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Environmental regulation and FDI: Mergers and Acquisitions versus Greenfield Investment

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Abstract

This paper investigates the impact of environmental regulation (ER) on foreign direct investment (FDI) location decisions, using a gravity model covering the period 2003–2018. We examine how ER in both origin and destination countries influences bilateral FDI flows, distinguishing between greenfield (GF) investments and cross-border mergers and acquisitions (M&As). To our knowledge, this is the first study of FDI location decisions to jointly analyse the responses of bilateral M&A and GF projects to ER across a large sample of developed and developing countries and manufacturing industries. Overall, we find no consistent evidence supporting either the pollution haven hypothesis (PHH) or the green haven hypothesis (GHH) for total FDI. However, results differ by mode of investment: stricter ER in the origin country encourages outward M&As, but has no significant effect on GF projects. Conversely, ER in host countries appears to exert limited pull effects. Further analysis by sector (clean versus dirty industries) and by country income level reveals important heterogeneity in these effects. For pollution-intensive sectors, tighter regulation in high-income countries is associated with greater outward M&A activity and GF investment directed toward low- and middle-income hosts—an allocation consistent with the PHH. In contrast, in clean industries, GF investment is positively associated with stricter ER in the origin country, lending support to the GHH. Taken together, these results suggest that stricter ER need not deter investment, especially in clean industries or via GF projects; however, in pollution-intensive activities, reallocation through cross-border M&As toward low- and middle-income countries remains a concern.

JEL codes: F21, F64, Q58.
Keywords: Environmental regulation; Foreign Direct Investment; Pollution Haven Hypothesis; Green Haven Hypothesis; Mergers and Acquisitions; Greenfield investments; Gravity model

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1 Introduction

Achieving substantial reductions in greenhouse gas emissions by 2030—one of the central aims embedded in the Sustainable Development Goals—requires, among other instruments, more stringent environmental regulation (ER). A long-standing concern, however, is that tighter regulation in some countries may shift pollution-intensive production abroad rather than reduce it globally (Borghesi et al., 2020). This "carbon leakage" mechanism underlies the pollution haven hypothesis (PHH), according to which differences in regulatory stringency alter the international allocation of polluting activities (Copeland and Taylor, 1994). The PHH emphasizes a push–pull logic: stricter ER in the origin country raises compliance costs and can push firms to relocate, while laxer ER in host countries can pull pollution-intensive investment by offering a cost advantage. Some countries may deliberately adopt less stringent regulation to attract FDI and stimulate short-term economic gains (Ben-David et al., 2021).

Despite the prominence of this concern in policy debates, the empirical evidence on ER and FDI is mixed. Many studies find that, on average, stricter environmental policies do not raise production costs enough to trigger large reallocation effects in aggregate FDI flows; estimated effect sizes are often small or statistically insignificant (Cole et al., 2017). A common interpretation is that environmental compliance costs, while potentially salient in pollution-intensive sectors, are often outweighed by other location fundamentals such as market size, institutions, capabilities and supply chains, meaning that ER changes have limited power to reshape investment patterns.

At the same time, a competing view—the green haven hypothesis (GHH), proposed by Poelhekke and Van der Ploeg (2015)—suggests that stringent ER can attract investment in cleaner activities. According to the GHH, in certain industries—particularly those that are relatively footloose—a strong reputation for sustainable management and corporate social responsibility (CSR) may be more valuable than the ability to avoid strict, well-enforced environmental policies. Taken together, these mechanisms imply that ER does not necessarily operate solely as a push factor for FDI; it may instead act as a pull factor—particularly for clean industries and for firms that prioritize environmental reputation and CSR. Stronger environmental policies can also serve as a signal of regulatory quality and long-term policy credibility (Kim and Rhee, 2019; Kirkpatrick and Shimamoto, 2008; Porter and Linde, 1995).

Climate policy, therefore, creates a potential trade-off for firms between incurring the costs of environmental compliance and strengthening their environmental reputation while operating within a stable regulatory framework. Instead of relocating production abroad to avoid strict regulation, as suggested by the PHH, or relocating to countries with stricter ER to benefit from reputational gains and reduced regulatory risk, as implied by the GHH, firms may choose to invest in green innovations. This approach aligns with the Porter hypothesis (Porter and Linde, 1995), which posits that more stringent environmental policies can stimulate innovation and technological upgrades that improve resource efficiency. Consequently, whether ER deters, attracts, or has no significant effect on FDI remains an open empirical question.

We contribute to the debate by examining how ER shapes FDI separately for mergers and acquisitions (M&As) and greenfield (GF) investment projects in a multi-country framework. We measure ER using the Executive Opinion Survey conducted by the World Economic Forum (WEF), which reports executives' assessments of regulatory stringency and the consistency of enforcement across countries. We combine this measure with bilateral project-level data on cross-border M&A and GF investment. The resulting dataset contains 79,696 FDI projects (54.5% GF) classified into 24 NACE Rev.2 two-digit manufacturing industries. This setting allows us to estimate a gravity model in a way that accounts for multilateral resistance, capturing countries' relative capacity to invest abroad and to attract FDI. The literature has rarely investigated mode heterogeneity, in part because of the limited availability of cross-country data that classify FDI by investment mode. A notable exception is the study by Bialek and Weichenrieder (2021), who use German firm-level data and show that stricter ER in host countries discourages inward GF investment in polluting industries, while effects on M&As are smaller. Our approach differs in that we leverage a multi-origin, multi-destination setting in which ER differences across both origin and host countries matter.

Using our bilateral dataset, we distinguish between clean and dirty industries and allow effects to vary by income levels of origin and destination countries. By so doing, we make three main contributions. First, we provide systematic evidence on how ER relates to investment mode, showing that M&A and GF investment can respond differently to the same regulatory changes. Second, our empirical strategy reduces omitted-variable and endogeneity concerns by exploiting bilateral variation through rich origin- and destination-specific effects and by controlling for multilateral resistance using the two-step strategy proposed by Freeman et al. (2025) for trade. Third, we document heterogeneous responses across sectors with varying pollution intensity and across country income groups, helping to clarify the conditions under which PHH- or GHH-type reallocation pressures are more likely to emerge.

Our findings indicate that, when FDI projects are aggregated, ER has no statistically significant effect on overall inflows or outflows—consistent with much of the existing literature. However, this aggregate conceals substantial heterogeneity. Stricter ER in the origin country is associated with higher outward M&A activity, but has no comparable effect on outward GF investment. Moreover, in pollution-intensive (dirty) industries, both M&A and GF projects tend to shift from high-income origins toward low- and middle-income destinations when high-income countries tighten ER, providing partial support for the PHH. In clean activities, by contrast, GF projects are more likely to remain in—or move toward—countries with relatively stringent ER (particularly within high-income pairs and, in some cases, among low- and middle-income flows), while M&A in clean activities appears largely unresponsive to ER stringency. These patterns are consistent with green haven mechanisms operating through GF investment, alongside pollution haven pressures in dirty activities.

In this paper, we refer to GF investment and cross-border M&As as distinct FDI modes or modes of investment, representing alternative ways in which firms allocate capital across borders. While the term "mode of entry" is commonly used in the literature—especially in firm-level or single-country analyses—we consider it too narrow for our purposes. Our focus is on bilateral FDI flows between multiple source and destination countries, where

GF and M&A projects are viewed not merely as entry strategies, but more broadly as alternative mechanisms through which firms invest, relocate, or expand internationally. Therefore, we adopt the more general terms "FDI modes" or "modes of investment" to better reflect this aggregate, multi-directional perspective.

The remainder of the paper is organized as follows. Section 2 reviews the literature on ER and FDI, highlighting the limited evidence on investment modes. Section 3 presents the empirical framework and identification strategy, and Section 4 the data. Section 5 reports the results and robustness checks. Section 7 concludes with policy implications.

2 ER and FDI: Does the mode of investment matter?

Multinational enterprises (MNEs) have heterogeneous motivations for investing abroad, which vary significantly across sectors, countries, and even among individual firms. FDI may be driven by a range of factors, including the pursuit of efficiency, the acquisition of natural resources or strategic assets, or the desire to access new markets. Accordingly, FDI location decisions involve a trade-off between the relative advantages and disadvantages offered by potential host economies compared to the firm's home country, with ER representing just one of many factors considered.

As discussed above, the PHH posits that firms respond to increasingly stringent environmental policies by relocating production to jurisdictions with more lenient regulations. Viewed through this lens, countries with weaker environmental standards may have a comparative advantage, particularly in pollution-intensive industries (Baumol and Oates, 1988; Pearson, 1987). However, several studies have challenged the underlying assumptions of the PHH. On the one hand, compliance costs associated with stricter environmental policies may not be substantial enough to influence FDI location decisions, especially when compared with other key determinants such as market size, institutional quality, productive capabilities, or supply chain integration. On the other hand, MNEs may actually perceive environmental stringency as beneficial—either because they value environmental reputation and CSR, in line with the GHH (Poelhekke and Van der Ploeg, 2015), or because strict regulation signals a more productive and innovative business environment, as suggested by the Porter hypothesis (Porter and Linde, 1995). Additionally, with rising global demand for environmentally friendly products and services, firms may seek early access to environmentally sensitive consumer markets, which are often located in countries with more stringent environmental standards (Rivera and Oh, 2013). In this line, Kirkpatrick and Shimamoto (2008) find that Japanese FDI tends to be attracted to countries that offer transparent and stable environmental regulatory frameworks, suggesting that the quality of regulation plays a more significant role than stringency in influencing investment decisions. Similarly, recent evidence from Pienknagura (2024) shows that a higher number of climate policies in host countries is associated with increased levels of GF investment. In the same vein, Fourné and Li (2025) find that investors concerned with climate issues allocate more resources to destinations that adopt more stringent climate mitigation policies.

We expect pollution-intensive industries to be more responsive to ER, as they typically face higher abatement costs and thus have stronger incentives to seek more lenient regulatory environments. However, since these industries also tend to be more capital-intensive, they may face higher sunk costs, making them less flexible when it comes to relocating production. Thus, for capital-intensive firms, access to cheaper capital may become a more decisive factor in location decisions than environmental stringency, as explained by various authors who study geographically flexible or "footloose" industries (Cole and Elliott, 2005; Ederington et al., 2005).

In sum, the PHH suggests that FDI would respond positively to greater ER stringency in the home country (as a push factor) and negatively to ER stringency in the host country (as a pull factor). In contrast, the GHH predicts that FDI would respond positively to environmental stringency in the host country. A third potential reaction is that firms adapt to ER through innovation, as proposed by the Porter hypothesis. This is supported by recent empirical findings (Bettarelli et al., 2025; Langinier et al., 2025), which show that stringent policies can stimulate innovation and technological upgrading. These innovations may enhance firm competitiveness by reducing—or even fully offsetting—the costs associated with regulatory compliance (Dechezleprêtre and Sato, 2017).

The controversy and mixed findings in the existing literature about the above-mentioned hypotheses highlight the need for a deeper understanding of how ER affects FDI. This paper aims to fill an important empirical gap, as most prior studies do not examine whether ER has differential effects on distinct modes of FDI. This distinction is crucial, because the determinants of GF and M&A investments differ fundamentally: M&A investment involves the transfer of ownership of existing assets in the host country and is typically more responsive to cross-border barriers between home and host economies. In contrast, GF investment relies on the internal capabilities of multinational firms and tends to be more closely linked to origin-country characteristics, such as technological capabilities and comparative advantage. GF is also more dependent on the firm's own resources and long-term planning, whereas M&A decisions are often more sensitive to short-term fluctuations in the host country. Indeed, many of the upfront costs associated with GF investment are incurred in the origin country during the planning phase (Davies et al., 2018). As a result, GF and M&A investments are expected to exhibit distinct responses to regulatory measures, including changes in ER. For example, Nagano (2013) finds that strengthened intellectual property rights protection in the host country significantly promotes GF investment, but has little effect on M&As. In contrast, stronger shareholder rights protection in the host country tends to influence M&A activity, while leaving GF investment largely unaffected. As Table 1 shows, these distinctions reinforce the importance of analysing the different modes of investment separately when evaluating the effects of ER on FDI.

Table 1: Differences between M&A and GF investments

	M&As	Greenfield investments
Strategy Davies et al. (2018) Ben-David et al. (2021)	MNEs internalize and leverage the existing assets and capabilities of local firms.	MNEs establish new subsidiaries and transfer their own capabilities and resources into the host economy.
Advantages	- Lower upfront investment in physical capital - Lower sunk costs- Faster market entry - Potential to benefit from regulatory grandfathering - Potential for opportunistic acquisitions	- Full control over operations, technology, and organizational culture -Lower volatility
Disadvantages	- Limited control over the acquired firm - Cultural and organizational integration difficulties	- Higher sunk costs (irreversible and long-term commitments) - Longer time to operationalize
Determinants Nocke and Yeaple (2007); Nagano (2013); Davies et al. (2018)	- Influenced by geographic and cultural proximity, trade costs. - More affected by destination-specific factors - More responsive to short-term shocks (e.g., currency crises)	-Less affected by host-country -specific characteristics (e.g., market potential, institutions) - Heavily reliant on firm-specific advantages and home-country knowledge
Regulatory Sensitivity Bialek and Weichenrieder (2021); Nagano (2013)	- Often less sensitive to host regulations due to existing firm structures and grandfathering	- More exposed to regulatory burdens

Note: Authors' own elaboration.

To the best of our knowledge, the only previous study that explicitly considers both modes of FDI—GF and M&A investments—is Bialek and Weichenrieder (2021), which focuses on a single origin country: Germany. The authors find that increased ER stringency in host countries significantly reduces German outward GF investment in pollution-intensive industries, while M&A activity appears much less affected. This difference may be explained by competitiveness effects linked to grandfathering rules, which typically subject only new investments (like GF projects) to the latest environmental standards, while pre-existing plants (often acquired via M&As) continue to operate under older, less stringent regulations. Moreover, in the case of M&As, the price of the target company already incorporates the expected costs of compliance with ER, as these factors are reflected in firm valuation.

Besides Bialek and Weichenrieder (2021), most previous studies do not distinguish between GF and M&A investments, which may partly explain the ambiguous findings. Among the few that do focus on a specific mode, Saussay and Zugravu-Soilita (2023) and Carril-Caccia and Milgram Baleix (2024) examine only M&As, while Pienknagura (2024) focuses exclusively on GF investment. The latter finds that countries with a greater number of active climate policies attract higher levels of green GF FDI (defined as investment in low-carbon activities), with the effect being more pronounced in emerging and developing economies than in advanced ones. Regarding the role of ER in source countries, Pienknagura (2024) reports that a higher number of climate policies is associated with increased non-green outward FDI. This may reflect the fact that climate policies in the source country potentially foster complementarities between green and non-green investments abroad; for instance, emission regulations in high-income countries could encourage firms to invest simultaneously in electric vehicle production (green) and related auto components (non-green).

Carril-Caccia and Milgram Baleix (2024), using a structural gravity model, find that laxer ER attracts more cross-border M&A investment, providing evidence consistent with the PHH. However, they note that the effect is similar across both clean and dirty sectors. Furthermore, they find that ER in emerging countries has a stronger deterrent effect on investors from developed economies than ER in developed countries does. Similarly, Saussay and Zugravu-Soilita (2023) conclude that stringent ER abroad deters cross-border M&As, particularly when the target firm operates in a highly polluting sector, supporting the idea that pollution-intensive industries are more sensitive to cross-country differences in ER.

Other sector-specific studies offer mixed results. For instance, Leon-Gonzalez and Tole (2015), focusing exclusively on M&A activity in the mining sector, find no evidence in support of the PHH. In contrast, Mulatu (2017) reports evidence of a pollution haven effect in the case of aggregate UK outbound FDI.

Finally, previous multi-country studies underscore the importance of differentiating the impact of ER according to the income level of both source and destination countries. This is notably the case in Fourné and Li (2025) and Chiappini and Gerard (2025). The latter finds that stricter ER is associated with a decline in inward FDI, providing support for the PHH. The study shows that this negative effect is more pronounced when the host country is an emerging economy, whereas the impact is significantly weaker in developed host economies. This pattern is consistent with the idea that FDI motivations differ between advanced and developing countries. In low- and middle-income economies, FDI tends to be driven by cost advantages and resource-seeking behaviour. In these contexts, stricter ER may represent an additional burden that investors aim to avoid. In contrast, FDI in high-income countries is more often motivated by market access and strategic considerations, which can compensate for the added costs associated with stringent ER. Thus, the net effect of ER on FDI is likely to vary depending on the host country's level of development.

Table 2 summarizes the main findings of the aforementioned studies. While each makes a valuable contribution to the literature, none explicitly considers that GF and M&A investments may respond differently to changes in ER. Recognizing this distinction is essential for understanding the effectiveness of policies aimed at attracting specific types of FDI. Our paper contributes to this literature by examining the differentiated impact of ER on both GF and M&A investments across a broad sample of countries encompassing both developed and developing economies. In addition, we account for potential heterogeneity in ER effects across clean and dirty industries within the manufacturing sector.

Table 2: Differences between M&As and GF

Study (Reference)	FDI Mode Considered	Sector Focus	Country Coverage	Host/ Source Country ER	Main Findings
Bialek and Weichenrieder (2021)	GF M&A	Polluting industries	Germany (outward FDI)	Host	Stricter ER discourages GF inflows in polluting sectors (PHH); M&A inflows less affected due to grandfathering rules.
Carril-Caccia and Milgram Baleix (2024)	M&A	Clean vs Dirty sectors	Developed vs Emerging	Host	Stringent ER discourages M&As inflows (PHH); stronger negative effect of ER in emerging vs developed countries.
Chiappini and Gerard (2025)	Total FDI	All sectors	Cross-country	Host	Stricter ER reduces inward FDI (PHH); stronger effect in emerging economies and smaller in developed economies. Bilateral FDI shaped by the gap in ER between source and host countries.
Fourné and Li (2025)	Total FDI, Portfolio equity, debt and banking assets	All sectors	Advanced and emerging	Host	International capital tends to gravitate toward destinations with rigorous climate policies. No significant role for the allocation of FDI.
Kim and Rhee (2019)	Total FDI	All sectors	Developing countries	Host	Stringent ER attract FDI. Lack of support for the PHH. Support for the GHH.
Kirkpatrick and Shimamoto (2008)	Total FDI	Dirty industries	Japan	Host	Support for the GHH
Leon-Gonzalez and Tole (2015)	M&A	Mining sector	Global	Host	No evidence for the PHH.
Mulatu (2017)	Total FDI	High-polluting industries	United Kingdom	Host	UK outward FDI shift to countries with laxer ER. Support for the PHH.
Pienknagura (2024)	GF	Green vs Non-Green; Manufacturing & Energy	Global	Host & Source	Greater number of active climate policies at the host country attract higher levels of green GF FDI (especially in emerging and developing economies). Higher number of climate policies in the source are associated with increased non-green outward FDI.
Poelhekke and Van der Ploeg (2015)	Total FDI	High-polluting sectors	Netherland	Host	PHH for the outward FDI in the more traditional capital-intensive industries. GHH for outward FDI in machines, electrical and automative industries
Rivera and Oh (2013)	Total FDI	Clean versus dirty sectors	European MNCs	Host	Support GHH. European MNCs are more likely to enter countries with ER that are more stringent than those of their home countries.
Saussay and Zugravu-Soilita (2023)	M&A	High-polluting sectors	Cross-country	Host	PHH especially in polluting sectors; high sensitivity to ER differences.

Note: Authors' own elaboration.

3 Empirical strategy

The present work relies on the gravity model to study the link between ER and FDI by mode of investment. The basic intuition behind the gravity model is that FDI is positively related with countries' economic mass, and negatively with bilateral transaction costs, often proxied by factors such as geographical distance and language differences. In addition, the gravity model accounts for the capacity a country has, in comparison with the rest of the world, to attract FDI or to engage in outward FDI, namely the multilateral resistance term (MRT).

Although the gravity model, underpinned by the aforementioned intuition, was initially introduced to analyse bilateral trade (Anderson and van Wincoop, 2003; Tinbergen, 1962), it has also been widely used to examine the determinants of bilateral FDI (e.g. Blonigen and Piger, 2014; Bradley et al., 2025; di Giovanni, 2005). In addition, the literature has established theoretical foundations to justify the application of the gravity model to FDI (e.g. Cuadros et al., 2022; Head and Ries, 2008; Kox and Rojas-Romagosa, 2020).

In the present work, we depart from the standard gravity model estimation strategy for FDI in two ways. First, since our focus is on the drivers of FDI by mode of investment, we distinguish between GF and cross-border M&As in the dependent variable. For instance, our dependent variable indicates the number of GF projects from Spain to Argentina and the number of M&As from Spain to Argentina. In this regard, it is important to highlight that most of the previous literature either separately analyses bilateral GF projects and M&As (e.g. Cuadros et al., 2022; di Giovanni, 2005) or considers overall bilateral FDI flows (Blonigen and Piger, 2014). There are, however, some exceptions. For example, using data on outward FDI from Germany, Bialek and Weichenrieder (2021) examine the effect of ER on FDI by mode of investment, while Hebous et al. (2011) investigate how corporate income tax influences the FDI location decision.

Second, we incorporate the MRT into the analysis by adopting the two-step strategy proposed by Freeman et al. (2025) for trade. This is particularly relevant because previous FDI literature has often neglected the time-varying MRT when studying the impact of country-specific variables, such as ER, on countries' ability to attract FDI (e.g. Bialek and Weichenrieder, 2021; Poelhekke and Van der Ploeg, 2015; Saussay and Zugravu-Soilita, 2023). Omitting the MRT from the gravity equation implies neglecting a country's capacity to invest abroad relative to the rest of the world or its ability to attract FDI in comparison to other countries. Additionally, if the analysis does not control for the MRT, potential diversion effects brought about by policy changes may be overlooked. Consequently, the absence of this term can bias the gravity model estimates (Anderson et al., 2019; Bradley et al., 2025; Head and Mayer, 2014).

Although the MRT index proposed by Freeman et al. (2025) lacks a theoretical foundation for FDI, we demonstrate that the omission of the MRT has notable implications for both the significance and magnitude of the estimated coefficients. In addition, we conduct further tests that suggest that the methodology proposed by Freeman et al. (2025) effectively controls for the MRT similarly to the country-year fixed effects that have been commonly used in previous FDI literature (Carril-Caccia and Milgram Baleix, 2024; Cuadros et al., 2022; Kox and Rojas-Romagosa, 2020).[1] Since the main focus of this paper is on the link between ER and FDI by mode of investment, we delegate these tests and the related discussion to Appendix B.

In the following, we first describe the methodology proposed by Freeman et al. (2025) for constructing the indexes that account for the MRT, and then present the empirical model used to analyse the relationship between ER and FDI. It is important to note that this strategy does not address potential endogeneity or reverse causality between FDI and ER. However, our sensitivity analysis includes a series of robustness tests which suggest that these issues are unlikely to constitute a major source of bias in our results.

As in Freeman et al. (2025) and building on the gravity model for FDI (e.g. Kox and Rojas-Romagosa, 2020), we estimate, in a first step, Equation (1) without constant using the Pseudo Poisson Maximum Likelihood (PPML) estimator:

$$FDI_{mijst} = \exp(B_{ij} + B_{ijt} + \lambda_{it} + \lambda_{jt} + \lambda_{st}) \times \varepsilon_{mijst} \tag{1}$$

[1] In the present analysis, we cannot use country-year fixed effects since they are collinear with our main variable of interest; namely, countries' ER.

where FDI_{mijst} is the number of FDI projects by mode (m= GF or M&As) from country i to country j ($i \neq j$) in sector s in year t. B_{ij} is a vector of time-invariant variables that includes the logarithm of bilateral geographical distance, and two indicator variables that indicate if a pair of countries share a border or a language. B_{ijt} is a vector of bilateral time-varying variables which include an indicator variable that takes the value one when the investment is GF (mode), and two indicator variables that take the value one when a country pair has signed a bilateral investment treaty (BIT) or a regional trade agreement (RTA).

The variables included in B_{ij} and B_{ijt} are standard in the FDI literature (Blonigen and Piger, 2014). Due to the higher transaction costs, FDI is generally expected to exhibit an inverse relationship with bilateral distance between countries. In addition, the signing of a BIT may promote FDI by reducing investment-related risks (Bergstrand and Egger, 2013) and RTA can have a positive effect on vertical and export-supporting FDI (Hanson et al., 2005; Krautheim, 2013).

Based on the estimation of Equation (1), we compute the Outward Multilateral Resistance (OMR) and Inward Multilateral Resistance (IMR) terms as follows:

$$\text{OMR}_{it} = \frac{Y_{it}}{\exp(\hat{\lambda}_{it})} \times \frac{Y_0}{Y_t} \tag{2}$$

$$\text{IMR}_{jt} = \frac{Y_{jt}}{\exp(\hat{\lambda}_{jt})} \times \frac{1}{Y_0} \tag{3}$$

where Y_{it} (respectively Y_{jt}) is the GDP of country i (respectively country j) in year t, Y_t is the GDP at world level and Y_0 is the GDP of a reference country (USA in year 2003) used as a numeraire. The choice of the reference country-year has no implications for the results.

OMR_{it} is inversely proportional to all home country time-varying fixed effects ($\hat{\lambda}_{it}$) that promote outward FDI, while IMR_{jt} is inversely proportional to all host country time-varying fixed effects ($\hat{\lambda}_{jt}$) that promote inward FDI. Thus, in the empirical Equation (4) described below, the estimated coefficients for OMR_{it} and IMR_{jt} are expected to be negative.

It is important to note that, ideally, the OMR and IMR indices should also have a sectoral dimension, as the dependent variable does. This is not possible due to data limitations: we would need sector-level production data by country and sector, which, to the best of our knowledge, are not available for our sample. Nevertheless, in Appendix B we provide evidence suggesting that the bias due to not incorporating the sectoral dimension is not large.

In a second step, we estimate Equation (4):

$$\begin{aligned} FDI_{mijst} = \exp(&ER_{it} + ER_{jt} + X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\ &+ \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst} \end{aligned} \tag{4}$$

where the number of FDI projects (FDI_{mijst}) is now explained by ER from the home and host country (ER_{it} and ER_{jt}), the key variables in our analysis constructed as described in section 4.[2] X_{it} and X_{jt} are other country-specific time-varying determinants of bilateral FDI included instead of the origin-year and destination-year fixed effects employed in Equation (1). These variables are GDP, GDP per capita and Rule of law. Accordingly, they account for home and host countries' economic size, wealth and institutional quality. The estimation also considers a vector of bilateral time-varying variables (B_{ijt}) that include the BIT and RTA indicator variables and incorporates the OMR_{it} and IMR_{jt} computed indexes described above.

In Equation (4) the bilateral time-invariant factors are controlled for by directional country pair fixed effects at the sector and mode level (λ_{mijs}). These fixed effects are employed instead of B_{ij} from Equation (1), as they are more likely to provide a closer approximation of the bilateral transaction costs between country pairs at the sector and

[2] We also examined the effect of the difference in ER between the home and host countries. The main conclusions remain unchanged. However, we prefer to assess ER in the origin and destination countries separately in order to better identify where the effect arises. To conserve space, the corresponding estimation results are available upon request.

mode of investment level, thereby reducing the omitted variable bias. In addition, they help reduce the potential endogeneity bias between FDI and bilateral agreements such as RTA or BIT (Baier and Bergstrand, 2007; Bergstrand and Egger, 2007). Equation (4) also includes sector-mode-year fixed effects (λ_{smt}), which control for sector-level global changes over time that may differentially impact GF projects and M&As.

To examine whether the determinants of bilateral M&A and GF investments differ, we interact all the independent variables included in Equation (4) by the indicator variables $M\&A$ and GF, which take the value one when the investment mode is M&A and GF, respectively:

$$\begin{aligned} FDI_{mijst} = \exp(& ER_{it} \times M\&A + ER_{it} \times GF + ER_{jt} \times M\&A + ER_{jt} \times GF \\ & + X_{it} \times M\&A + X_{it} \times GF + X_{jt} \times M\&A + X_{jt} \times GF \\ & + B_{ijt} \times M\&A + B_{ijt} \times GF + ln(OMR_{it}) + ln(IMR_{jt}) \\ & + \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst} \end{aligned} \tag{5}$$

This approach enables us to determine whether GF and M&A investments respond differently to changes in ER. It is important to note that interacting the rest of the independent variables included in Equation (4) by M&A and GF modes allows us to explore the link between FDI by mode of investment and ER, as it ensures that the estimated coefficient associated with ER is not capturing the link between FDI by mode of investment and other variables highly correlated with ER (e.g. the correlation between GDP per capita and ER is 0.73). In addition, this interaction is in line with previous literature that points out that M&A and GF modes have different determinants (e.g. Davies et al., 2018; Nocke and Yeaple, 2007).

Lastly, as noted above, Equations (1), (4) and (5) are estimated with PPML. This estimator overcomes the heteroskedasticity issues from the OLS estimates and allows the zeros usually present in bilateral FDI databases to be incorporated into the analysis (Santos Silva and Tenreyro, 2006). We cluster standard errors by origin, destination, sector and mode level.

4 Data overview

M&As and GF projects

We built a database that covers the FDI projects by mode of investment in the manufacturing sector during the period 2003-2018 from 75 source countries into 105 destination countries. In total, the database comprises 79,696 FDI projects, of which 54.5% are GF. The FDI projects are classified in 24 NACE Rev.2 2-digit manufacturing divisions (which we refer to interchangeably as industries or sectors). Data on M&As are retrieved from LSEG and data on GF projects are obtained from fDi Markets. Both data sources are employed by UNCTAD for describing FDI by mode of investment (UNCTAD, 2015). Consistent with the definition of FDI (OECD, 2008), we focus on all the transactions that affect at least 10% of the ownership of the subsidiary located abroad.

In the present work, we classify countries as high-income or low- and middle-income economies. To this end, we follow the World Bank's 2011 country classification to identify high-income countries, while the rest are considered low- and middle-income (see classification in Table A.1 in Appendix A).[3] Also, we distinguish between dirty and clean industries (see Table A.2 in Appendix A). Following the existing trade and FDI literature (e.g. Brandi et al., 2020; Di Ubaldo and Gasiorek, 2022), industries are classified as clean or dirty based on their abatement costs.

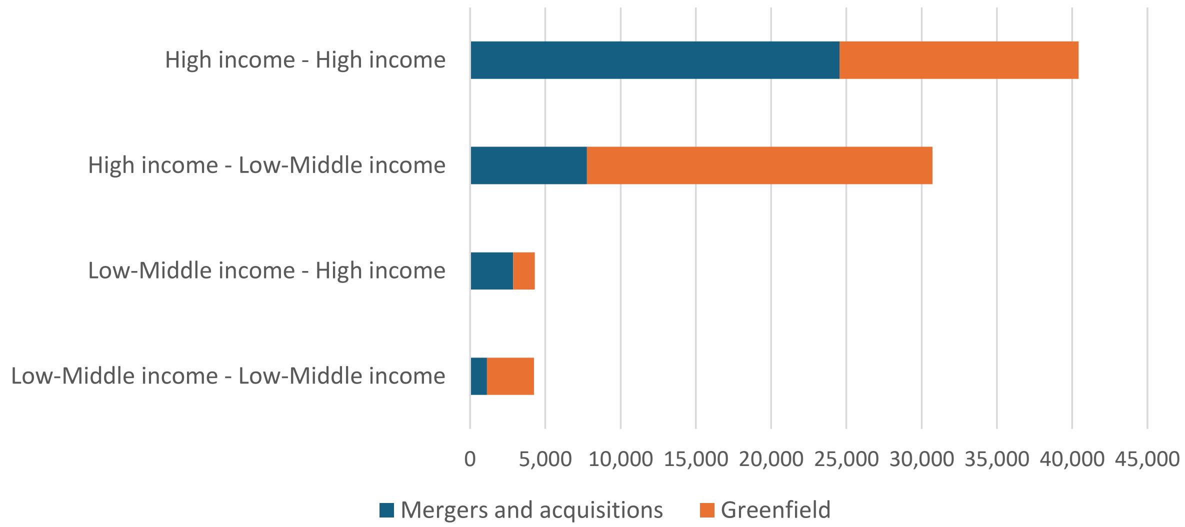
Figures 1 and 2 show the number and share of M&As and GF projects for four origin-destination flows. Not surprisingly, the bulk of the FDI projects originate in high-income countries (almost 9 out of 10 FDI projects). Of these nine projects, five go to other high-income countries, while approximately four go to low- and middle-income countries (Figure 1). There appears to be very little FDI from low- and middle-income countries. GF is the main mode of FDI worldwide (54% of all the FDI projects). However, as illustrated in Figure 2, M&A is the main mode of investment in high-income countries (more than 60% of inward FDI) while GF is the main mode of investment in low- and middle-income countries (more than 70% of inward FDI). High-income countries attract

[3] Accordingly, "low- and middle-income" encompasses the remaining three World Bank categories of low-, lower-middle- and upper-middle-income economies.

56.1% of global FDI.

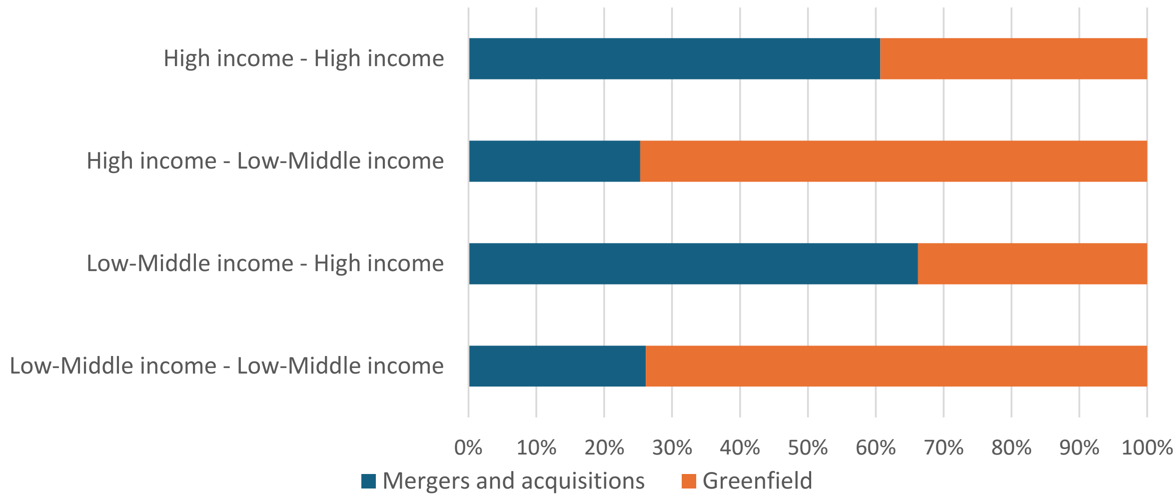
More than two-thirds of FDI projects are concentrated in clean industries, with GF showing a slightly higher share in clean industries compared to M&As (56% versus 51%). FDI projects are highly concentrated in five manufacturing industries, which together account for half of the FDI projects (see Table A.2 in Appendix A): Machinery and equipment; Chemicals and chemical products; Computer, electronic and optical products; Food products; Rubber and plastic products. Of these five industries, the most polluting is Chemicals and chemical products.

Figure 1: Number of M&As and GF projects by origin-destination income level (2003-2018)



Note: Authors' own elaboration based on data on M&A and GF investments in the manufacturing sector retrieved from LSEG and fDi Markets, respectively. Countries' income is classified according to the World Bank's 2011 country classification.

Figure 2: Shares of M&As and GF projects by origin-destination income level



Note: Authors' own elaboration based on data on M&A and GF investments in the manufacturing sector retrieved from LSEG and fDi Markets, respectively. Countries' income is classified according to the World Bank's 2011 country classification.

Environmental policy

To measure countries' environmental policy stringency, we use the WEF Executive Opinion Survey. This survey includes two different questions posed to business CEOs in several countries around the world about the stringency and enforcement of ER:

- Stringency of ER is measured using the question "How do you assess the stringency of overall ER in your country: (1=lax compared with most other countries, 7= among the world's most stringent)"

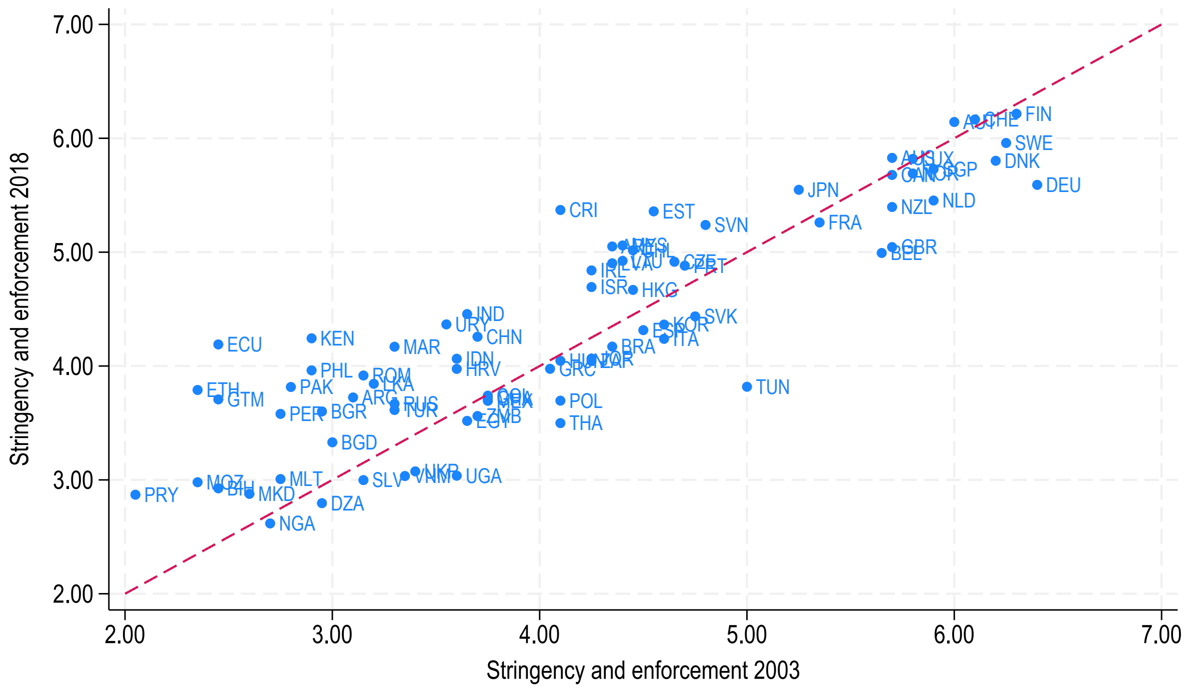
- Consistency of regulation enforcement is measured using the question "How do you assess the enforcement of ER in your country: (1=not enforced or enforced erratically, 7= enforced consistently and fairly)"

The ER indexes based on this survey have been widely used in the previous literature (e.g. Bialek and Weichenrieder, 2021; Kellenberg, 2009; Poelhekke and Van der Ploeg, 2015; Wagner and Timmins, 2009). In the present study, as in Poelhekke and Van der Ploeg (2015), we employ the logarithm of the average of the stringency and enforcement indexes to assess the effect on FDI by mode of investment during the period 2003-2018.

In this way, the proxy we employ for ER captures the idea that stringent environmental policy is only relevant if it is enforced.

To provide an overview of the evolution of ER, Figure 3 plots the average levels of stringency and enforcement in 2003 (horizontal axis) and in 2018 (vertical axis). This graph highlights the substantial heterogeneity among countries in ER levels. It also shows that, in countries with relatively lax regulation in 2003, ER stringency generally increased, whereas in countries that were already strict in 2003, ER stringency tended to remain stable or even relax.

Figure 3: ER Stringency and Consistency of enforcement (2003 and 2018)



Note: Authors' own elaboration based on data from the WEF Executive Opinion Survey. The stringency and enforcement index is calculated by taking the average of the stringency index and the enforcement index. The higher the value, the higher the stringency and enforcement.

Other data sources

Besides the FDI by mode of investment and the ER index, we employ data on GDP and GDP per capita in constant prices base 2017 and in purchasing parity power (GDP and $GDPpc$), which we retrieve from the World Bank's database of World Development Indicators. From the Worldwide Governance Indicators (Kaufmann et al., 2011), we obtained the Rule of Law index (*RuleofLaw*). Data on RTA are from CEPII (Conte et al., 2022), and data on BIT are from UNCTAD's International Investment Agreement Navigator (UNCTAD, 2020). Descriptive statistics of all variables are available in Table A.3 in Appendix A.

5 Results

This section examines how ER influences the extensive margin of FDI—measured by the number of cross-border M&As and GF projects. We distinguish these effects by sector pollution intensity (clean vs. dirty) and by income levels of both origin and destination countries. We interpret the findings through the lenses of the PHH and the GHH, considering both the ER in the origin country (capturing push effects) and in the destination country (capturing pull effects).

5.1 Effect of ER on total FDI, M&As and GF projects

Our results show that ER has no significant effect on firms' FDI location decision in general. Table 3 displays the baseline results of the estimations explaining the number of FDI projects in general and the effect of ER and other variables by modes of investments. Neither the ER of the origin countries nor the ER of the destination countries has a significant effect on the number of FDI projects (Table 3, column 1). Thus, our results provide no evidence that stricter ER functions as a push factor for FDI, as implied by the PHH. Likewise, we find no support for the view that ER operates as a pull factor; ceteris paribus, laxer ER is unlikely to be an effective instrument for attracting FDI. This result could reflect the fact that ER compliance costs are not sufficiently large to outweigh the influence of other pull and push factors on FDI location choices. However, disentangling by modes of investment reveals a different picture.

When differentiating by the modes of investment (Table 3, column 2), we find that ER in the source country has opposite and significant effects on M&A and GF investments. Specifically, stricter ER promotes outward M&As, while it has no statistically significant impact on outward GF investment. According to our estimates, a 10% increase in ER —comparable to changes observed in certain years in countries such as Canada or Japan— could lead to a 3% rise in outward M&A activity. This corresponds to an increase of approximately three to four M&A projects.[4] This suggests that M&As serve as a strategy for escaping from stringent ER, whereas GF investment is not sensitive to more stringent ER in the source country. ER in the destination country has no significant effect on either M&As or GF investment. Therefore, according to our results, the PHH is (in part) corroborated for M&As but not for GF investment.

The different responses between the two modes of FDI may be explained by the fact that MNEs' sunk costs when acquiring a foreign target are often lower than those involved in establishing a new subsidiary in another country, as the existing infrastructure of the acquired firm can be utilized (See Ben-David et al. (2021)). Therefore, the lower sensitivity of GF mode to ER could be explained by the fact that higher environmental compliance costs would be more than offset by other pull factors such as agglomeration economies, raw material supplies, availability and cost of labour, energy, physical and/or human capital, infrastructure etc. Additionally, M&As may benefit from regulatory grandfathering and allow a faster response to regulatory changes in that a firm can continue its activity abroad more quickly. This result aligns with the evidence provided by Davies et al. (2018), showing that GF investment relies much more on the firm's own capacities, which are linked to origin country attributes, whereas M&As are more affected by destination factors.

Our study clearly complements the findings of other research focused on M&As and on smaller samples of countries (Carril-Caccia and Milgram Baleix, 2024; Saussay and Zugravu-Soilita, 2023). To the best of our knowledge, Bialek and Weichenrieder (2021) is the only previous work that examines the different responses of FDI to ER depending on the mode of investment. However, unlike our study, theirs focuses on investments originating from a single country—Germany—which allows them to test whether stricter ER in the destination country deters both M&A and GF investments, as predicted by the

[4]The growth in M&As is calculated based on the average number of outward M&As from these countries during the period of analysis.

PHH. Their results show that tighter ER in host countries significantly reduces the number of GF projects, especially in pollution-intensive industries. This finding is not confirmed by our analysis of the overall sample since we do not find any effect of destination country ER on either inward M&As or inward GF projects..

Concerning the other determinants of FDI included in the benchmark models reported in Table 3, the coefficients broadly display the expected signs when focusing on the total number of FDI projects, but some results are surprising when we disentangle by mode of investment. Both supply and demand, proxied by the GDP of the origin and destination countries, respectively, have positive and significant effects on FDI; however, the size of the source country is not relevant for M&As.

GDP per capita and Rule of law in the origin and destination countries have no impact on FDI in general, but opposite effects on M&As and GF projects. GDP per capita and Rule of law in the origin country foster outward M&As and discourage outward GF investment: in line with our descriptive statistics, our findings show that the richest countries and countries with better institutions carry out more M&As abroad and make fewer GF investments.[5]

RTA and BIT foster FDI in general. As predicted by Nocke and Yeaple (2007), M&A investment is more responsive to trade costs between the origin and destination countries than GF investment. In line with Freeman et al. (2025), OMR and IMR have the expected negative signs for FDI in general, and for both M&As and GF projects.

[5]Given that ER is highly correlated with Rule of Law, we tested the sensitivity of our results to excluding Rule of Law. Results remain unchanged (see Table A.4 in Appendix A).

Table 3: ER and FDI

	(1) FDI	(2) MAGI
$log(ER_{it})$	0.062	
	(0.112)	
$log(ER_{it}) \times M\&A$		0.301*
		(0.156)
$log(ER_{it}) \times GF$		-0.166
		(0.154)
$log(ER_{jt})$	0.065	
	(0.081)	
$log(ER_{jt}) \times M\&A$		-0.095
		(0.137)
$log(ER_{jt}) \times GF$		0.133
		(0.101)
$log(GDP_{it})$	0.813***	
	(0.168)	
$log(GDP_{it}) \times M\&A$		0.071
		(0.206)
$log(GDP_{it}) \times GF$		1.380***
		(0.250)
$log(GDP_{jt})$	1.073***	
	(0.128)	
$log(GDP_{jt}) \times M\&A$		0.767***
		(0.251)
$log(GDP_{jt}) \times GF$		1.052***
		(0.148)
$log(GDPpc_{it})$	0.168	
	(0.170)	
$log(GDPpc_{it}) \times M\&A$		0.862***
		(0.224)
$log(GDPpc_{it}) \times GF$		-0.387
		(0.256)
$log(GDPpc_{jt})$	-0.208	
	(0.138)	
$log(GDPpc_{jt}) \times M\&A$		-0.241
		(0.265)
$log(GDPpc_{jt}) \times GF$		0.005
		(0.154)
$RuleofLaw_{it}$	0.036	
	(0.062)	
$RuleofLaw_{it} \times M\&A$		0.224***
		(0.085)
$RuleofLaw_{it} \times GF$		-0.084
		(0.083)
$RuleofLaw_{jt}$	-0.007	
	(0.047)	
$RuleofLaw_{jt} \times M\&A$		0.093
		(0.077)
$RuleofLaw_{jt} \times GF$		-0.073
		(0.058)
RTA_{ijt}	0.060*	
	(0.032)	
$RTA_{ijt} \times M\&A$		0.185***
		(0.047)
$RTA_{ijt} \times GF$		-0.014
		(0.041)
BIT_{ijt}	0.100**	
	(0.041)	
$BIT_{ijt} \times M\&A$		0.112*
		(0.068)
$BIT_{ijt} \times GF$		0.093*
		(0.052)
OMR_{it}	-1.013***	

Continues on next page

Table 3: ER and FDI (continued)

	(1) FDI	(2) MAGI
	(0.025)	
OMR_{it} $\times M\&A$		-1.057***
		(0.034)
OMR_{it} $\times GF$		-0.944***
		(0.035)
IMR_{jt}	-0.937***	
	(0.026)	
IMR_{jt} $\times M\&A$		-0.547***
		(0.037)
IMR_{jt} $\times GF$		-1.137***
		(0.032)
Observations	227702	227702
Origin-Destination-Sector-Mode	X	X
Year-Sector-Mode	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. Estimates in columns (1) and (2) correspond to Equations (4) and (5), respectively. The estimator is PPML. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

5.2 Impact of ER on M&A and GF investments: Clean versus dirty industries

To shed more light on the mechanisms behind the results reported above, we explore the link between FDI by mode of investment and ER depending on the industry's pollution intensity and the countries' income level. In this section, we examine the differential effects of ER on investments in clean versus dirty industries within the manufacturing sector. To this end, we extend Equations (4) and (5) by interacting ER with two indicator variables ($Clean$ and $Dirty$) that take the value one if the investment is in a clean industry or in a dirty industry, respectively. To conserve space, these empirical models are presented in Appendix C.

Estimates are reported in Table 4. On the one hand, ER imposes larger costs on dirty activities than on clean activities, but on the other hand, dirty activities are often more capital -intensive (Cole and Elliott, 2005) and less footloose (Ederington et al., 2005) than clean activities, so they are more difficult to relocate. Thus, it is not clear ex ante whether or not FDI is more sensitive to ER in dirty industries. However, as long as M&As face lower sunk costs than GF projects, acquiring existing assets abroad may be a more appropriate strategy for dirty, capital-intensive industries than establishing a new subsidiary in a foreign country.

In clean industries, stringent and enforced regulation in the source country would discourage outflows through GF investment but would not affect the decision to invest abroad through M&As. Thus, in these industries, the GHH would apply for GF projects but not for M&As. In clean industries, stricter ER in the origin country discourages investors from establishing new subsidiaries abroad but has no effect on the decision to acquire a foreign company. In the same vein, stricter ER in the destination country encourages the creation of new subsidiaries from foreign investors but has no effect on inward M&As. This result is in line with Pienknagura (2024), who recently emphasized the clear positive connection between climate policies and GF inflows for both green and non-green GF FDI. MNEs operating in clean industries prefer to create new subsidiaries in countries with stricter ER.

In dirty industries, M&A investment reacts positively to stringent and enforced regulation in the source country, whereas GF investment does not. Thus, the PHH is supported for M&A activity in dirty industries, but not for GF activity. For dirty industries, M&As serve as an escape strategy when facing tightening ER in the origin country. MNEs would favour this mode of investment over the creation of a new subsidiary abroad (GF). Indeed, acquiring a foreign company instead of establishing a new subsidiary allows MNEs to avoid high sunk costs and to benefit from regulatory grandfathering. Nonetheless, investors do not seem to necessarily prefer host countries with laxer ER. In section 5.3, we offer further insight on the mechanism behind these results.

The above results differ from those obtained by Bialek and Weichenrieder (2021). In contrast to our findings, their study finds that FDI responds more negatively to a tightening of ER stringency in pollution-intensive industries. However, they observe a greater sensitivity to host country ER for GF mode than for M&A mode, whereas we find no significant effects of host ER on either mode of investment. Nonetheless, consistent with their findings, we also find that M&As tend to be more mobile than GF projects in pollution-intensive industries. Along the same lines, Saussay and Zugravu-Soilita (2023) suggest that high-polluting industries are the most sensitive to cross-country differences in ER.

Table 4: ER and FDI in clean and dirty industries

	(1) FDI	(2) MAGI
$log(ER_{it}) \times Clean$	-0.117	
	(0.138)	
$log(ER_{it}) \times M\&A \times Clean$		0.176
		(0.190)
$log(ER_{it}) \times GF \times Clean$		-0.382**
		(0.189)
$log(ER_{it}) \times Dirty$	0.444**	
	(0.180)	
$log(ER_{it}) \times M\&A \times Dirty$		0.536**
		(0.253)
$log(ER_{it}) \times GF \times Dirty$		0.341
		(0.252)
$log(ER_{jt}) \times Clean$	0.152	
	(0.096)	
$log(ER_{jt}) \times M\&A \times Clean$		-0.184
		(0.166)
$log(ER_{jt}) \times GF \times Clean$		0.293**
		(0.118)
$log(ER_{jt}) \times Dirty$	-0.123	
	(0.149)	
$log(ER_{jt}) \times M\&A \times Dirty$		0.069
		(0.221)
$log(ER_{jt}) \times GF \times Dirty$		-0.244
		(0.194)
Observations	227702	227702
Origin-Destination-Sector-Mode	X	X
Year-Sector-Mode	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. The estimates in Columns (1) and (2) correspond to Equations (A.1) and (A.2) available in Appendix C. To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. In column (2), all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

5.3 Impact of ER on M&As and GF investment by origin-destination income levels

In this section, we investigate whether the level of income of the host and home countries sheds further light on the mechanisms behind the FDI-ER link. FDI in high-income and low- and middle-income countries is driven by distinct motivations. In low- and middle-income economies, investments are often efficiency-oriented, with a stronger focus on cost reduction or resource acquisition. In this context, ER may impose additional costs that firms aim to avoid when investing in low- and middle-income countries. By contrast, FDI in high-income countries is more likely to be driven by market access and strategic considerations. In the latter case, ER involves additional costs that may be compensated for by the other advantages of the location, such as lower capital costs, market access, agglomeration economies, etc. Nonetheless, Figure 1 shows that high-income countries already face the most stringent ER; additional restrictions may therefore be a burden too far and could deter FDI, particularly M&As.

In order to perform this analysis, we estimate four different empirical models, in which we interact (1) ER, (2) $ER \times Clean$ and $ER \times Dirty$, (3) $ER \times M\&A$ and $ER \times GF$, and (4) $ER \times M\&A \times Clean$, $ER \times M\&A \times Dirty$, $ER \times GF \times Dirty$, and $ER \times GF \times Dirty$ by a set of indicator variables that identify whether the investment occurs between high-income countries, between low- and middle-income countries, or from high-income to low- and middle-income countries. To conserve space, these empirical models are specified in Appendix C. Estimates are summarized in Tables 5, 6, 7, and 8.

FDI from high-income to high-income countries

Table 5 presents the results for FDI between high-income countries, which represents approximately 50% of global FDI. These flows are primarily driven by market-seeking and asset-seeking motivations. As shown in column (1), MNEs do not appear to relocate in response to stringent ER, nor are they attracted by more lenient ER. On the contrary, stricter ER in the origin country is associated with a lower likelihood of establishing new subsidiaries in other high-income countries, consistent with the predictions of the GHH. However, these regulations do not appear to influence cross-border M&As. For flows between high-income countries, the PHH is not supported for either GF investment or M&As. MNEs may choose to remain and adapt to stricter ER, as the associated compliance costs are likely offset by other location advantages. In some cases, more stringent ER may even act as a retention factor, encouraging firms to stay.

These patterns are largely driven by clean industries, as indicated in column (2). In contrast, for dirty industries (column 3), more stringent ER in the source country has no significant effect on the decision to invest in another high-income country. If any effect is observed, it points toward a dissuasive influence on the creation of new subsidiaries in the destination countries' dirty sectors, which is consistent with the PHH.

The estimates reported in Table 5 indicate that a 10% increase in ER stringency leads to a 5.8% decline in outward GF investment flows in clean industries to other high-income countries. For a country such as Germany, which on average engages in 119 GF projects in other high-income countries in clean industries , this percentage reduction corresponds to approximately seven projects. Similarly, the same increase in ER is associated with a 7.05% decrease in inward GF projects from other high-income countries in dirty industries. Given that Germany receive an average of 26 of such projects, this would imply a decline of about two GF investments.

Table 5: ER and FDI from high-income to high-income countries

		All industries	Clean	Dirty
ER_{it}	**FDI**	0.017	-0.030	0.065
		(0.165)	(0.200)	(0.286)
	M&As	0.343	0.372	0.284
		(0.214)	(0.261)	(0.365)
	GF	-0.496**	-0.581*	-0.281
		(0.252)	(0.303)	(0.450)
ER_{jt}	**FDI**	0.044	0.184	-0.188
		(0.154)	(0.185)	(0.270)
	M&As	0.249	0.281	0.176
		(0.204)	(0.250)	(0.351)
	GF	-0.149	0.077	-0.705*
		(0.229)	(0.272)	(0.419)

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. The empirical models used to produce this table are presented in Appendix C. Estimates of FDI for All industries come from the results of Equation (A.3). Estimates for M&A and GF for All industries come from the results of Equation (A.4). Estimates for FDI for Clean and Dirty industries come from the results of Equation (A.5). Estimates for M&A and GF for Clean and Dirty industries come from the results of Equation (A.6). To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. For M&A and GF estimates all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

FDI from high-income to low- and middle-income countries

Table 6 presents the results for FDI originating from high-income countries and directed toward low- and middle-income countries, which accounts for approximately 38% of global FDI. These investment flows are typically motivated by efficiency- or resource-seeking objectives. When high-income countries implement more stringent environmental policies, MNEs operating in pollution-intensive industries tend to relocate to low- and middle-income countries, both through GF projects and M&As.

Since stricter ER increases production costs, the PHH mechanism is more pronounced for efficiency-seeking FDI—especially in flows from high-income to low- and middle-income countries—where relocating to jurisdictions with more lenient ER can further reduce operating expenses. M&As appear to be more responsive to environmental stringency in the country of origin compared to GF. This may reflect the lower sunk costs and the potential to benefit from grandfathering provisions when acquiring existing firms, making M&As a more attractive channel for relocation under tighter ER.

According to our results, a 10% increase in ER stringency could lead to a 15.9% increase in outward M&A investment flows and a 7.5% increase in GF investment flows from high-income to low- and middle-income countries. For a country like the USA, which averages 36 outward M&A projects in dirty sectors, this would imply an increase of nearly six projects. In the case of GF investment, with an average of 72 projects, the same policy change could result in approximately five additional projects.

However, lenient environmental policies in host countries do not significantly act as pull factors for attracting FDI in dirty industries. Interestingly, stricter ER in low- and middle-income countries tends to discourage MNEs from acquiring firms in clean industries, likely because the anticipated compliance costs outweigh the expected efficiency gains. Thus, while the environmental policy of the origin country decisively influences relocation decisions for MNEs in dirty sectors, host-country regulations appear to play a more limited role in attracting or deterring such investments.

In sum, the results indicate that MNEs operating in pollution-intensive industries are more inclined to relocate to poorer countries when ER becomes too stringent at home, as these lower-income countries generally maintain more relaxed environmental standards (see Figure 3). Nonetheless, among the group of host countries with relatively flexible ER, investors do not necessarily prefer those with the most lenient regulations. Therefore, in cases where host-country ER is already less stringent than that of the home country, MNEs are generally not highly responsive to small increases in regulatory stringency—provided the destination remains less stringent overall.

Table 6: ER and FDI from high-income to low- and middle-income countries

		All industries	**Clean**	**Dirty**
ER_{it}	**FDI**	0.097	-0.319	1.021***
		(0.223)	(0.269)	(0.336)
	M&As	0.707*	0.206	1.593***
		(0.375)	(0.471)	(0.567)
	GF	-0.150	-0.502	0.745*
		(0.261)	(0.320)	(0.412)
ER_{jt}	**FDI**	0.058	0.070	-0.066
		(0.104)	(0.121)	(0.197)
	M&As	-0.219	-0.443*	0.155
		(0.203)	(0.248)	(0.316)
	GF	0.109	0.228	-0.168
		(0.120)	(0.139)	(0.246)

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. The empirical models used to produce this table are presented in Appendix C. Estimates of FDI for All industries come from the results of Equation (A.3). Estimates for M&A and GF for All industries come from the results of Equation (A.4). Estimates for FDI for Clean and Dirty industries come from the results of Equation (A.5). Estimates for M&A and GF for Clean and Dirty industries come from the results of Equation (A.6). To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. For M&A and GF estimates, all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

FDI from low- and middle-income to low- and middle-income countries

Table 7 reports the results for FDI flows between low- and middle-income countries, which account for only 5.3% of global FDI. For these countries, GF projects tend to be the preferred mode of investment into other low- and middle-income economies.

Estimates in column (1) indicate that ER in the origin country does not significantly influence MNEs' decisions to invest abroad. However, stricter ER in the host country appears to encourage inward GF investment in clean industries. This finding is consistent with the GHH.

According to these results, if a low- and middle-income country increases its ER stringency by 10%, it could expect a 12.1% increase in GF from other low- and middle-income countries. For a country such as India, which on average undertakes approximately nine GF projects in other low- and middle-income countries, such a policy change could result in an increase of about one project.

Table 7: ER and FDI from low- and middle-income to low- and middle-income countries

		All industries	**Clean**	**Dirty**
ER_{it}	**FDI**	-0.119	-0.499	0.657
		(0.265)	(0.323)	(0.453)
	M&As	-0.072	-1.011	1.245
		(0.524)	(0.691)	(0.814)
	GF	-0.089	-0.328	0.451
		(0.311)	(0.368)	(0.544)
ER_{jt}	**FDI**	0.538**	0.697**	0.158
		(0.248)	(0.317)	(0.397)
	M&As	-0.673	-1.110*	-0.014
		(0.505)	(0.659)	(0.789)
	GF	0.895***	1.211***	0.247
		(0.291)	(0.363)	(0.461)

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. The empirical models used to produce this table are presented in Appendix C. Estimates of FDI for All industries come from the results of Equation (A.3). Estimates for M&A and GF for All industries come from the results of Equation (A.4). Estimates for FDI for Clean and Dirty industries come from the results of Equation (A.5). Estimates for M&A and GF for Clean and Dirty industries come from the results of Equation (A.6). To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. For M&A and GF estimates, all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

FDI from low- and middle-income to high-income countries

Table 8 presents the results for FDI flows from low- and middle-income countries to high-income countries, which represent only 5.4% of global FDI but have been increasing in recent years. These flows are predominantly composed of M&As, driven by market- and asset-seeking motivations. In particular, emerging-market MNEs aim to acquire advanced technologies, established brands, organizational capabilities, and closer access to consumers.

ER in the origin country does not significantly influence outbound investment decisions. However, stricter ER in high-income countries tends to discourage M&As in pollution-intensive (dirty) industries by firms from emerging economies. This finding is consistent with the PHH. If ER becomes 10% stricter in high-income countries, this could lead to a 17.3% decline in M&As from low- and middle-income countries. In the case of China, which on average undertakes 16 outward M&A projects in high-income countries, such a policy change would imply a reduction of nearly three projects.

Table 8: ER and FDI from low- and middle-income to high-income countries

		All industries	Clean	Dirty
ER_{it}	**FDI**	0.234	0.276	-0.061
		(0.248)	(0.303)	(0.397)
	M&As	-0.010	0.065	-0.186
		(0.306)	(0.365)	(0.482)
	GF	0.534	0.709	0.193
		(0.439)	(0.540)	(0.702)
ER_{jt}	**FDI**	-1.039**	-0.793	-1.648**
		(0.421)	(0.522)	(0.688)
	M&As	-1.224**	-0.995	-1.734**
		(0.533)	(0.663)	(0.853)
	GF	-0.750	-0.353	-1.483
		(0.683)	(0.833)	(1.160)

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. The empirical models used to produce this table are presented in Appendix C. Estimates of FDI for All industries come from the results of Equation (A.3). Estimates for M&A and GF for All industries come from the results of Equation (A.4). Estimates for FDI for Clean and Dirty industries come from the results of Equation (A.5). Estimates for M&A and GF for Clean and Dirty industries come from the results of Equation (A.6). To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. For M&A and GF estimates, all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

6 Sensitivity analysis

One of the main concerns when examining the FDI–ER link is the potential endogeneity and reverse causality. Foreign investors may have sufficient power to influence ER in the host country (or in their home country). In this vein, some studies suggest that FDI affects ER. For instance, Cheng et al. (2018) show that FDI inflows increase both the number and severity of local regulations. Other works show that FDI may also affect countries' environmental performance (e.g. Ahouangbe and Turcu, 2024; Demena and Afesorgbor, 2020), which could be linked to ER. Since our analysis is based on bilateral FDI, the scope for bias due to reverse causality is likely limited. Nevertheless, we perform a battery of tests to assess whether our results are significantly affected by this issue.

First, we lag the ER variables by one period, as current FDI projects are less likely to affect past ER. Estimates are reported in Table 9. As can be seen, the results are similar to the ones reported in Table 3, except for the fact that, in this case, ER in the source country becomes negative and significant for outward GF investment.

Second, following previous works such as Bialek and Weichenrieder (2021) and Bradley et al. (2025), we adopt a two-step control function approach and consider three alternative instruments for ER. In line with Davies and Vadlamannati (2013), our first instrument is the distance-weighted average of ER across all countries other than i (respectively, other than j) for ER_{it} (respectively, ER_{jt}). The intuition behind this instrument is that ER exhibits spatial correlation due to policy diffusion, common regulatory frameworks, and learning across geographically proximate countries, so that the ER of nearby countries is predictive of domestic ER. At the same time, because the weights depend only on geographic distance and exclude country i (j), the instrument is unlikely to be related to country-specific characteristics that may affect outward or inward FDI once we control for observables and fixed effects.

As another instrument, we use the trade-weighted average of partner countries' ER, following Bialek and Weichenrieder (2021). Similar to the instrument described above, the underlying intuition is that a country's ER is likely to be shaped by regulatory and competitive pressures originating from its main trading partners. This implies that domestic ER should be positively correlated with the trade-weighted ER of its partners, while partner countries' ER need not be directly related to the country's inward or outward FDI. To construct the instrument, we combine ER data with bilateral export flows from Borchert et al. (2021) to compute a weighted average of partners' ER, where the weights are given by the country's export shares.

As an alternative, following Kellenberg (2009) and Mulatu (2017), we instrument ER using agricultural value added per worker. The intuition is that this variable proxies a country's level of development and technology, which tends to be positively associated with stricter environmental policy. At the same time, it should not be directly related to investment in the manufacturing sector (conditional on controls and fixed effects).

To implement the control function approach, we take the following steps. First, we obtain the residual from the OLS estimation of the following Equation:

$$\begin{aligned} log(ER_{it}) =& IV_{it} + X_{it} + X_{jt} + B_{ijt} + log(OMR_{it}) + log(IMR_{jt}) \\ &+ \lambda_{mijs} + \lambda_{smt} + \varepsilon_{mijst} \end{aligned} \tag{6}$$

where IV_{it} is one of the aforementioned instruments. This is also done with ER_{jt} and IV_{jt}. Accordingly, we obtain two residuals ($residcf_{it}$ and $residcf_{it}$), which are included as independent variables in Equation (4). Clustered standard errors are bootstrapped with 200 replications. The same approach is taken for the regressions in which all independent variables are interacted with the M&A and GF indicator variables. In this case, in Equation (6) the instrument is also interacted with M&A and GF indicator variables.

To conserve space, Table 10 reports only the coefficients on ER and the corresponding control-function residuals; the full set of estimates is provided in Appendix A. The estimated coefficients on the residual terms are not statistically significant, suggesting that—conditional on the included controls and fixed effects—we do not find evidence of endogeneity (or reverse causality) between ER and FDI in our specification. Given that the residual terms are not statistically significant, the preferred specification is the baseline without residuals (Table 3).

Besides endogeneity, a potential concern is that ER captures aspects from the source and destination countries linked to their level of development and institutional quality, which are potential drivers of FDI. To minimize this potential source of bias, we replace the ER variables with the residual ($ERresid_{it}$ and $ERresid_{jt}$) from estimating the following equation with OLS for i and j:

$$log(ER_{it}) = log(GDPpc)_{it} + Ruleoflaw_{it} + \varepsilon_{it} \tag{7}$$

Estimates are presented in Table 11. As can be seen, results are identical to those presented in Table 3.

Table 9: Sensitivity analysis with lagged ER variables

	(1) FDI	(2) MAGI
$log(ER_{it-1})$	0.017	
	(0.127)	
$log(ER_{it-1})\ \times M\&A$		0.450***
		(0.159)
$log(ER_{it-1})\ \times GF$		-0.307*
		(0.176)
$log(ER_{jt-1})$	0.050	
	(0.083)	
$log(ER_{jt-1})\ \times M\&A$		-0.109
		(0.140)
$log(ER_{jt-1})\ \times GF$		0.105
		(0.102)
Observations	227702	227702
Origin-Destination-Sector-Mode	X	X
Year-Sector-Mode	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates in columns (1) and (2) correspond to Equations (4) and (5), respectively. To conserve space, estimates for control variables are not reported. These are the same as in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. In column (2), all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

Table 10: Sensitivity analysis with control function approach

	Distance weighted ER		Export weighted ER		Agricultural value added per worker	
	(1)	(2)	(3)	(4)	(5)	(6)
$log(ER_{it})$	0.401		0.493		1.089	
	(1.574)		(2.363)		(1.515)	
$log(ER_{it})\ \times M\&A$		-0.061		0.394		1.164
		(1.569)		(2.453)		(1.492)
$log(ER_{it})\ \times GF$		-0.526		-0.069		0.699
		(1.580)		(2.451)		(1.504)
$log(ER_{jt})$	-0.008		3.875		0.555	
	(2.443)		(288.381)		(2.602)	
$log(ER_{jt})\ \times M\&A$		1.502		22.680		0.458
		(2.017)		(37.403)		(2.671)
$log(ER_{jt})\ \times GF$		1.744		22.902		0.693
		(2.043)		(37.414)		(2.670)
$residcf_{it}$	-0.343	0.364	-0.431	-0.088	-1.037	-0.874
	(1.576)	(1.576)	(2.369)	(2.460)	(1.521)	(1.500)
$residcf_{jt}$	0.073	-1.611	-3.809	-22.774	-0.491	-0.559
	(2.445)	(2.033)	(288.378)	(37.405)	(2.597)	(2.668)

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates in columns (1), (3) and (5) correspond to Equation (4) with $residcf_{it}$ and $residcf_{jt}$. Estimates in columns (1), (3) and (5) correspond to Equation (5) with $residcf_{it}$ and $residcf_{jt}$. To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. In columns (2), (4) and (6), all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Full estimates are available in Table A.5. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

Table 11: Sensitivity analysis with residual of ER

	(1) FDI	(2) MAGI
$ERresid_{it}$	0.062	
	(0.112)	
$ERresid_{it} \times M\&A$		0.301*
		(0.156)
$ERresid_{it} \times GF$		-0.166
		(0.154)
$ERresid_{jt}$	0.065	
	(0.081)	
$ERresid_{jt} \times M\&A$		-0.095
		(0.137)
$ERresid_{jt} \times GF$		0.133
		(0.101)
Observations	227702	227702
Origin-Destination-Sector-Mode	X	X
Year-Sector-Mode	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates in columns (1) and (2) correspond to Equations (4) and (5), respectively. Instead of employing the ER index from WEF, we employ the residual calculated with Equation 7. To conserve space, the estimates for control variables are not reported; they are identical to those presented in Table 3 i.e.: GDP_{it}, GDP_{jt}, $GDPpc_{it}$, $GDPpc_{jt}$, $RuleofLaw_{it}$, $RuleofLaw_{jt}$, RTA_{ijt}, BIT_{ijt}, OMR_{jt}, and IMR_{jt}. In column (2), all these variables are interacted with a dummy that identifies GF mode and a dummy that identifies M&A mode. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

7 Concluding remarks

Despite the increasing policy relevance of ER, relatively few studies have examined how FDI responds to changes in regulatory stringency, particularly across different modes of investment. This paper contributes to filling that gap by examining how environmental policies affect the location of FDI projects—both outward and inward—through two distinct investment modes: cross-border M&As and GF investment. To this end, we exploit a large panel of bilateral data, covering 75 source and 105 destination countries over 15 years, and distinguishing between clean and dirty manufacturing industries.

Our baseline results indicate that, when all FDI projects are aggregated, ER exerts no statistically significant influence on either inflows or outflows. This suggests that, in general, compliance costs associated with environmental policies may not be large enough to alter multinational firms' location decisions. However, this average effect conceals substantial heterogeneity across FDI modes, industries categorized by pollution intensity, and countries classified by income level. When we differentiate between M&A and GF investments and focus on FDI from high-income countries, which represents the lion share of FDI, a more nuanced pattern emerges.

In pollution-intensive industries, stricter ER appears to stimulate outward M&A and GF investment flows to low- and middle-income countries. This result is consistent with the PHH and would suggest a clear efficiency-seeking strategy. It is worrisome because it points to a clear risk of carbon leakage.

In contrast, in clean industries, GF investment appears to be positively associated with stricter ER in the origin, lending support to the GHH. These firms may be more capable of adapting to stringent ER due to technological readiness and long-term investment strategies, and may even view such regulation as a signal of a stable and sustainable investment environment. Additionally, firms engaged in clean activities are often more sensitive to reputational concerns and CSR, which can make them more inclined to operate in jurisdictions with strong environmental standards. One explanation also lies in the different sunk costs and regulatory constraints faced by the two modes: M&As allow faster entry and often benefit from grandfathering provisions, whereas GF projects face higher upfront costs and must meet current regulatory standards.

Conversely, ER in host countries is not a decisive attraction factor for FDI from high-income countries. This asymmetry suggests that ER acts more as a push factor from the origin rather than a pull factor toward the destination.

Overall, our study underscores the importance of disaggregating FDI by mode of investment, industry, and origin-destination country, when assessing the effects of ER. Stricter ER is not universally detrimental to investment. Rather, it affects firms differently depending on the mode of the investment, the pollution intensity of the activity, and the income level of the countries involved. M&A and GF investments reflect distinct strategic responses to ER—one more reactive and cost-avoidant, the other potentially aligned with long-term sustainability goals.

From a policy perspective, our results suggest that tightening environmental standards does not necessarily drive investment away—especially in clean industries or when firms invest via GF projects. However, in dirty industries, the risk of capital flight through M&As remains a concern, particularly for high-income countries tightening their regulations. This raises important considerations for global climate policy coordination and the design of border carbon adjustment mechanisms.

Finally, our study opens promising avenues for future research. Further work is needed to explore how ER affects divestments, domestic activity reduction, or substitution across countries or modes—dimensions we are unable to capture here. Moreover, firm-level data could help disentangle how MNEs' strategies vary in response to ER, depending on their technological capabilities, environmental reputations, and sectors.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used ChatGPT (OpenAI) in order to improve the language and readability of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Data Availability Statement

The data on greenfield foreign direct investment used in this study were obtained from fDi Markets (Financial Times Ltd) and data from M&A from LSEG. Access to these data is subject to strict licensing agreements that prohibit the sharing or public dissemination of the data by users. As a result, the data cannot be made publicly available. Researchers may obtain access directly from the data provider, subject to their own licensing arrangements.

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A Appendix: Additional tables

Table A.1: Sample of countries

High income	**Low and Middle income**	
Australia	Algeria	*Mauritius*
Austria	Argentina	Mexico
Bahrain	*Azerbaijan*	*Mongolia*
Belgium	*Bangladesh*	Morocco
Canada	*Bolivia*	*Mozambique*
Cyprus	*Bosnia and Herzegovina*	*Myanmar*
Czech Republic	*Botswana*	*Namibia*
Denmark	Brazil	Nigeria
Estonia	Bulgaria	Pakistan
Finland	*Cambodia*	*Panama*
France	*Cameroon*	*Paraguay*
Germany	Chile	Peru
Greece	China	Philippines
Hong Kong SAR, China	Colombia	Poland
Hungary	Costa Rica	Romania
Iceland	*Cote d'Ivoire*	Russian Federation
Ireland	Croatia	South Africa
Israel	*Dominican Republic*	Sri Lanka
Italy	*Ecuador*	*Tanzania*
Japan	Egypt, Arab Rep.	Thailand
Korea, Rep.	*El Salvador*	Tunisia
Kuwait	*Ethiopia*	Turkey
Luxembourg	*Georgia*	*Uganda*
Malta	*Ghana*	Ukraine
Netherlands	Guatemala	*Uruguay*
New Zealand	India	Vietnam
Norway	Indonesia	*Zambia*
Oman	*Iran, Islamic Rep.*	*Zimbabwe*
Portugal	Jamaica	
Qatar	Jordan	
Saudi Arabia	Kazakhstan	
Singapore	Kenya	
Slovak Republic	Kyrgyz Republic	
Slovenia	Latvia	
Spain	**Lebanon**	
Sweden	*Lesotho*	
Switzerland	*Libya*	
United Arab Emirates	Lithuania	
United Kingdom	*Macedonia, FYR*	
United States	Malaysia	

Note: Authors' own elaboration. Countries' income classification is from the World Bank's 2011 country income classification. Countries in bold are the ones that only appear as a source of FDI, while countries in italics are the ones that only appear as a destination for FDI.

Table A.2: FDI by mode of investment and sector

Clean/Dirty	Sector	NACE code	No. of projects			% of projects in destination sector		% of All sectors flows		
			M&A	GF	Total FDI	M&A	GI	M&A	GI	Total FDI
Clean	Manufacture of machinery and equipment n.e.c.	28	3722	9322	13044	28.53	71.47	10.26	21.46	16.37
Dirty	Manufacture of chemicals and chemical products	20	3767	4826	8593	43.84	56.16	10.39	11.11	10.78
Clean	Manufacture of computer, electronic and optical products	26	5293	2035	7328	72.23	27.77	14.59	4.69	9.19
Clean	Manufacture of food products	10	3177	3545	6722	47.26	52.74	8.76	8.16	8.43
Clean	Manufacture of rubber and plastic products	22	1435	4180	5615	25.56	74.44	3.96	9.62	7.05
Clean	Manufacture of basic pharmaceutical products and pharmaceutical preparations	21	3507	1269	4776	73.43	26.57	9.67	2.92	5.99
Clean	Manufacture of electrical equipment	27	1686	2933	4619	36.50	63.50	4.65	6.75	5.80
Dirty	Manufacture of other non-metallic mineral products	23	1822	2566	4388	41.52	58.48	5.02	5.91	5.51
Dirty	Manufacture of basic metals	24	1583	2199	3782	41.86	58.14	4.36	5.06	4.75
Dirty	Manufacture of fabricated metal products, except machinery and equipment	25	2217	1565	3782	58.62	41.38	6.11	3.60	4.75
Clean	Manufacture of motor vehicles, trailers and semi-trailers	29	641	2218	2859	22.42	77.58	1.77	5.11	3.59
Clean	Other manufacturing	32	730	1497	2227	32.78	67.22	2.01	3.45	2.79
Clean	Manufacture of textiles	13	899	1104	2003	44.88	55.12	2.48	2.54	2.51
Dirty	Manufacture of paper and paper products	17	828	1090	1918	43.17	56.83	2.28	2.51	2.41
Clean	Manufacture of beverages	11	1002	908	1910	52.46	47.54	2.76	2.09	2.40
Dirty	Printing and reproduction of recorded media	18	1336	122	1458	91.63	8.37	3.68	0.28	1.83
Clean	Manufacture of other transport equipment	30	594	649	1243	47.79	52.21	1.64	1.49	1.56
Dirty	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	16	492	417	909	54.13	45.87	1.36	0.96	1.14
Clean	Manufacture of furniture	31	289	455	744	38.84	61.16	0.80	1.05	0.93
Dirty	Manufacture of coke and refined petroleum products	19	414	290	704	58.81	41.19	1.14	0.67	0.88
Clean	Manufacture of wearing apparel	14	597	32	629	94.91	5.09	1.65	0.07	0.79
Clean	Manufacture of leather and related products	15	153	123	276	55.43	44.57	0.42	0.28	0.35
Clean	Manufacture of tobacco products	12	82	85	167	49.10	50.90	0.23	0.20	0.21
	All sectors		36266	43430	79696	45.51	54.49	100.00	100.00	100.00

Note: Authors' own elaboration based on M&A and GF data from LSEG and fDi Markets respectively.

Table A.3: Descriptive statistics

Variable	**Mean**	**Std. dev.**	**Min**	**Max**
FDI_{mijst}	0.35	1.03	0.00	58.00
$Log(ER_{it})$	1.63	0.19	0.61	1.87
$Log(ER_{jt})$	1.51	0.23	0.48	1.87
$Log(GDP_{it})$	27.89	1.43	23.25	30.69
$Log(GDP_{jt})$	27.99	1.37	22.22	30.69
$Log(GDPpc_{it})$	10.53	0.65	7.96	11.70
$Log(GDPpc_{jt})$	10.17	0.79	6.58	11.70
$RuleofLaw_{it}$	1.22	0.78	-1.41	2.10
$RuleofLaw_{jt}$	0.74	0.95	-1.85	2.10
RTA_{ijt}	0.47	0.50	0.00	1.00
BIT_{ijt}	0.42	0.49	0.00	1.00
OMR_{it}	20.42	1.17	14.96	24.05
IMR_{jt}	-1.45	1.14	-8.94	1.03

Note: Authors' own elaboration. All variables have 227,702 observations.

Table A.4: Baseline estimates (Table 3) without rule of law

	(1) FDI	(2) MAGI
$log(ER_{it})$	0.074	
	(0.114)	
$log(ER_{it})$ $\times M\&A$		0.375**
		(0.152)
$log(ER_{it})$ $\times GF$		-0.197
		(0.160)
$log(ER_{jt})$	0.061	
	(0.079)	
$log(ER_{jt})$ $\times M\&A$		-0.066
		(0.134)
$log(ER_{jt})$ $\times GF$		0.093
		(0.098)
$log(GDP_{it})$	0.808***	
	(0.169)	
$log(GDP_{it}) \times M\&A$		0.072
		(0.206)
$log(GDP_{it}) \times GF$		1.400***
		(0.255)
$log(GDP_{jt})$	1.076***	
	(0.128)	
$log(GDP_{jt})$ $\times M\&A$		0.772***
		(0.251)
$log(GDP_{jt})$ $\times GF$		1.056***
		(0.148)
$log(GDPpc_{it})$	0.176	
	(0.171)	
$log(GDPpc_{it})$ $\times M\&A$		0.891***
		(0.224)
$log(GDPpc_{it})$ $\times GF$		-0.421
		(0.260)
$log(GDPpc_{jt})$	-0.209	
	(0.138)	
$log(GDPpc_{jt})$ $\times M\&A$		-0.224
		(0.265)
$log(GDPpc_{jt})$ $\times GF$		-0.004
		(0.153)
RTA_{ijt}	0.061*	
	(0.032)	
RTA_{ijt} $\times M\&A$		0.186***
		(0.047)
RTA_{ijt} $\times GF$		-0.016
		(0.041)
BIT_{ijt}	0.101**	
	(0.041)	
BIT_{ijt} $\times M\&A$		0.118*
		(0.068)
BIT_{ijt} $\times GF$		0.089*
		(0.052)
OMR_{it}	-1.015***	
	(0.025)	
OMR_{it} $\times M\&A$		-1.067***
		(0.034)
OMR_{it} $\times GF$		-0.942***
		(0.035)
IMR_{jt}	-0.937***	
	(0.026)	
IMR_{jt} $\times M\&A$		-0.541***
		(0.037)
IMR_{jt} $\times GF$		-1.142***
		(0.032)
Observations	227702	227702
Origin-Destination-Sector-Mode	X	X
Year-Sector-Mode	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates in columns (1) and (2) correspond to Equations (4) and (5), respectively. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

Table A.5: Full estimates of the control function approach

	Distance weighted ER		Export weighted ER		Agricultural value added per worker	
	(1)	(2)	(3)	(4)	(5)	(6)
$log(ER_{it})$	0.401		0.493		1.089	
	(1.574)		(2.363)		(1.515)	
$log(ER_{it})$ $\times M\&A$		-0.061		0.394		1.164
		(1.569)		(2.453)		(1.492)
$log(ER_{it})$ $\times GF$		-0.526		-0.069		0.699
		(1.580)		(2.451)		(1.504)
$log(ER_{jt})$	-0.008		3.875		0.555	
	(2.443)		(288.381)		(2.602)	
$log(ER_{jt})$ $\times M\&A$		1.502		22.680		0.458
		(2.017)		(37.403)		(2.671)
$log(ER_{jt})$ $\times GF$		1.744		22.902		0.693
		(2.043)		(37.414)		(2.670)
$residcf_{it}$	-0.343	0.364	-0.431	-0.088	-1.037	-0.874
	(1.576)	(1.576)	(2.369)	(2.460)	(1.521)	(1.500)
$residcf_{jt}$	0.073	-1.611	-3.809	-22.774	-0.491	-0.559
	(2.445)	(2.033)	(288.378)	(37.405)	(2.597)	(2.668)
$log(GDP_{it})$	0.755**		0.802		0.664**	
	(0.321)		(4.726)		(0.317)	
$log(GDP_{it})\times M\&A$		0.150		0.388		-0.066
		(0.313)		(0.773)		(0.308)
$log(GDP_{it})$ $\times GF$		1.476***		1.808**		1.255***
		(0.372)		(0.860)		(0.386)
$log(GDP_{jt})$	1.093**		0.335		0.998*	
	(0.494)		(56.333)		(0.533)	
$log(GDP_{jt})$ $\times M\&A$		0.545		-2.195		0.704
		(0.362)		(4.920)		(0.449)
$log(GDP_{jt})$ $\times GF$		0.690		-3.966		0.953
		(0.469)		(8.289)		(0.616)
$log(GDPpc_{it})$	0.186		0.164		0.204	
	(0.194)		(2.484)		(0.198)	
$log(GDPpc_{it})$ $\times M\&A$		0.839***		0.726		0.909***
		(0.222)		(0.470)		(0.242)
$log(GDPpc_{it})$ $\times GF$		-0.427		-0.610		-0.360
		(0.276)		(0.500)		(0.282)
$log(GDPpc_{jt})$	-0.212		-0.102		-0.206	
	(0.153)		(8.034)		(0.167)	
$log(GDPpc_{jt})$ $\times M\&A$		-0.277		-0.953		-0.256
		(0.276)		(1.182)		(0.288)
$log(GDPpc_{jt})$ $\times GF$		0.084		1.059		0.012
		(0.186)		(1.793)		(0.210)
$RuleofLaw_{it}$	0.005		0.014		-0.059	
	(0.160)		(1.963)		(0.151)	
$RuleofLaw_{it}$ $\times M\&A$		0.260		0.274		0.144
		(0.171)		(0.275)		(0.173)
$RuleofLaw_{it}$ $\times GF$		-0.043		0.050		-0.160
		(0.172)		(0.327)		(0.148)
$RuleofLaw_{jt}$	0.002		-0.531		-0.076	
	(0.341)		(39.582)		(0.367)	
$RuleofLaw_{jt}$ $\times M\&A$		-0.095		-2.551		0.033
		(0.253)		(4.384)		(0.321)
$RuleofLaw_{jt}$ $\times GF$		-0.313		-3.486		-0.161
		(0.311)		(5.643)		(0.412)
RTA_{ijt}	0.061		0.080		0.067*	
	(0.037)		(1.308)		(0.036)	
RTA_{ijt} $\times M\&A$		0.189***		0.249*		0.191***
		(0.046)		(0.130)		(0.043)
RTA_{ijt} $\times GF$		-0.006		0.130		-0.006
		(0.049)		(0.238)		(0.044)
BIT_{ijt}	0.102**		0.137		0.114**	
	(0.048)		(2.784)		(0.055)	
BIT_{ijt} $\times M\&A$		0.117*		0.245		0.130*
		(0.069)		(0.233)		(0.068)
BIT_{ijt} $\times GF$		0.110*		0.355		0.104
		(0.061)		(0.452)		(0.065)

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Table A.5: Full estimates of the control function approach (continued)

	Distance weighted ER		Export weighted ER		Agricultural value added per worker	
	(1)	(2)	(3)	(4)	(5)	(6)
OMR_{it}	-1.011***		-1.010***		-1.006***	
	(0.025)		(0.113)		(0.029)	
OMR_{it} $\times M\&A$		-1.061***		-1.055***		-1.047***
		(0.035)		(0.048)		(0.041)
OMR_{it} $\times GF$		-0.946***		-0.946***		-0.942***
		(0.035)		(0.049)		(0.036)
IMR_{jt}	-0.939***		-0.870		-0.929***	
	(0.048)		(5.277)		(0.054)	
IMR_{jt} $\times M\&A$		-0.526***		-0.264		-0.544***
		(0.046)		(0.465)		(0.051)
IMR_{jt} $\times GF$		-1.102***		-0.654		-1.125***
		(0.053)		(0.795)		(0.065)
Observations	227702	227702	227702	227702	227301	227301
Orig-Dest-Sect-Mode	X	X	X	X	X	X
Year-Sector-Mode	X	X	X	X	X	X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates in columns (1), (3) and (5) correspond to Equation (4) with $residcf_{it}$ and $residcf_{jt}$. Estimates in columns (1), (3) and (5) correspond to Equation (5) with $residcf_{it}$ and $residcf_{jt}$. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

B Testing Freeman et al. (2025)

As described in Section 3, the strategy proposed by Freeman et al. (2025) to account for multilateral resistance is theoretically grounded in structural gravity models of trade, but not for FDI. In the FDI gravity literature, multilateral resistance is therefore typically absorbed by including origin-year and destination-year (or destination-sector-year) fixed effects. With these fixed effects, however, the coefficient on ER_{jt} is not separately identified because of collinearity.

To assess whether the multilateral-resistance correction based on Freeman et al. (2025) performs similarly in the FDI setting, we compare the estimated coefficients for bilateral policy variables (RTA and BIT) under alternative ways of accounting for multilateral resistance: (i) no multilateral-resistance controls, (ii) origin-year and destination-sector-year fixed effects, and (iii) the constructed OMR and IMR indices following Freeman et al. (2025). This comparison is reported in Table A.6, respectively, in columns (1), (2) and (3).

The estimates in column (1) differ markedly from those in column (3): ER_{jt} becomes positive and statistically significant, and the coefficients of other variables are generally larger and more precisely estimated. The estimated effect of BIT in column (1) is about 70% larger than in column (3). This pattern is consistent with omitted multilateral resistance bias: when multilateral resistance is not controlled for, bilateral policy variables may partly capture diversion effects and other general-equilibrium forces, leading to an overstatement of their positive impact on FDI.

Importantly, the BIT coefficient in column (2) is identical to that in column (3), suggesting that the OMR and IMR indices successfully proxy for the origin-year and destination-sector-year fixed effects in this application. This is noteworthy given that OMR and IMR are not sector-specific; nevertheless, they appear to capture the relevant time-varying multilateral component that would otherwise be absorbed by these fixed effects.

Table A.6: Testing Freeman et al. (2025)

	(1) No MRT	(2) MRT FE	(3) MRT index
$log(ER_{it})$	0.173		0.062
	(0.117)		(0.112)
$log(ER_{jt})$	0.459***		0.065
	(0.085)		(0.081)
$log(GDP_{it})$	0.167		0.813***
	(0.172)		(0.168)
$log(GDP_{jt})$	0.958***		1.073***
	(0.163)		(0.128)
$log(GDPpc_{it})$	0.947***		0.168
	(0.170)		(0.170)
$log(GDPpc_{jt})$	-1.596***		-0.208
	(0.180)		(0.138)
$RuleofLaw_{it}$	0.256***		0.036
	(0.068)		(0.062)
$RuleofLaw_{jt}$	-0.269***		-0.007
	(0.054)		(0.047)
RTA_{ijt}	0.065*	0.082**	0.060*
	(0.034)	(0.040)	(0.032)
BIT_{ijt}	0.173***	0.118**	0.100**
	(0.041)	(0.050)	(0.041)
OMR_{it}			-1.013***
			(0.025)
IMR_{jt}			-0.937***
			(0.026)
Observations	227702	227702	227702
MRT	No	Yes	Yes
Origin-Destination-Sector-Mode	X	X	X
Origin-Year		X	
Destination-Sector-Year		X	
Year-Sector-Mode	X		X
Source and dest control vars	X		X

Note: The dependent variable is the number of FDI projects by mode, GF or M&A. The estimator is PPML. Estimates correspond to Equations (4) but with different fixed effects when indicated. Standard errors clustered by origin, destination, sector and mode are in parentheses. * p<0.10, **p< 0.05, *** p<0.01.

C Empirical models

Estimates from Table 4 are obtained from the following two empirical models:

$$\begin{aligned} FDI_{mijst} = \exp(&ER_{it} \times Clean + ER_{it} \times Dirty + ER_{jt} \times Clean + ER_{jt} \times Dirty \\ &+ X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\ &+ \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst} \end{aligned} \tag{A.1}$$

$$\begin{aligned} FDI_{mijst} = \exp(&ER_{it} \times M\&A \times Clean + ER_{it} \times GF \times Clean + ER_{it} \times MA \times Dirty \\ &+ ER_{it} \times GF \times Dirty + ER_{jt} \times M\&A \times Clean \\ &+ ER_{jt} \times GF \times Clean + ER_{jt} \times M\&A \times Dirty \\ &+ ER_{jt} \times GF \times Dirty + X_{it} \times M\&A + X_{it} \times GF + X_{jt} \times M\&A \\ &+ X_{jt} \times GF + B_{ijt} \times M\&A + B_{ijt} \times GF + ln(OMR_{it}) \\ &+ ln(IMR_{jt}) + \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst} \end{aligned} \tag{A.2}$$

in which *Clean* and *Dirty* are two indicator variables that take the value one when investment is in a clean and dirty sector, respectively.

Estimates from Tables 5, 6, 7, and 8 are obtained by estimating the following empirical models:

$$
\begin{aligned}
FDI_{mijst} = \exp(& ER_{it} \times hh_{ij} + ER_{it} \times hl_{ij} + ER_{it} \times ll_{ij} + ER_{it} \times lh_{ij} \\
& ER_{jt} \times hh_{ij} + ER_{jt} \times hl_{ij} + ER_{jt} \times ll_{ij} + ER_{jt} \times lh_{ij} \\
& X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\
& + \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst}
\end{aligned} \tag{A.3}
$$

$$
\begin{aligned}
FDI_{mijst} = \exp(& ER_{it} \times hh_{ij} \times Clean + ER_{it} \times hh_{ij} \times Dirty + ER_{it} \times hl_{ij} \times Clean \\
& + ER_{it} \times hl_{ij} \times Dirty + ER_{it} \times ll_{ij} \times Clean + ER_{it} \times ll_{ij} \times Dirty \\
& + ER_{it} \times lh_{ij} \times Clean + ER_{it} \times lh_{ij} \times Dirty \\
& ER_{jt} \times hh_{ij} \times Clean + ER_{jt} \times hh_{ij} \times Dirty + ER_{jt} \times hl_{ij} \times Clean \\
& + ER_{jt} \times hl_{ij} \times Dirty + ER_{jt} \times ll_{ij} \times Clean + ER_{jt} \times ll_{ij} \times Dirty \\
& + ER_{jt} \times lh_{ij} \times Clean + ER_{jt} \times lh_{ij} \times Dirty \\
& X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\
& + \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst}
\end{aligned} \tag{A.4}
$$

$$
\begin{aligned}
FDI_{mijst} = \exp(& ER_{it} \times hh_{ij} \times GF + ER_{it} \times hh_{ij} \times M\&A \\
& + ER_{it} \times hl_{ij} \times GF + ER_{it} \times hl_{ij} \times M\&A \\
& + ER_{it} \times ll_{ij} \times GF + ER_{it} \times ll_{ij} \times M\&A \\
& + ER_{it} \times lh_{ij} \times GF + ER_{it} \times lh_{ij} \times M\&A \\
& + ER_{jt} \times hh_{ij} \times GF + ER_{jt} \times hh_{ij} \times M\&A \\
& + ER_{jt} \times hl_{ij} \times GF + ER_{jt} \times hl_{ij} \times M\&A \\
& + ER_{jt} \times ll_{ij} \times GF + ER_{jt} \times ll_{ij} \times M\&A \\
& + ER_{jt} \times lh_{ij} \times GF + ER_{jt} \times lh_{ij} \times M\&A \\
& + X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\
& + \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst}
\end{aligned} \tag{A.5}
$$

$$
\begin{aligned}
FDI_{mijst} = \exp(&ER_{it} \times hh_{ij} \times Clean \times GF + ER_{it} \times hh_{ij} \times Clean \times M\&A \\
&+ ER_{it} \times hh_{ij} \times Dirty \times GF + ER_{it} \times hh_{ij} \times Dirty \times M\&A \\
&+ ER_{it} \times hl_{ij} \times Clean \times GF + ER_{it} \times hl_{ij} \times Clean \times M\&A \\
&+ ER_{it} \times hl_{ij} \times Dirty \times GF + ER_{it} \times hl_{ij} \times Dirty \times M\&A \\
&+ ER_{it} \times ll_{ij} \times Clean \times GF + ER_{it} \times ll_{ij} \times Clean \times M\&A \\
&+ ER_{it} \times ll_{ij} \times Dirty \times GF + ER_{it} \times ll_{ij} \times Dirty \times M\&A \\
&+ ER_{it} \times lh_{ij} \times Clean \times GF + ER_{it} \times lh_{ij} \times Clean \times M\&A \\
&+ ER_{it} \times lh_{ij} \times Dirty \times GF + ER_{it} \times lh_{ij} \times Dirty \times M\&A \\
&+ ER_{jt} \times hh_{ij} \times Clean \times GF + ER_{jt} \times hh_{ij} \times Clean \times M\&A \\
&+ ER_{jt} \times hh_{ij} \times Dirty \times GF + ER_{jt} \times hh_{ij} \times Dirty \times M\&A \\
&+ ER_{jt} \times hl_{ij} \times Clean \times GF + ER_{jt} \times hl_{ij} \times Clean \times M\&A \\
&+ ER_{jt} \times hl_{ij} \times Dirty \times GF + ER_{jt} \times hl_{ij} \times Dirty \times M\&A \\
&+ ER_{jt} \times ll_{ij} \times Clean \times GF + ER_{jt} \times ll_{ij} \times Clean \times M\&A \\
&+ ER_{jt} \times ll_{ij} \times Dirty \times GF + ER_{jt} \times ll_{ij} \times Dirty \times M\&A \\
&+ ER_{jt} \times lh_{ij} \times Clean \times GF + ER_{jt} \times lh_{ij} \times Clean \times M\&A \\
&+ ER_{jt} \times lh_{ij} \times Dirty \times GF + ER_{jt} \times lh_{ij} \times Dirty \times M\&A \\
&+ X_{it} + X_{jt} + B_{ijt} + ln(OMR_{it}) + ln(IMR_{jt}) \\
&+ \lambda_{mijs} + \lambda_{smt}) \times \varepsilon_{mijst}
\end{aligned} \tag{A.6}
$$