a given country. The weights correspond to the shares of the partner countries in total exports. This reflects the expectation that the partner countries exert pressure on the exporters in case the exporters' environmental regulation is lenient compared to the regulation of importing partner. The pressure could come from consumer groups, importing companies protecting their "responsible" image or from legislation imposing certain requirements on the imported goods. To avoid any connection between our instrument and the FDI decision, we leave out Germany in constructing the variable[12].

Table 6: Estimation results for the first stage of CF approach - regression of environemntal stringency *envI*.

	linear
ext_press	.2879***
ctax	.0026***
Greenf # ctax	.0001
population	.0152
gdp	.245***
openness	.0009**
dist	-.1618***
corruption fr	.0346***
labor fr	.003*
FDI stock	- .2363***
M&A # medP # ext_press	-.0027
M&A # highP # ext_press	.0076***
Greenf # lowP # ext_press	-.001
Greenf # medP # ext_press	-.0013
Greenf # highP # ext_press	-.0036*
R2	.8354
F(15,333)	.160.19

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Clustered standard errors at the country-year level were used. Number of clusters: 715.

The control function approach has some limitations compared to two-

[12] Median country shipped 2,7% of its exports to Germany, mean country 5,5%; Germany was the crucial importer for some Central European countries (Czech Republic, Poland and Hungary) and Luxemburg with maximum export share of 33%.

stage least squares. In particular, it requires the first-stage model to be correctly specified and the exactly right set of instruments to be found for the consistency of the estimators (Lewbel et al., [33]). On the other hand, we believe that what makes the relationships we study particularly interesting, the control function allows us to keep the (potential) non-linearities and the heterogeneity of the tastes of the companies in our study. Conversly, this would be difficult with 2SLS.[13].

Additionally, we are encouraged to the usage of the method by its successful application in many areas, for example in estimation of demand for differentiated products (see, e.g. Ferreira [17]).

Our implementation of control function approach follows Petrin and Train [42] with bootstrapped standard errors of the coefficients of the residual in the second stage.

The first stage is reported in table 6 (t-value of *ext_pressure* is 3.92), its implementation for logit (IIIc) and conditional logit (IIId) in table 7. The regression results point to the fact that endogeneity may not be a problem in our study in the first place. As reported in table 7, when the residual from the first stage is used in the second stage it fails to be a significant predictor of the firms' behaviour at conventional levels. This seems to support our previous findings[14].

This being said, instrumenting the environmental stringency makes *envI* lose its significance. If interpreted as the the result of some weak endogeneity, this suggest that the endogeneity may conceal some of the negative effects of the regulation, i.e. the true effect of environmental stringency may be more negative than reported in the previous chapters. At the same time, the effect of environmental regulation at clean mergers and acquisitions is never negative. The main object of our interest - difference between M&A and

[13] Estimating linear 2SLS corresponds to estimation of a linear probability model with instrumental variables and, as explained before, LPM is not of central interest for us. Additionally, with 2SLS not only the environmental stringency needs to be instrumented but also all nonlinear functions of it, which in our case are five interaction terms. When applying this procedure, the first stage turns largely insignificant.

An idea of combining a linear first stage regression with a simplified logit model on the second stage is not appropriate (Angrist and Pischke, p. 192, [4]).

[14] We implemented also other instrumental variables used in the literature. Population density and infant mortality turned out to be insignificant in the first stage. Using lagged environmental stringency, on the other hand, gave results very similar to those described above.

Greenfield is preserved, the same holds true for "monotonicity" of estimated coefficients in the pollution-intensiveness.

Table 7: Second stage of control function estimation of investment decision - logit and conditional logit model

	(IIIc) **logit**	**(IIId)** **cond. logit**
resid	-.39	-.2332
envI	.518*	.4873
ctax	-.0209***	-.0242***
Greenf # ctax	.0191***	.0179***
population	.8001***	.8022***
gdp	.9351***	1.005***
openness	.002***	.0021***
dist	-.3114***	-.3183***
corruption fr	-.0137	-.0095
labor fr	.0001	-.0004
FDI stock	.1806**	.1538
M&A # medP # envI	-.0296**	-.3665***
M&A # highP # envI	-.0536***	-.4179***
Greenf # lowP # envI	-226***	-.2264***
Greenf # medP # envI	-.3137***	- .9667***
Greenf # highP # envI	-.3149***	-.9405***
(pseudo) R2	.1753	.1679
Log-likelihood	-43551	-22948

Note: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Clustered standard errors at the investing company level were used. Number of observations: 958798.

4. Economic importance of the results and policy implications

The PHH presumes environmental stringency to be a main location determinant for polluting industries. To make a point here, we compare the marginal effects of environmental stringency to the marginal effects associated with the variables corporate tax, gdp per capita and stock of FDI which have been shown to be important location factors in the FDI literature. We perform this exercise for various countries. The marginal effects are determined by all the independent variables at the same time therefore comparison of several countries allows us to fully explore the relative importance of environmental policy. We concentrated on US, France, China and UK, which are vital hosts for German foreign investments as shown in figure 2 but are quite diverse in terms of their environmental policy, openness, taxation etc.

Table 8 reports some of the results for *IIIa, IIIc* and *IIId* specifications (logit, conditional logit and mixed logit models with all the interaction terms). For every location, the AMEs of environmental stringency and corporate tax calculated for this particular location are reported on the left side of the table, together with the CMEs. In our search for evidence for PHH we decided to concentrate on dirty Greenfield projects as from the previous analysis we know that dirty M&A investment do not react strongly to environmental regulation. For illustration of the supposed allurement effect of environmental legislation we also provide the results for clean M&A projects. The investment probabilities are shown as a benchmark to enable the reader assessing the economic importance of the marginal changes in control variables. For example, a unit increase in Chinese environmental index would reduce, *ceteris paribus*, the probability of some German multinational choosing China as a location for its Greenfield project in polluting industry from 8.7% to 3.2% according to the mixed logit model. Analogically, a unit increase in the U.S. corporate tax rate would decline the probability of some multinational choosing U.S. as a location for its clean M&A by 0.2% to 11% according to the conditional logit model.

The fact that calculated marginal effects are much smaller for the corporate tax then environmental policy is partly attributable to the different scales, on which the variables are measured – environmental stringency ranges from 0.4 to 4.2 in our sample whereas tax rates vary from 10 to 40.7. It needs to be reiterated that a unit increase in environmental index of a country marks a major step in the environmental protection (e.g. moving from the environmental regulation stringency of Benin to that of Chile in 2009). To alleviate the problem of incomparability of the marginal effects, we calculated the effect of a one standard deviation change (St. dev. change) of the discussed explanatory variables. The results are also reported in table 6. While the effects of a one standard deviation change of the FDI Stock and GDP per capita are larger than the effect of a one standard deviation change of environmental stringency, the effect of environmental stringency are in the same order of magnitude as tax effects.

Table 8: Importance of the environmental policy changes for selected countries - comparison between countries and different investment types.

		France						U.S.					
		Marginal effects			St. dev. change			Marginal effects			St. dev. change		
setup	Variable	AME	CME Greenf. high	CME M&A low	Average	For Greenf. high	For M&A low	AME	CME Greenf. high	CME M&A low	Average	For Greenf. high	For M&A low
setup IIIc (logit)	envI	.001	-.0119	.008	.0013	-.0101	.0078	.0007	-.0186	.0108	.0011	-.016	.0104
	ctax	-.0007	.0001	-.0012	-.0045	.0009	-.0082	-.0009	.0002	-.0016	-.0061	.0015	-.0111
	gdp per cap	.0657	.0538	.0679	.0918	.0766	.0947	.0929	.0843	.0912	.124	.1143	.1222
	FDI stock	.0082	.0067	.0085	.0166	.0136	.0171	.0116	.0105	.0114	.0232	.0212	.0228
	Probability	.0758	.0611	.0787				.1117	.1001	.1093			
setup IIId (conditional logit)	envI	.0026	-.0354	.0167	.0037	-.0245	.017	.0023	-.0625	.0226	.004	-.0443	.0227
	ctax	-.001	-.0001	-.0015	-.0064	-.0009	-.0102	-.0013	-.0002	-.0021	-.0092	-.0016	-.0139
	gdp per cap	.0686	.0472	.072	.0963	.0692	.1015	.0994	.0832	.0972	.1335	.1145	.1312
	FDI stock	.0091	.0062	.0095	.0184	.0128	.0194	.0131	.011	.0128	.0264	.0223	.0259
	Probability	.0763	.051	.0803				.1155	.0947	.1124			
setup IIIa (mixed logit)	envI	.0052	-.0359	.0148	.0096	-.0246	.0149	.0043	-.0627	.0211	.0046	-.0473	.0206
	ctax	-.0001	.0006	-.0005	.0055	.0102	.0029	.0014	.0023	.0007	.0141	.0214	.0097
	gdp per cap	.0679	.0525	.0729	.1019	.0814	.0109	.1034	.0933	.1068	.1233	.1143	.127
	FDI stock	.0116	.0088	.0125	.0254	.0195	.0271	.017	.0151	.0176	.0346	.0311	.0357
	Probability	.0686	.0505	.0742				.1343	.1132	.1388			
		China						Great Britain					
setup IIIc (logit)	envI	-.0001	-.008	.0037	.0002	-.0068	.0036	.0015	-.0129	.0094	.0018	-.0119	.0098
	ctax	-.0003	.0001	-.0006	.0021	.0006	-.0038	-.0008	.0001	-.0014	-.0008	.0001	-.0013
	gdp per cap	.0342	.0361	.0316	.0502	.0531	.0466	.0748	.0586	.0795	.107	.0861	.1129
	FDI stock	.0043	.0044	.0039	.0087	.0092	.008	.0093	.0073	.0099	.0102	.008	.0109
	Probability	.038	.0402	.035				.0876	.067	.0936			
setup IIId (conditional logit)	envI	-.0024	-.0512	.0061	-.001	-.0358	.0063	.0034	-.0376	.0197	.005	-.0281	.0214
	ctax	-.0004	-.0002	-.0006	-.003	-.0013	-.0037	-.0011	-.0001	-.0018	-.0011	-.0001	-.0017
	gdp per cap	.0349	.0681	.0265	.052	.9623	.0401	.078	.0502	.08449	.113	.0762	.1212
	FDI stock	.0046	.009	.0035	.0095	.0183	.0072	.0103	.0066	.0111	.0113	.0074	.0123
	Probability	.0374	.0756	.0279				.0879	.0545	.0959			
setup IIIa (mixed logit)	envI	-.0068	-.0545	.0086	-.0027	-.0398	.0085	.0055	-.0384	.0163	.011	-.0287	.0176
	ctax	-.0009	-.0007	-.0011	-.0216	.002	-.0039	-.0016	-.0006	-.002	-.0005	.0002	-.0009
	gdp per cap	.0418	.0651	.0359	.0574	.0866	.0503	.0745	.0565	.081	.1142	-.0898	.1231
	FDI stock	.0074	.0116	.0064	.0157	.0244	.0136	.0128	.0094	.0138	.0105	.0112	.0162
	Probability	.055	.0868	.047				.0756	.0551	.0824			

Note: "Probability" gives the calculated probability of a new investment project of a given type locating in the investigated country.

5. Discussion

The policymakers in some of the industrialized countries have been balking at sharpening the environmental requirements for fear of impairing the international competitiveness of the economy and losing workplaces. They tend to support their arguments with predictions of pollution haven hypothesis. However, even though a host of high-quality studies on the PHH has been conducted, its existence is still disputed as the gathered empirical evidence has been mixed.

This paper is an empirical analysis of whether, and if yes, to what extent, the German investment location decisions are sensitive towards the spatial variation of the environmental stringency. Our main contribution has been to distinguish between different modes of entry. Using the information on the German outgoing FDI in 2005-2009 we have shown that the M&A projects respond structurally differently to pollution requirements and that the governments can influence the composition of FDI by setting the environmental standards.

The application of the mixed logit model allowed us to make some potentially insightful statements about the heterogeneity of tastes of the firms that would not be otherwise possible.

Our findings reveal that tightened environmental stringency is an important deterrent for the FDI inflow in case of polluting Greenfield projects. Importantly though, increased restrictiveness of regulation has a positive or neutral effect on the decision of clean M&As locating in a given jurisdiction. This could be due to competitiveness effects associated with grandfathering as well as the "green image" that German firms are trying to keep.

Our result appear to be robust to different specifications.

6. Appendix

Table 9: Classification of the industries according to their pollution intensity

code	industry	poll. clas.	code	industry	poll. clas.
1700	Manufacture of textiles	M	6570	Financial leasing	L
1800	Manufacture of textile products	L	6580	Other financial intermediaries	L
1900	Manufacture of leather, leather products	L	6590	Investment funds	L
2000	Manufacture of wood and wood products	H	6600	Insurance and pension funding,	L
2100	Manufacture of pulp and paper products	H	6700	Activities auxiliary to financial intermediation	L
2200	Publishing, printing and reproduction of recorded media	M	7050	Housing enterprises	M
2300	Manufacture of coke, refined petroleum products etc.	H	7060	Other real estate activities	M
2400	Manufacture of chemicals and chemical products	H	7100	Renting of machinery and equipment without operator	L
2440	Manufacture of pharmaceutical products	M	7200	Computer and related activities	L
2500	Manufacture of rubber and plastic products	M	7300	Research and development	L
2600	Manufacture of other non-metallic mineral products	M	7411	Legal activities	L
2700	Manufacture of basic metals	H	7412	Accounting, book-keeping and auditing activities	L
2800	Manufacture of metal products	M	7413	Market research and public opinion polling	L
2900	Manufacture of machinery and equipment n.e.c.	L	7414	Business and management consultancy activities	L
3000	Manufacture of office machinery and computers	L	7420	Architectural and engineering activities and related technical consultancy	L
3100	Manufacture of electrical machinery and apparatus n.e.c.	L	7430	Technical testing and analysis	M

3200	Manufacture of radio, television and communication equipment and apparatus	L	7440	Advertising	L
3300	Manufacture of medical, precision and optical instruments	L	7450	Labour recruitment and provision of personnel.	L
3400	Manufacture of motor vehicles, trailers and semi-trailers	M	7460	Investigation and security activities	L
3510	Building and repairing of ships and boats	L	7470	Industrial cleaning	L
3520	Manufacture of railed vehicles	L	7480	Miscellaneous business activities n.e.c	L
3530	Manufacture of aircraft and spacecraft	L	7490	Management activities of holding companies	L
3540	Manufacture of motorcycles, bicycles, invalid carriages	L	8000	Education	L
3550	Manufacture of other transport equipment n.e.c.	L	8500	Health and social work	L
3600	Manufacure of furniture, manufacturing n.e.c.	M	9000	Sewage and refuse disposal, sanitations	H
3700	Recycling	H	9100	Activities of other membership organizations.	L
4000	Electricity, gas, steam and hot water supply	H	9210	Motion picture and video activities	L
4100	Collection, purification and distribution of water	H	9220	Radio and television activities	L
4500	Construction sector	M	9230	Other entertainment activities	L
5000	Sale, repair of motor vehicles; retail sale of automotive fuel	L	9240	News agency activities	L
5100	Wholesale trade and commission trade	L	9250	Library, archives, museums, other cultural activities	L
5200	Retail trade, repair of personal goods	L	9260	Sporting activities	L
5500	Hotels and restaurants	L	9270	Other recreational activities	L
6410	Post and telecommunications	M	9300	Other service activities n.e.c	L

References

[1] Frank Ackerman, Bruce Biewald, David White, Tim Woolf, and William Moomaw. Grandfathering and Coal Plant Emissions : the Cost of Cleaning up the Clean Air Act. *Energy Policy*, 27:929–940, 1999.

[2] Chunrong Ai and Edward C. Norton. Interaction Terms in Logit and Probit Models. *Economic Letters*, 80:123–129, 2003.

[3] Rahel Aichele and Gabriel Felbermayr. Kyoto and the Carbon Footprint of Nations. *Journal of Environmental Economics and Management*, 63:336–354, 2012.

[4] Joshua D. Angrist and Jörn Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton, NJ, 2008.

[5] Badi H. Baltagi, Peter Egger, and Michael Pfaffermayr. Estimating Models of Complex FDI: Are There Third-Country Effects? *Journal of Econometrics*, 140:260–281, 2007.

[6] Timothy J. Bartik. The Effects of Environmental Regulation on Business Location in the United States. *Growth and Change*, 19:22–44, 1988.

[7] Bruce A. Blonigen, Ronald B. Davies, Glen R. Waddell, and Helen T. Naughton. FDI in Space: Spatial Autoregressive Relationships in Foreign Direct Investment. *European Economic Review*, 51:1303–1325, 2007.

[8] Smita B Brunnermeier and Arik Levinson. Examining the Evidence on Environmental Regulations and Industry Location. *The Journal of Environment & Development*, 13:6–41, 2004.

[9] James M Buchanan and Gordon Tullock. Polluters' Profts and Political Response: Direct Controls versus Taxes. *The American Economic Review*, 65:139–147, 1975.

[10] Sunghoon Chung. Environmental Regulation and Foreign Direct Investment: Evidence from South Korea. *Journal of Development Economics*, 108:222–236, 2014.

[11] Matthew A Cole, Robert J R Elliott, and Per G Fredriksson. Endogenous Pollution Havens: Does FDI Influence Environmental Regulations? *Scandinavian Journal of Economics*, 108(1):157–178, 2006.

[12] Matthew a. Cole and Per G. Fredriksson. Institutionalized pollution havens. *Ecological Economics*, 68(4):1239–1256, 2009.

[13] Judith M Dean, Mary E Lovely, and Hua Wang. Are Foreign Investors Attracted to Weak Environmental Regulations? Evaluating the Evidence from China. *Journal of Development Economics*, 90:1–13, 2009.

[14] Vincent Delbecque, Isabelle Mejean, and Lise Patreau. Labor Market Institutions and Firms' Location Choices. *Review of World Economics*, 150:115–148, 2014.

[15] Baomin Dong, Jiong Gong, and Xin Zhao. FDI and Environmental Regulation: Pollution Haven or a Race to the Top? *Journal of Regulatory Economics*, 41:216–237, 2012.

[16] Robert J R Elliott and Ying Zhou. Environmental Regulation Induced Foreign Direct Investment. *Environmental and Resource Economics*, 55:141–158, 2013.

[17] Fernando Ferreira. You Can Take It With You: Proposition 13 Tax Benefits, Residential Mobility, and Willingness to Pay for Housing Amenities. *Journal of Public Economics*, 94:661–673, 2010.

[18] Ng Francis. Data on Trade and Import Barriers, Trade Research. Technical report, World Bank, 2011.

[19] Per G. Fredriksson, John A. List, and Daniel L. Millimet. Bureaucratic Corruption, Environmental Policy and Inbound US FDI: Theory and Evidence. *Journal of Public Economics*, 87(7):1407–1430, 2003.

[20] Howard K Gruenspecht. Differentiated Regulation : The Case of Auto Emissions Standards. *The American Economic Review*, 72:328–331, 1982.

[21] Rema Hanna. US Environmental Regulation and FDI: Evidence from a Panel of US-Based Multinational Firms. *Americal Economic Journal: Applied Economics*, 2:158–189, 2010.

[22] Keith Head and Thierry Mayer. The Empirics of Agglomeration and Trade. In J Vernon Henderson and Jacques-François Thisse, editors, *Handbook of Regional and Urban Economics*, volume 4, chapter 59, pages 2609–2669. Elsevier, 1st edition, 2004.

[23] Shafik Hebous, Alfons J Weichenrieder, and Martin Ruf. The Effects of Taxation on the Location Decision of Multinational Firms: M&A vs. Greenfield Investments. *National Tax Journal*, 64:817–838, 2011.

[24] Daniel J. Henderson and Daniel L. Millimet. Notes. Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States: A Nonparametric Reassessment. *The Review of Economics and Statistics*, 89:178–183, 2007.

[25] Harry Huizinga, Johannes Voget, and Wolf Wagner. Who Bears the Burden of International Taxation? Evidence from Cross-Border M&As. *Journal of International Economics*, 88:186–197, 2012.

[26] Beata Javorcik and Shang-Jin Wei. Pollution Havens and Foreign Direct Investment: Dirty Secret or Popular Myth? *The B.E. Journal of Economic Analysis & Policy*, 2:8–40, 2005.

[27] Derek K Kellenberg. An Empirical Investigation of the Pollution Haven Effect with Strategic Environment and Trade Policy. *Journal of International Economics*, 78(2):242–255, 2009.

[28] Sonia Ben Kheder and Natalia Zugravu. Environmental Regulation and French Firms Location Abroad: An Economic Geography Model in an International Comparative Study. *Ecological Economics*, 77:48–61, 2012.

[29] Arik Levinson. Environmental Regulations and Manufacturers' Location Choices: Evidence from the Census of Manufactures. *Journal of Public Economics*, 62:5–29, 1996.

[30] Arik Levinson. Grandfather Regulations, New Source Bias, and State Air Toxics Regulations. *Ecological Economics*, 28:299–311, 1999.

[31] Arik Levinson. Pollution and International Trade in Services. *International Environmental Agreements: Politics, Law and Economics*, 10:93–105, 2010.

[32] Arik Levinson and M. Scott Taylor. Unmasking the Pollution Haven Effect. *International Economic Review*, 49:223–254, 2008.

[33] Arthur Lewbel, Yingying Dong, and T. Tao Yang. Comparing Features of Convenient Estimators for Binary Choice Models with Endogenous Regressors. *Canadian Journal of Economics*, 45:809–829, 2012.

[34] John A. List and Catherine Y. Co. The Effects of Environmental Regulations on Foreign Direct Investment. *Journal of Environmental Economics and Management*, 40:1–20, 2000.

[35] John A. List, W. Warren McHone, and Daniel L. Millimet. Effects of Air Quality Regulation on the Destination Choice of Relocating Plants. *Oxford Economic Papers*, 55:657–678, 2003.

[36] John A. List, Daniel L. Millimet, Per G. Fredriksson, and W. Warren McHone. Effects of Environmental Regulations on Manufacturing Plant Births: Evidence from a Propensity Score Matching Estimator. *The Review of Economics and Statistics*, 85:944–952, 2003.

[37] Edward Manderson and Richard Kneller. Environmental Regulations, Outward FDI and Heterogeneous Firms: Are Countries Used as Pollution Havens? *Environmental and Resource Economics*, 51:317–352, 2011.

[38] James R. Markusen, Edward R. Morey, and Nancy D. Olewiler. Environmental Policy When Market Structure and Plant Locations Are Endogenous. *Journal of Environmental Economics and Management*, 24:69–86, 1993.

[39] Martin C. McGuire. Regulation, Factor Rewards, and International Trade. *Journal of Public Economics*, 17:335–354, 1982.

[40] Jonathan Remy Nash and Richard L. Revesz. Grandfathering and Environmental Regulation: The Law and Economics Of. New Source Review. *Northwestern University Law Review*, 101(4):1677–1734, 2007.

[41] Rüdiger Pethig. Pollution, Welfare, and Environmental Policy in the Theory of Comparative Advantage. *Journal of Environmental Economics and Management*, 2:160–169, 1976.

[42] Amil Petrin and Kenneth Train. A Control Function Approach to Endogeneity in Consumer Choice Models. *Journal of Marketing Research*, 47:3–13, 2009.

[43] Steven Poelhekke and Frederick van der Ploeg. Green Havens and Pollution Havens. *The World Economy*, (Forthcoming), 2014.

[44] David Revelt and Kenneth Train. Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level. *The Review of Economics and Statistics*, 80:647–657, 1998.

[45] Alief A. Rezza. FDI and Pollution Havens: Evidence from the Norwegian Manufacturing Sector. *Ecological Economics*, 90:140–149, 2013.

[46] Horst Siebert. Environmental Protection and International Specialization. *Weltwirtschaftliches Archiv*, 110:494–508, 1974.

[47] Statistisches Bundesamt. Umwelt. Investitionen für den Umweltschutz im Produzierenden Gewerbe 2009. *Fachserie 19*, Reihe 3.1, 2011.

[48] Kenneth Train. Halton Sequences for Mixed Logit. *Econometrics*, (0012002), 2001.

[49] U.S. Census Bureaus. Pollution Abatement Costs and Expenditures: 2005. *Current Industrial Reports*, 200(05), 2008.

[50] Ulrich J. Wagner and Christopher D. Timmins. Agglomeration Effects in Foreign Direct Investment and the Pollution Haven Hypothesis. *Environmental and Resource Economics*, 43:231–256, 2009.

[51] Yuquing Xing and Charles D Kolstad. Do Lax Environmental Regulations Attract Foreign Investment? *Environmental and Resource Economics*, 21:1–22, 2002.