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The impact of energy prices on industrial investment location: evidence from global firm level data

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Abstract

This study examines the influence of relative energy prices on the geographical distribution of industrial investments across 41 countries. Employing a gravity model framework to analyse firms' investment location decisions, we estimate the model using global bilateral investment flows derived from firm-level M&A data. Our findings reveal that a 10% increase in the energy price differential between two countries results in a 3.2% rise in cross-border acquisitions. This effect is most pronounced in energy-intensive industries and transactions targeting emerging economies. Furthermore, policy simulations suggest that the impact of unilateral carbon pricing on cross-border investments is modest.

Keywords: FDI; Mergers and Acquisitions; energy prices; firm location; competitiveness impacts; carbon leakage

JEL codes: F21, F64, H23, Q52

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1 Introduction

One of the main obstacles to ramping up regulation on industrial emissions in the race to net zero is concerns about competitiveness loss and industrial offshoring. In a closed economy, CO_2 price signals that regulated firms face are passed forward throughout the value chain, thus discouraging high-carbon goods and services at each stage of production and consumption. Instead, in an open economy with competition from trade, domestic firms' ability to pass forward carbon costs may be restricted (Ganapati et al., 2020). In addition to the fear of being undercut by foreign competition depressing domestic prices and eroding profit margins, a key political concern is that rising costs of energy or climate policies make abroad seem like a safer place to invest new capital for industrial sectors.

Recent empirical studies generally find limited evidence of significant leakage and relocation responses from carbon pricing policies (Ellis et al., 2019; Verde, 2020; Caron, 2022; Naegele and Zaklan, 2019; Koch and Mama, 2019). This is in some ways unsurprising given that most policies regulating industrial emissions embed measures to prevent leakage such as free allowance allocations in emissions trading and exemptions from carbon taxes, and most empirical studies have been conducted using data during periods of low CO_2 prices.

Instead, studies using industrial energy prices as a proxy for the added climate policy costs suggest that cross-country differences may matter for energy-intensive sector investment location decisions (e.g. Panhans et al., 2016; Garsous et al., 2020). In particular, two studies in this vein using the U.S. shale gas boom as an exogenous shock find evidence in support of theoretical predictions that an increase in the price gap with other countries will increase U.S. energy intensive industries' investments (as well as output, factor usage, and exports) (Arezki et al., 2017; Manderson and Kneller, 2020). Developing countries remain poorly represented in existing empirical studies, however.

Indeed, the fear of leakage still prevails, as is evident from the heated debate on how to strengthen leakage protection, for example, through border carbon adjustments and other consumption based measures (Grubb et al., 2022). In turn, these developments reflect the growing recognition that incentives for industrial decarbonisation need to be strengthened, particularly for rich countries to meet mid-century carbon neutrality goals, and the expectation that large differences in CO_2 prices will continue globally, as countries advance climate action at different speeds under the bottom-up approach of the Paris Agreement (Robiou du Pont and Meinshausen, 2018).

To advance these debates, this paper analyses the role of energy prices in firms' investment location decisions in the manufacturing sector using a global setting, that allows deriving general results across a wide geographical context. To this end we use an exhaustive Thomson-Reuters dataset of all cross-border M&A deals in the manufacturing sector. Our data includes information on over 70,000 M&A deals – of which 22,000 are cross-border – between firms in 22 sectors in 33 industrialised countries and 10 emerging economies during the period 1995 and 2014. This goes well beyond previous multi country studies in this literature. In particular, our data covers emerging economies which are central to concerns around investment and leakage such as China, India, Mexico and Turkey, where carbon pricing is likely to ramp up later. Moreover, the bilateral data structure allows controlling for multitude of confounding factors e.g. sector, country, pair level trends, overcoming challenges in identifying comparative cost advantage in previous studies.[1] [2]

To motivate our empirical strategy, we specify a conditional logit model that links bilateral foreign direct investment (FDI) activity to relative bilateral energy prices. Our model builds on the dartboard model of M&A of Head and Ries (2008), an application of discrete choice theory to the firm location problem. It predicts that conditional on having decided to make an investment in an external firm, an acquiring firm will choose its target by considering, among other factors, the ratio between the energy cost it faces domestically and the one its target acquisition faces.

Empirically, the bilateral nature of the M&A transaction counts considered in our model gives rise to a gravity-like specification, including a multilateral resistance term. We thus draw from the recent literature on the determinants of cross-border investments, which uses bilateral flows and a base model consisting of gravity-type covariates, borrowing from the empirical bilateral trade literature (e.g. Anderson, 2011; Head and Mayer, 2014; Anderson and Yotov, 2012) to motivate our estimation strategy and specify an appropriate fixed effects structure. For computational tractability, the bilateral firm-level transaction count data is aggregated at the ISIC 2-digit pair level, and our identification strategy rests on within-country cross-sectoral energy price differentials, enabling to control for the large number of potential confounding factors.

We find that the basic logic of comparative advantage, and specifically cross-country energy cost differences, contributes to explaining the patterns of industrial firms' investment location decisions in two specific instances. Namely, they matter for deals involving a global South-based firm – most of which consist of North-South deals, when a firm based in an industrialised country acquires a firm based in a developing country; and North-North horizontal deals involving acquiring and target firms that are operating in the same high energy intensive sector.[3] The former accounts for 15.9% of total cross-border deals and the latter 18.1% from 1995 to 2014, such that energy price differences matter in 34% of cross-border M&A activity over those two decades. The role of energy price differences is heterogeneous and has no effect in the majority of deals. In the cases of North-South deals and North-North horizontal deals in energy intensive sectors, we find that a 10% increase in the relative energy price differential between two countries is expected to increase the number of deals by around 5% and 3% respectively. Counterfactual simulations reveal that a CO_2 price gap of \$50/tCO_2 led by various coalitions of countries is expected to have a limited influence on the FDI attractiveness of economies. Our main contribution is to use a truly multi-country framework and sufficiently disaggregated data that allows obtaining comparable estimates to understand the heterogeneity in effects across sectors and geography.

Our findings confirm that fears of industrial offshoring are warranted but only in relatively well-defined specific situations and cannot be generalised. Most cross-border deals in manufacturing occur between firms in industrialised countries (84.1% in our sample), and the majority of them are not in energy-intensive sectors. For example,

[1] Instead, many previous studies utilised within country variation to look at inbound FDI location choice/ outbound FDI rates, or variation in target country environmental policy stringency to test outbound FDI location choice and did not directly test relative measures of policy stringency between host acquirer and target.

[2] While focusing on M&A transactions means that greenfield investments are excluded from our analysis, M&A represents the majority of FDI flows accounting for 50% of cross-border investment flows by value over the period 2003–2014 in OECD and BRICS countries (UNCTAD, 2018).

[3] For the purpose of this paper, we use the membership of the OECD to define the North, while South are defined as non-OECD countries.

the U.S. has been shown to have a unique advantage in energy-intensive manufacturing, thanks in part to the expansion of shale oil (Arezki et al., 2017; Manderson and Kneller, 2020). This highlights the imperative of harmonising climate policy stringency within industrialised nations for the most energy-intensive sectors to prevent leakage. Our results also suggest that supporting measures against carbon leakage, such as carbon boarder adjustments need not be economy wide, but may warrant being used sparingly. Our simulation shows that the overall effects on global M&A patters will be small if the CO_2 price gap stays with \$50/tCO_2.

We draw on and contribute to several strands of literature. The first literature explores how energy price differences influence manufacturing production, employment, trade and investments (Ratti et al., 2011; Kahn and Mansur, 2013; Aldy and Pizer, 2015; Sato and Dechezleprêtre, 2015; Panhans et al., 2016). So far, U.S. or European data have been used in this literature, and studies tend to find that energy-intensive industry activity concentrates in areas with low energy prices. Exploring the role of energy prices is interesting in its own right, but it also helps us understand the impacts of environmental policies. This is because energy prices capture a significant share of the variation in environmental policy (Sato et al., 2019) and environmental policy stringency is notoriously difficult to measure in a quantifiable and comparable manner across countries.

We also contribute to the long-standing literature on the pollution haven effect and the link between environmental regulation and trade flows or investment decisions (McGuire, 1982; Taylor, 2004; Cole et al., 2017; Koch and Mama, 2019; Borghesi et al., 2020). Altogether, empirical studies yield mixed conclusions (Rezza, 2015) but provides valuable insights. For example, one important barrier to leakage of carbon intensive production is the high capital intensity nature of these sectors, making them less mobile than their more 'footloose' counterparts (Ederington et al., 2005).

Several empirical challenges are highlighted in this literature. First, wide geographical coverage of the data is important, because the strongest effects observed tend to be found in studies with smaller geographical scopes, which feature less variation in other determinants of production location (Jeppesen et al., 2002). Second, data should be sufficiently spatially disaggregated to control for the multitude of confounding factors. In particular, the effect of stricter regulation is spatially heterogeneous and varies systematically on location specific attributes such as unemployment levels. Third, disaggregated data is also important to address endogeneity issues. Treating environmental regulation as endogenous is important, because an influx of FDI can lead to a change in environmental regulation (Frankel and Rose, 2005). Fourth, recent studies argue the importance of testing pollution haven effects using bilateral data and accounting for *relative* policy stringency (e.g. Tang, 2015; Rezza, 2015) in line with the theory that predicts plant location and trade as a function of differences in relative factor endowments (Helpman, 1984). Using aggregated FDI data of total inward or outward flows for a given country prevents any differential analysis at the bilateral level.[4] Fifth, as noted, variables capturing environmental regulation stringency of a particular location are often subject to measurement error, due to its multidimensional nature (Brunel and Levinson, 2016).[5][6] Lastly and also

[4]A common approach is to exploit the variation in environmental regulation within a country, and assess if jurisdictions with lax policy can attract more inbound FDI flows (List et al., 2004; Millimet and Roy, 2015), or discourage outbound FDI flows (Cole and Elliott, 2005; Hanna, 2010).

[5]Regulations target different pollutants arising from different media such as air, water and land, and different polluters such as industry and households, and can take many forms such as pollution reduction targets and technology standards.

[6]A group of studies use data in a specific country, and measures of environmental policy stringency

as previously noted, some environmental policies embed mechanism to prevent trade and investment impacts.[7]

Lastly, this article contributes to the broader literature that examines the impact of production factor costs on FDI and cross border M&A activity, using both theoretical and empirical approaches. Studies highlight the importance of traditional gravity factors such as geographical and cultural proximity, and market size (Breinlich, 2008; Blonigen and Piger, 2014). Other determinants explored include taxation (Giroud and Rauh, 2019; Todtenhaupt and Voget, 2021), stock market valuations and exchange rates (Erel et al., 2012), tariff-jumping and trade costs (Brainard, 1997), and financial and institutional constraints (Alquist et al., 2019). Energy vectors – for our purposes electricity, coal, natural gas, and petroleum products – has received less attention but are arguably an appealing case for assessing the impact of factor costs on investment location decisions. This is because compared, for example, to labour, energy products are homogeneous goods that for the most part do not vary in quality and are priced using standardised units across the globe (Siggel, 2006; Atkeson and Burstein, 2008).

The paper proceeds as follows. Section 2 develops a simple theoretical framework to guide our analysis. Section 3 presents our empirical strategy. Section 4 describes the sources and structure of our M&A dataset and the industrial energy price data. Section 5 assesses the impact of energy prices on investment location decisions and presents the main results before exploring the heterogeneity of these impacts across the global North-South divide and across sectors. Finally, we present our counterfactual policy simulations in section 6 before concluding.

2 Theoretical determinants of cross-border investment location

Reduced form analyses examining the impact of energy or environmental policy on industrial investment locations generally ignore the bilateral structure of cross-border investment flows. To overcome this limitation, we construct a model of the firm's choice of investment location conditional on the decision to invest. We build on Head and Ries (2008)'s dartboard model, which applies McFadden (1974)'s discrete choice theory to the firm location problem. We also draw from applications of this model by Hijzen et al. (2008) and Coeurdacier et al. (2009), who study the impact of trade costs and European integration on FDI, respectively. In effect, we consider the firm's investment decision as a two-step process: first, the firm decides whether to invest in another firm, and second, it chooses its target. We are primarily concerned with the second step of this decision process, which determines the location of the investment.

Let g be a firm operating in sector $k \in \mathcal{S}$ and country $i \in \mathcal{C}$, with $\mathcal{S}$ the set of all sectors and $\mathcal{C}$ the set of all countries. Consider now a second firm h, $h \neq g$, operating in sector l and country j – $(j, l) \in \mathcal{C} \times \mathcal{S}$. This framework encompasses the baseline case where the firm decides to invest in a domestic firm $(i = j)$ operating in the same sector

across potential host countries, to assess if the latter can explain the destination choice for outbound FDI flows (Wagner and Timmins, 2009; Raspiller and Riedinger, 2008; Manderson and Kneller, 2012; Ben Kheder and Zugravu, 2012).

[7]For example this caveat is relevant for studies on the EU emissions trading system (e.g. Branger et al., 2016; Boutabba and Lardic, 2017; Naegele and Zaklan, 2019; Borghesi et al., 2020)

$(k = l)$[8]. We are interested in deriving the probability that g acquires h conditional on g having decided to invest in another firm.

Let π_h be the profit that firm g can expect if it acquires h. We consider a reduced-form profit function π_h , log-linear in the characteristics of h. In the following, we consider only the variation in these characteristics observed at the country and sector levels. Therefore, for a given characteristic X_c, we assume that reduced form profit π_h depends only on the locational and sectoral characteristics of h, hence $X_{c,h} = X_{c,jl}$. Examples of $X_{c,jl}$ include covariates such as sectoral energy prices or labour costs. We have, with ε_h a stochastic component:

$$\pi_h \equiv \sum_c \beta_c \log X_{c,h} + \varepsilon_h = \sum_c \beta_c \log X_{c,jl} + \varepsilon_h \tag{1}$$

Under the assumption that the perturbation term ε_h is distributed as a Type I extreme value (McFadden, 1974), we obtain from discrete choice theory the following familiar multinomial logit expression for the probability $P_{g,h}$ that g acquires h:

$$P_{g,h} = \frac{\exp(\pi_h)}{\sum\limits_{h'} \exp(\pi_{h'})} \tag{2}$$

We now write n_{jl} the number of firms that operate in country j and sector l. Aggregating at the target sectoral and country levels, we obtain the probability that g acquires a firm in country j and sector l:

$$P_{g,jl} = \frac{n_{jl} \exp(\pi_{jl})}{\sum\limits_{j' \in \mathcal{C}, l' \in \mathcal{S}} n_{j'l'} \exp(\pi_{j'l'})} \tag{3}$$

Summing all firms in acquiring country i and sector k, we can express the number of deals m_{ijkl} observed between country-sector pairs (i, k) and (j, l):

$$m_{ijkl} = \frac{n_{ik} n_{jl} \exp(\pi_{jl})}{\sum\limits_{j' \in \mathcal{C}, l' \in \mathcal{S}} n_{j'l'} \exp(\pi_{j'l'})} \tag{4}$$

Because $i \in \mathcal{C}$ and $k \in \mathcal{S}$, we finally get:

$$m_{ijkl} = \frac{n_{ik} n_{jl} \exp(\pi_{jl} - \pi_{ik})}{\Omega_{ijkl}} \tag{5}$$

with $\Omega_{ijkl} \equiv \sum\limits_{j' \in \mathcal{C}, l' \in \mathcal{S}} n_{j'l'} \exp(\pi_{j'l'} - \pi_{ik})$.

This expression is functionally similar to the gravity equation commonly used in the trade literature (Head and Mayer, 2014). The number of deals[9] between two country sector pairs is proportional to the economic size of the two sectors considered, measured here by the number of firms operating in each sector. Further, Ω_{ijkl} can be interpreted as an indicator of the financial attractiveness of a sector in a given country, and therefore the

[8]In effect, in the discrete choice model introduced below, this configuration – same-sector domestic investment – is functionally equivalent to the outside good in a consumption model, and thus constitutes the control against which other options are compared.

[9]Note that this model uses the number of transactions to proxy for M&A activity, yet an improved measure is the deal values. Unfortunately, data availability constraints prevent using M&A deal values as the outcome variable. Nonetheless, we rise to the challenge in Appendix D.

difficulty in acquiring one of its targets. The more profitable targets in a given country-sector pair are, the larger Ω_{ijkl} becomes, and the smaller the probability for potential acquirers to outcompete the rest of the world and achieve a deal. Ω_{ijkl} is therefore a remoteness index comparable to that found in trade theory (Anderson, 2011). It plays the role of a multi-lateral resistance (MLR) term in equation (5).[10]

Injecting equation (1) into (5), we get:

$$m_{ijkl} = \frac{n_{ik} n_{jl} \prod_c \left(\frac{X_{c,jl}}{X_{c,ik}}\right)^{\beta_c}}{\Omega_{ijkl}} \tag{6}$$

In the case of sectoral energy prices, (6) implies that the number of deals is directly related to the ratio of energy prices between the target and host countries and thus to the sectoral energy price of the target country *relative* to that of the host country. A decrease (resp. increase) in this ratio is thus expected to cause an increase (resp. decrease) in the number of deals observed between the country pairs considered. This result is intuitive: when energy prices in country j become cheaper relative to those in country i, firms in country i are expected to be encouraged to invest in country j.

3 Empirical strategy

Our objective is to estimate the impact of relative energy prices on firm's investment location decisions. In the context of our theoretical framework, the coefficient of interest is therefore the β_c related to relative energy prices. To estimate this model, we first rearrange equation (6) as follows:

$$m_{ijklt} = \exp\left[\log n_{ikt} + \log n_{jlt} + \sum_c \beta_c \left(\log X_{c,jlt} - \log X_{c,ikt}\right) - \log \Omega_{ijklt}\right] \tag{7}$$

This formulation highlights that our model follows the "general gravity" form[11] defined by Head and Mayer (2014). The main challenge in estimating this class of models is to adequately control for the multi-lateral resistance term Ω_{ijkl} (Anderson and Yotov, 2012). Fally (2015) shows that this specification form is equivalent to a structural gravity setting, where MLR terms can be accounted for by an appropriately designed set of fixed effects. In our context, where the number of deals is repeatedly observed at the country-sector level over time, the fixed effects structure consistent with structural gravity is as follows (Piermartini and Yotov, 2016):

$$m_{ijklt} = \exp\left[\log n_{ikt} + \log n_{jlt} + \sum_c \beta_c \left(\log X_{c,jlt} - \log X_{c,ikt}\right) + \alpha_{ij} + \eta_{ikt} + \nu_{jlt}\right] \tag{8}$$

In equation (8), α_{ij} capture time-invariant country-pair effects, while η_{ikt} and ν_{jlt} are country-sector-year fixed effects. However, under this specification, our coefficients of interest, the β_c, are not identifiable. The locational characteristics of the acquiring and

[10] The empirical trade literature has shown that it is necessary to account not only for bilateral trade resistance (the barriers to trade between a pair of countries) but also for multilateral trade resistance (the barriers to trade that a country faces with all its trading partners).

[11] Equation (7) illustrates that our model is of the form $X_{ij} = exp\left[e_i - \theta \log D_{ij} + m_j\right]$, with e_i invariant across exporters i and m_j invariant across importers j.

target country-sector pairs are collinear with the country-sector-year fixed effects η_{ikt} and ν_{jlt} respectively.[12]

To overcome this difficulty, we relax the fixed effect structure to account for most of the confounding factors that may influence firms' choice of investment location while maintaining the identifiability of the β_c. In our main specification, we include country-pair, country-year, and sectoral fixed effects.[13] Country-pair fixed effects account for the time-invariant characteristics commonly considered in gravity models, including but not limited to: distance, commonality of language or system of law, and colonial history. Since these factors do not form the focus of this study, identifying their individual impact on investment activity is not relevant in our context. Sectoral effects allow us to capture systematic differences in cross-border investment activity between sectors. Such variation can be explained by differences in market structure, technology, or specificities of the manufactured product.

Country-year form the largest group of fixed effects included. They account for the country-specific macroeconomic environment and any independent variable that varies at the country-time granularity. This includes a number of factors identified in the M&A literature to be correlated with the number of deals between two given countries, irrespective of their market sizes (Di Giovanni, 2005), such as exchange rates or stocks valuations. Importantly, country-year fixed effects control for production factor costs at the aggregate level in the countries on both sides of the transaction: namely, country-wide mean labour, capital and energy costs. They also control for country-level policies that may influence investment decisions in the manufacturing sector, such as cross-sectoral environmental policies. Furthermore, country-time fixed effects also encompass time fixed effects, which control for the highly cyclical nature of global merger and acquisition flows (Erel et al., 2012). Finally, we control for the existence of a free-trade agreement between a given country pair.

This rich set of fixed effects allows us to control for confounding factors that may influence firms' choice of investment location other than our regressor of interest, relative energy costs, as is common in the gravity literature (Head and Mayer, 2014; Arvis and Shepherd, 2013). We note that in this specification, identification rests on within-country cross-sectoral energy price differences.

Estimating equation (9) requires an estimate of the number of potential acquiring and target companies, n_{ik} and n_{jl}, in the countries and sectors considered. We follow Hijzen et al. (2008) and approximate this using sectoral GDP in the acquiring and target countries. In the reduced form profit function, we include our main regressor of interest, the ratio of energy prices in the country-sector of the acquiring and target companies. We complement it with country-sector level estimates for the cost of labour and capital, since cross-sectoral differences in the cost of these two production factors could also have an impact on firms' investment decisions (Wheeler and Mody, 1992). Other industry-wide cost components are accounted for by country-time fixed effects.

[12] This stems from the fact that our main regressors of interest, the logarithms of the ratios of locational characteristics in the acquiring and target country-sectors, are not truly dyadic variables. Instead, these ratios result from a linear combination – a difference – of two monadic variables: the log of the characteristics X_c, observed for the acquiring and target firms.

[13] Additional sets of fixed effects are also considered as robustness checks in section 5.4

Our baseline specification is therefore:

$$m_{ijkl,t} = \exp\Big[\beta_1 \log GDP_{ik,t} + \beta_2 \log GDP_{jl,t} + \beta_e \log e_{ijkl,t} + \\ \beta_5\, fta_{ij,t} + \alpha_{0,ij} + \alpha_{1,k} + \alpha_{2,l} + \alpha_{3,it} + \alpha_{4,jt}\Big] + \varepsilon_{ijkl,t} \tag{9}$$

where for each country-sector pair ik (acquirer) or jl (target), $GDP_{ik,t}$ and $GDP_{jl,t}$ are the sectoral GDP, $fta_{ij,t}$ is a dummy indicating the presence of a free-trade agreement concerning the exchange of goods between countries i and j. Our main parameter of interest is β_e, which captures the impact of relative energy prices on investment activity between two country-sector pairs.

$e_{ijkl,t}$ measures the ratio of energy prices between the acquiring and target country-sector pairs. In our dataset, we also consider transactions in which a firm invests in a sector distinct from its main activity. However, when deciding the location of an investment in a given target sector l, the investing firm compares energy costs in this sector l across locations, including its own domestic country. Therefore, between two given country-sector pairs, the relevant energy price ratio should be calculated between the energy cost *in sector* l in the target country and that of the acquirer, regardless of the acquirer's main sector of activity. For a transaction between country-sector pairs ik and jl, we consider the following log-ratio:

$$e_{ijkl,t} = \log\left(\frac{E_{jl,t}}{E_{il,t}}\right) \tag{10}$$

where E is our measure of sectoral energy costs in each country, as defined in section 4. While our structural model yields a direct link between the energy price ratio or *differentials*, and the number of transactions observed between a given bilateral country-sector pair, it is also possible that the energy prices in the origin and destination countries independently matter and we will also explore this in Section 5.

Estimator choice and computational feasibility

To keep the estimation computationally manageable, we aggregate the original sectoral breakdown, available in our dataset at the 4-digit SIC level, up to the 2-digit ISIC (revision 3.1) level, distinguishing 22 sectors [14] (see Appendix Table C.1 for the list of included ISIC sectors). Despite this aggregation, our sample of 41 countries over a 20-year period yields more than 16 million potential observations.[15] Data availability reduces this sample size to between 6 and 8 million observations depending on the covariates included in the estimated specifications.

As is often the case in balanced bilateral datasets, most observations in the sample are zero. Failure to properly consider these zero values would lead to biased estimates, which rules out estimations by OLS on the log of our dependent variable. In their seminal contribution, Silva and Tenreyro (2006) show that the best estimator in this context is Poisson Pseudo-Maximum Likelihood (PPML) with heteroscedasticity-consistent standard errors, which can handle potential overdispersion and consistently outperforms potential alternatives such as zero-inflated Poisson or negative binomial. The panel nature of our dataset

[14] Our dataset is restricted to the manufacturing sectors both on the acquirer and target sides. In particular, acquisitions by non-manufacturing firms are excluded.

[15] 41 origin countries × 41 target countries × 22 origin sectors × 22 destination sectors × 20 years = 16,272,080.

requires applying clustering to the standard errors. We opt for the most conservative design by clustering at the country-sector pair level, which is the unit of observation in our panel.

However, the size of the dataset makes a straight maximum likelihood estimation intractable. Instead, we use the PPML with high-dimensional fixed effects estimator[16] proposed by Bergé (2018) and Correia et al. (2019).

4 Data

4.1 The Mergers and Acquisitions dataset

To implement our strategy to test the influence of energy prices on investment flows, we depart from previous literature that relies on aggregated FDI data and instead use bilateral firm level M&A transactions data to capture investment activity to construct our dependent variable. Specifically, we use the number of transactions by sector and country pair in time t as a measure of investment activity.[17]

Firm level M&A data is obtained from the proprietary Thomson-Reuters Mergers and Acquisitions database. This is one of the worlds most comprehensive data on mergers and acquisitions activity, and according to the provider, covers the universe of deals globally ranging from small, undisclosed value transactions to multi-billion dollar ones since the 1970s.[18] We only consider realised deals.[19] Reported data includes transaction date[20] and deal type, as well as a set of variables describing both acquiring and target companies such as country of origin and main 4-digit SIC sector activity.

We restrict the sample in two main ways. To ensure that we select only deals that represent significant, strategic external capital acquisitions, we restrict our sample to deals that fall under the four main M&A deal type categories, specifically "Merger", "Acquisition of Majority Interest", "Acquisition of Remaining Interest" and "Acquisition of Assets". [21] Deals of different types may be driven by different motivations, such as corporate strategy, access to markets, market power, or production costs. "Acquisition of Assets" deals are assessed separately in the estimation to explore this distinction because we are

[16]A separate version of this estimator was implemented by the authors during the initial redaction of this article, which occurred before the publication of both Bergé (2018) and Correia et al. (2019). The source code for this estimator was provided in a working paper version of this article, LSE-GRI Working Paper No. 311 (2018). All estimation results provided in this article were obtained using R's *fixest* package Bergé (2018) on the London School of Economics' Fabian high-performance computing cluster.

[17]Obtaining data on deal values would give a better measure of foreign capital flows, but unfortunately M&A deal values are only reliably reported for a small subset of deals (between publicly listed companies). Hence, the number of deals represents the best approximation of investment flows given data limitations (See Appendix D for analysis of the subset of deals where deal values are available).

[18]It is a trusted source used by financial, legal, corporate, government and research institutions, for example, by the United Nation Conference on Trade and Development to compile its annual World Investment Report (UNCTAD, 2018).

[19]The Thomson-Reuters database also include deals that were announced but fell through.

[20]We take the deal announcement date rather than the completion date. The announcement date corresponds to the first public statement by any of the involved parties regarding the merger, acquisition or acquisition of assets considered. We consider this closer to the relevant time period in which the acquirer obtains information on production factor costs. The mean time to completion is less than a month, and for most transactions observed, both dates are identical.

[21]Respectively, these correspond to 1) full merger with the target company; 2) increase of interest from below to above 50% and 3) acquisition of the remaining interest already owned; and 4) acquisition of assets of a target company, subsidiary, division, production unit, branch, or single plant

primarily interested in assessing the determinants of manufacturing production capacity acquisition. In terms of sectors, as carbon leakage primarily concerns energy-intensive and trade-exposed sectors (Sato et al., 2014), deals observed outside the manufacturing sectors were eliminated from the analysis. Table 1 provides an overview of our sectoral coverage.[22]

Further, we reorganise the data by aggregating to the level of 2-digit (ISIC Rev 3.1) sector level for computational feasibility, except for 'Basic metals" sector (27). This 2-digit sector combines *Iron and steel* (2710) and *Non-ferrous metals* (2720), and conflating them is problematic for our analysis because the two are highly heterogeneous in terms of energy mix and therefore energy prices. Hence, we retain this separation in our analysis.[23]

Table 1: Number of transactions by manufacturing subsectors (1995-2014)

Manufacturing subsector	Within-country	Cross-border
Chemicals and chemical products	6,839	3,649
Food and beverages	5,657	2,224
Printing and publishing	4,673	998
Machinery and equipment n.e.c.	4,507	2,834
Medical, precision and optical instruments	2,652	1,265
Fabricated metal products	2,456	1,253
Rubber and plastics products	2,221	1,221
Coke,refined petroleum products,nuclear fuel	2,201	1,073
Basic metals	2,050	896
Non-metallic mineral products	1,980	1,082
Electrical machinery and apparatus	1,808	1,021
Radio,television and communication equipment	1,772	710
Motor vehicles, trailers, semi-trailers	1,620	1,000
Textiles	1,443	699
Paper and paper products	1,258	617
Furniture; manufacturing n.e.c.	1,063	424
Other transport equipment	942	358
Wearing apparel, fur	773	193
Wood products (excl. furniture)	750	236
Office, accounting and computing machinery	814	333
Leather, leather products and footwear	206	90
Tobacco products	53	65

Notes: This table shows the number of within-country and cross-border transactions by 2-digit sector (ISIC Rev 3.1) for the period 1995-2014. Data from Thomson-Reuters Mergers and Acquisitions database.

Our ultimate sample includes a total of 69,979 deals that occurred between 1995 and

[22]In manufacturing, we exclude ISIC (Rev 3.1) sectors 36, *Furniture; manufacturing n.e.c.* due to the large heterogeneity of firms included in that category, which makes it impractical to attribute a single corresponding energy price; and 37, *Recycling*, due to an absence of transactions observed in our dataset.

[23]Energy consumption for iron and steel production is dominated by coal use, while non-ferrous metals, which comprise mostly aluminium smelting in most countries, require electricity. These two sectors are complemented, respectively, by *Casting of iron and steel* (2731) and *Casting of non-ferrous metals* (2732).

2014 across 41 countries and in 22 manufacturing sectors, of which 22,241 are cross-border and the rest are domestic deals (see Appendix Figure A.1). The majority of deals involve firms located in North America, Western Europe, and Japan, whether as acquirers or targets. Locations of target firms are more dispersed as expected, for example, with deals involving firms in China, India, Australia, Southeast Asia and Brazil (see Appendix Figure A.2 and Figure A.3).

4.2 Energy prices

To test whether energy costs can explain the pattern of international cross-border investments, we need to accurately assess the level of energy costs faced by the acquiring firm at home and in target countries. Information on energy prices paid by industry at the sector level is publicly available from some national statistical offices, but international databases report only average industrial energy prices. We obtain unique sector-country level energy price data from Sato et al. (2019) which offers the most comprehensive and internationally comparable industrial energy price data to our knowledge, covering 12 industrial sectors (see Appendix Table C.2) in 32 OECD and 16 non-OECD countries between 1995 and 2015.[24] While the underlying datasets from the International Energy Agency have large gaps, the authors improve the data coverage by supplementing these sources with other governmental data and by developing transparent methods to reduce missing data points.

Acknowledging that energy costs exhibit great diversity between sectors within a country and that differences in fuel composition are a key driver for this cross-sectoral difference, Sato et al. (2019) computes an energy price index (Fixed Energy Price Index, FEPI) by weighting country-level industrial fuel prices for four carriers (oil, natural gas, coal and electricity) by the consumption of each fuel type for a given country i, sector k, and year t, according to the following equation:

$$FEPI_{ikt} = \sum_j \frac{F_{ik}^j}{\sum_j F_{ik}^j} \cdot \log(P_{it}^j) = \sum_j w_{ik}^j \cdot \log(P_{it}^j) \tag{11}$$

Here, F_{ik}^j are the input quantity of fuel type j in tons of oil equivalent (TOE) for sector k in country i and P_{it}^j denotes the real TOE price of fuel type j for total manufacturing in country i at time t in constant 2010 USD. The prices P_{it}^j are expressed in real terms and transformed into logs before applying the weights so that the log of the individual prices enter linearly in the equation.[25,26] FEPI operates in effect as a shift-share instrument: the weights w_{ik}^j applied to fuel prices are fixed over time, such that FEPI captures only variation that come from changes in fuel prices, and not through changes in fuel inputs mix over time, which could be endogenous.[27]

Figure 1 illustrates there is cross-sectoral variations in the energy price index over our

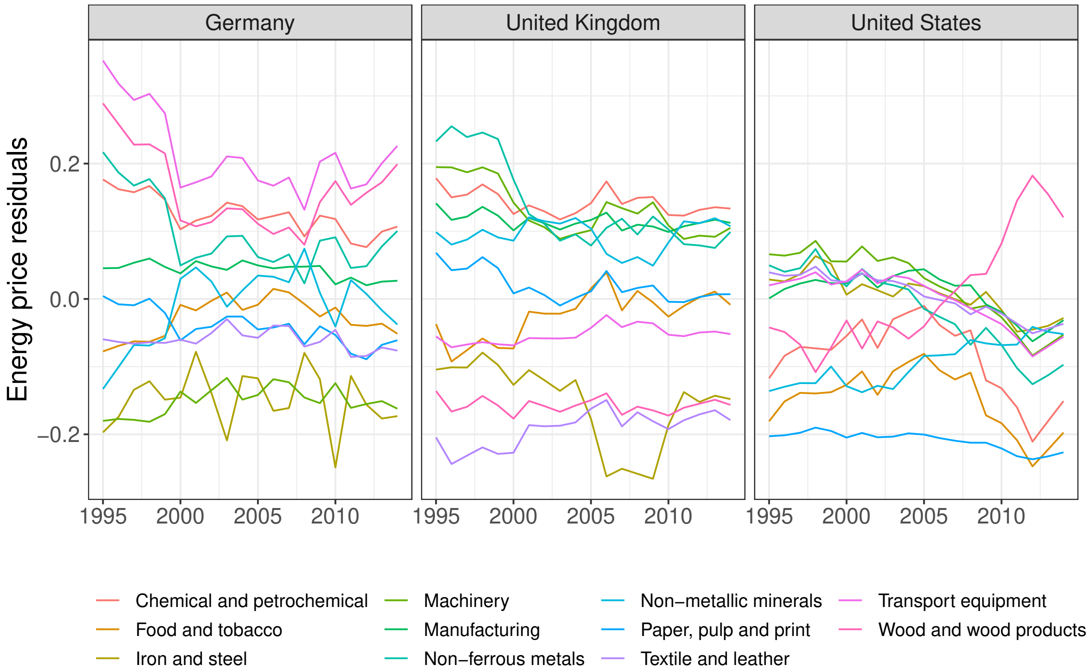
[24] The US energy price ends in 2014. Since it represents 30% of the transactions (either as acquirer or target), we have truncated the entire dataset to 2014.

[25] Note that taking the exponential of the FEPI yields the weighted geometric mean of the different fuel prices, so equation (11) is the log of the weighted geometric mean.

[26] The same methodology is employed in the construction of the country level index.

[27] The FEPI used in our main results takes average weights corresponding to the mean energy mix over the period 1995-2015. Section 5.4 tests the robustness of the results to alternative fuel weight specifications.

Figure 1: Energy prices cross-sectoral variation (1995-2014)



Notes: This Figure shows the cross-sectoral variations in energy prices. Specifically we plot the residuals of the energy price index (FEPI) regressed on year fixed effects by sector for the period 1995-2014. *Source:* Author calculations using data from Sato et al. (2019).

period of observation, using the examples of Germany, the UK and the US.[28] All three countries exhibit substantial industrial energy price volatility over time, but patterns of cross-sectoral variance differ significantly. This is particularly notable in energy-intensive sectors such as *Chemicals and petrochemicals*, which experienced a large reduction in energy prices in the US that was not observed in Europe. This is a result of the collapse in natural gas prices following the shale gas revolution in the US. Other energy-intensive sectors such as *Iron and steel* and *Non-metallic minerals* have also experienced volatility in all three countries. The figure illustrates that the within-sector variation in energy prices over time differs by sector and across countries, implying that an analysis simply comparing country-level energy prices may suffer from bias associated with these trends.

4.3 Other covariates

We bring together additional data sources to determine the impact of energy prices on foreign investment location choices. We use Exiobase 3 to observe GDP, labour intensity, and capital intensity at the sectoral level. The Exiobase 3 MRIO dataset is an input-output database that provides a detailed representation of the economic activities of countries around the world (Stadler et al., 2018). It offers a wealth of information on the production, consumption, environmental externalities, and trade of goods and services across 163 sectors of activity in 42 major economies, allowing for the analysis of complex economic interdependencies and the quantification of the environmental impacts

[28] Additionally, we show cross-sectoral variations for three non-OECD countries – Brazil, South Africa and Turkey in the Appendix Figure A.4.

of economic activities. Exiobase 3 is increasingly used as the standard MRIO database in environmental economic settings (e.g. Shapiro, 2021).

We also obtained from the CEPII gravity dataset (CEPII, 2018) a variable indicating the existence of free-trade agreements between country pairs and time. Appendix Table A.1 presents summary statistics for the dependent and independent variables used in the estimations.

5 Results: effects of relative energy prices on M&A transactions

5.1 Baseline results

Table 2 shows the results from estimating specification (9) over the period 1995 to 2014. In columns 1-3, the sample includes all deal types, whereas the sample is restricted to the "Acquisition of assets" in columns 4-6. In columns 1 and 4, both domestic and cross-border deals are included following our theoretical model (equation (6), but we also examine the case of cross-border transactions only in columns 2 and 5. Columns 3 and 6 examine cross-border transactions between firms operating in the same sector (defined at the ISIC 2-digits level), which is the transaction type most relevant to the carbon leakage debate. The main coefficient of interest, β_e, is reported; a negative value of β_e implies that firms tend to engage in more cross-border or cross-sector domestic investments if the energy prices they face increase relative to those in another country or sector.

We also control for other production factor costs, namely labour and capital. If firms' investment location choices are sensitive to relative energy costs at the sector level rather than at the country level, then it is reasonable to assume that they also consider other relative production factor costs such as labour or capital costs at the sector level (e.g. Erel et al., 2012). Indeed, failing to capture sectoral differences and controlling for factors only at the aggregate country level may be more problematic for inputs such as labour, where variation in factor productivity is more pronounced than in energy. More specifically, we control for differences in labour productivity between sectors with sectoral cost-shares of labour in value added on both sides of the transaction (Head and Ries, 1996; Chen and Moore, 2010). These cost shares are computed by taking the ratio of total sectoral labour compensation and sectoral value added.[29] A similar strategy is adopted to control for sectoral differences in capital costs by including the cost share of capital in value added.

[29] An alternative approach is to compute a ratio of sectoral unit labour costs between each country-sector pair in line with our theoretical model similar to Ceglowski and Golub (2012):$RULC_{ijkl} = \frac{w_{il}}{w_{jl}} \frac{e^{PPP}_{ijl}}{e_{ij}}$ with $w_{il} = \frac{a_{il}W_{il}}{p_{il}}$, $a_{il} = \frac{L_{il}}{GDP_{il}}$, $e^{PPP}_{ijl} = \frac{p_{il}}{p_{jl}}$ where W_{il} is the average annual wage in country i and sector l (national currency), p_{il} is the sectoral price index, L_{il} is the sectoral labour employment, and a_{il} is the sectoral unit labour requirement (the inverse of productivity). e_{ij} is the market exchange rate between countries i and j. e^{PPP}_{ijl} is the *sectoral* purchasing power parity exchange rate for sector l between countries i and j. The RULC equation implies that relative unit labour costs between two country-sector pairs depend on relative sectoral labour productivity, relative sectoral real wages, and the ratio between the sectoral PPP exchange rate and the aggregate market exchange rate. Yet data issues limit the feasibility of this approach e.g. sector-level PPP exchange rates are available only for some 2-digit ISIC sectors for a few countries in 2005 (The Groningen Growth and Development Center's Productivity Level Database). Furthermore, the heterogeneity of skilled labour quality across countries and sectors is ignored here, which could also bias unit labour cost ratio estimates (Noorbakhsh et al., 2001).

Table 2: PPML estimates of the effects of relative energy prices on the number of M&A transactions

	All transactions			Acq. of Assets		
	All	Cross-border	Horizontal	All	Cross-border	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(e_{ijkl,t})$	-0.316***	-0.301***	-0.321***	-0.388***	-0.358***	-0.350***
	(0.097)	(0.097)	(0.099)	(0.120)	(0.120)	(0.120)
$\log(GDP_{ik,t})$	0.665***	0.656***	0.628***	0.679***	0.674***	0.644***
	(0.053)	(0.024)	(0.025)	(0.063)	(0.028)	(0.029)
$\log(GDP_{jl,t})$	0.655***	0.651***	0.638***	0.670***	0.673***	0.663***
	(0.052)	(0.022)	(0.023)	(0.062)	(0.026)	(0.027)
$\log(L^{int}_{ik,t})$	0.184*	0.365***	0.319***	0.324***	0.360***	0.329***
	(0.102)	(0.069)	(0.068)	(0.114)	(0.087)	(0.084)
$\log(L^{int}_{jl,t})$	0.140*	0.129**	0.080*	0.288***	0.159**	0.094
	(0.082)	(0.052)	(0.049)	(0.109)	(0.068)	(0.062)
$\log(K^{int}_{ik,t})$	0.037	0.146***	0.107***	0.050	0.143***	0.102**
	(0.080)	(0.041)	(0.041)	(0.095)	(0.048)	(0.047)
$\log(K^{int}_{jl,t})$	0.027	0.088**	0.044	0.056	0.123***	0.064
	(0.077)	(0.034)	(0.034)	(0.093)	(0.043)	(0.041)
FTA	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	463,901	214,846	111,823	308,715	143,092	79,185
Observations	7,472,422	6,781,642	800,040	5,490,973	4,845,490	665,607

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the PPML (with high-dimensional fixed effects) estimates of the effect of relative energy prices on the number of M&A deals, estimating equation (9). Standard errors are clustered at the country-sector pair level.

In addition, all specifications include sectoral GDP, a free-trade agreement dummy, country pair fixed effects, country time fixed effects, and sector fixed effects. The total number of transactions actually observed in the sample is much smaller than the number of observations, which includes all combinations of country-sector-year in which we observe covariates because no transactions occurred for most combinations.[30].

In all specifications and consistent with existing literature, we find that relative energy prices have a significant impact on firms' investment location decisions. Specifically, we find that an increase in the energy price differential between country-sector pairs leads to an increase in investment flows towards the lower energy cost country-sector pair. This result holds for all types of transactions, including cross-border and horizontal transactions. Furthermore, the impact of energy price differentials on industrial investment location is stronger for acquisition of assets transactions than for all other types of transactions.

In terms of effect size, an estimate for β_e of -0.3 implies that a 10% increase in the

[30]Hence, restricting the sample to cross-border transactions does not significantly impact the sample size, but it does reduce the number of transactions observed by nearly 70%. This is consistent with the share of cross-border transactions reported in section 4.1

relative industrial energy price differential between two countries is expected to increase the number of cross-border acquisitions by 3%. We also note that controls enter with the expected relative magnitudes, with target country-sector pairs offering a lower labour cost intensity, while capital intensity is higher in acquiring country-sectors. Combined with our rich set of additional controls, including country-pair, year, and sectoral fixed effects, this allows our specification to identify the specific impact of energy prices on firms' investment decisions.

We find that the elasticity of industrial investment activity with respect to relative energy prices is -0.316 for all transactions and -0.301 when restricting the sample to cross-border transactions. We also examine the subset of transactions where the acquiring and target firms operate in the same industrial sector[31], since drivers for horizontal (within the same sector) and vertical transactions (across sectors) have been found to vary.[32] It may be hypothesised that horizontal deals are more sensitive to energy cost differentials because such a deal represents the offshoring of production capacity abroad, while a vertical deal may represent different objectives e.g., to acquire firms upstream or downstream in its own supply chain or to diversify its product portfolio (Erel et al., 2012). Indeed, we find a larger elasticity of -0.321 on the subset of cross-border horizontal transactions, although it should be noted that all estimates for columns (1)-(3) are not statistically different from one another. Taken together, these results indicate that relative energy prices impact the choice of investment location of manufacturing firms for all types of transactions.

Furthermore, we find that the impact of energy prices on investment location decisions tends to be stronger for acquisition of assets transactions, although this difference is not statistically significant. These transactions involve the purchase of a subset of given a target company *e.g.* a division, a production site, or even a single plant. The estimate for β_e is -0.388 for all acquisition of assets transactions, -0.358 for cross-border acquisition of assets transactions, and -0.350 for horizontal acquisition of assets transactions. These results tend to suggest that an increase in energy price differentials leads to a larger impact on investments carried out as acquisition of assets transactions compared with other types of transactions.

In an alternative specification where energy prices in the origin and destination enter separately (see Appendix Table B.1 in Appendix), we find evidence consistent with the underlying push and pull effects from the two sides of the transactions. Energy prices in origin countries have a positive and statistically significant effect, while those in destination countries have a negative effect as expected that is not significant. This suggests that high energy prices at home pushes firms to seek deals in the first place, and this effect is stronger than the pull effect of low energy prices in destinations abroad.

Combined, our results suggest that higher energy prices are associated with more M&A activity, and once a firm decides to invest, relative energy costs are indeed a relevant factor among the multitude of factors that affect location choice, such as business environment, access to local markets, and availability of skilled labour. However, these aggregate results may hide a significant degree of heterogeneity across geographies, sectors, or particular supply chain links. We now turn to the potential heterogeneous effects of relative energy prices on investment location in the remainder of this section.

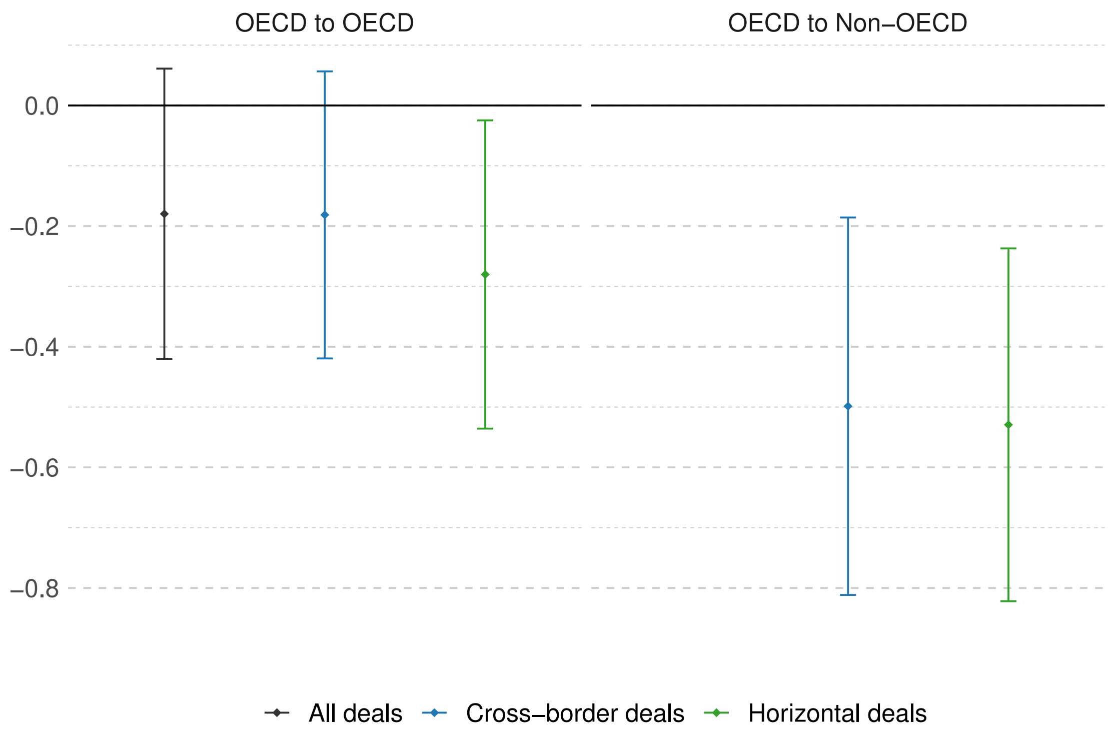
[31] Identified at the 2-digits ISIC level

[32] For example Hijzen et al. (2008) find that horizontal mergers are less negatively affected by trade costs, consistent with the tariff-jumping argument)

5.2 Developed vs emerging economies

A central concern surrounding the implementation of environmental policies is the fear that high regulatory costs can force firms to shift manufacturing capacity to low-cost countries – the pollution haven hypothesis. While we cannot directly assess whether firms will disproportionately increase investment in developing nations when the energy price gap widens, we can test if the number of deals is more sensitive to energy price differences for North to South deals. To do so, we interact our coefficient of interest β_e in specification (9) with an indicator variable for whether the deal is between two OECD countries, OECD to non-OECD, non-OECD to OECD, or two non-OECD.

Figure 2: Effects of relative energy prices on M&A transaction numbers as a function of OECD membership



Notes: This figure shows the PPML estimates of coefficient β_e in specification (9) when interacting the relative difference in energy prices with dummies indicating whether the acquiring and target firms are based in OECD or non-OECD countries. Note that for OECD to non-OECD transactions, estimates on all and cross-border deals are identical. Transactions originating from non-OECD acquirers, which represent a very small share of the sample of the sample (8.6%) are reported in Appendix Table B.2. Error bars represent 95% confidence intervals.

Most deals are between firms based in OECD countries (85% of our sample), and the effect of relative energy costs on investment activity is small and not significant for these deals (Figure 2 and Appendix Table B.2). The effect is more pronounced and significant for deals involving an OECD-based acquirer and non-OECD target but this represents a small subset of deals (around -0.5 for all transaction types and -0.65 for the acquisition of assets). Energy price gaps are much larger for OECD and non-OECD country-pairs. Comparing mean energy price difference weighted by origin sectoral GDP, the gap between two OECD countries is -0.365 compared to -0.925 for OECD and non-OECD country pairs.

Further exploring heterogeneity across cross-border and horizontal transactions (Figure 2 and Appendix Table B.2) reveals that for acquisitions within the same sector, relative energy prices matter even when both the acquirer and target firms are OECD-based, but especially when the deal is between an OECD-based and non-OECD firm. This finding is of particular relevance in the context of economic, political, or geopolitical shocks that have opened large energy and CO_2 price gaps between OECD countries, such as *e.g.* the shale oil and gas revolution in the United States, or more recently the invasion of Ukraine by the Russian Federation in Europe, as well as green deals or climate policies (World Bank, 2022).

In contrast, acquisitions originating from non-OECD countries consistently exhibit a statistically significant effect of relative energy prices, except for horizontal transactions. However, these deals with non-OECD acquirers only represent only 10% of the transactions in our sample. Estimates for β_e are larger for this subset, ranging from -0.55 to -1.17 for all transaction types (see Appendix Table B.2) but less precisely estimated due to the smaller sample size.

5.3 Sectoral heterogeneity

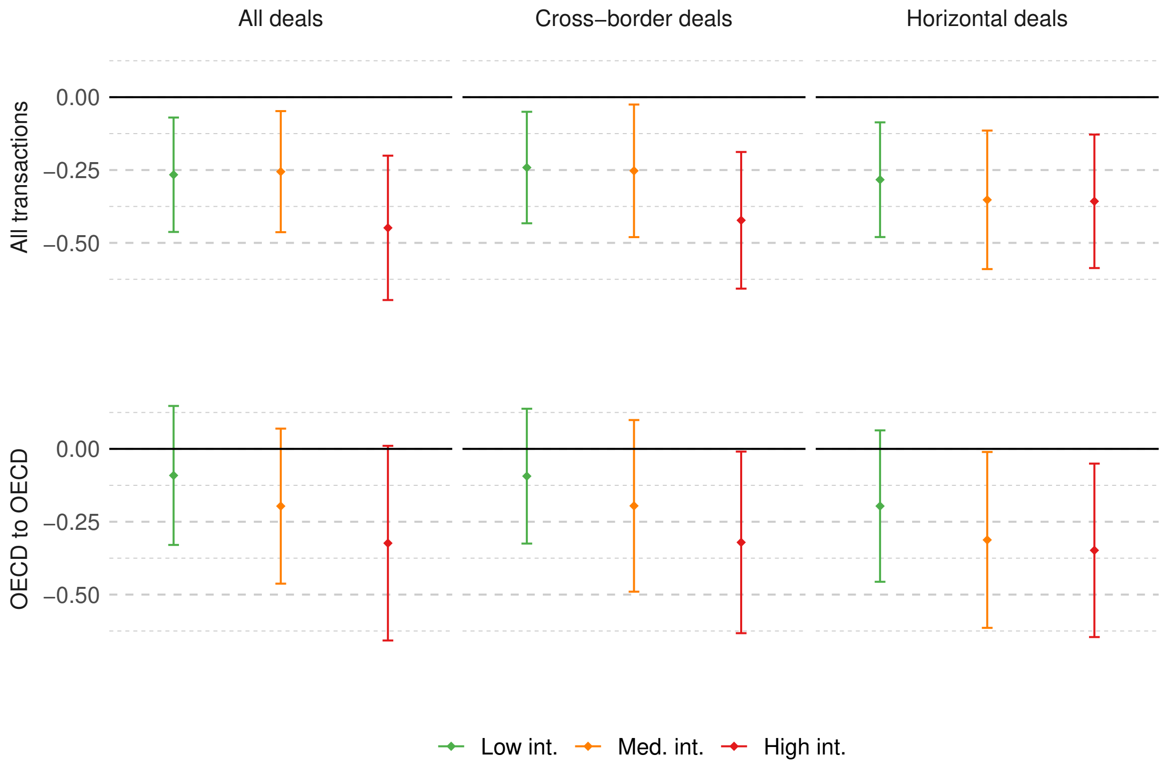
Another indication that multinationals seek weaker environmental policies or lower input factor costs by investing in developing nations is if foreign investments flow disproportionately in dirty industries relative to cleaner ones. The prediction that the effect of energy prices on foreign investment decisions is more pronounced in energy-intensive sectors where energy costs represent a higher share of overall production costs is broadly supported by empirical papers (e.g. Panhans et al., 2016; Aldy and Pizer, 2015; Sato and Dechezleprêtre, 2015). Here we delineate groups of sectors defined by their energy intensity: low energy intensity (energy cost share of less than 1.5%); medium intensity (1.5% and 4%); and high intensity (above 4%)[33].

The top panel of Figure 3 presents evidence of sectoral differences when considering the entire sample. High energy intensity sectors consistently exhibit a greater sensitivity to relative energy prices with a β_e estimate of -0.45 across all transactions, compared with -0.27 and -0.26 for low and medium intensity sectors, although that difference is not statistically significant (Z-score of 1.19). Results are very similar when we restrict the sample to cross-border deals, while β_e heterogeneity is less pronounced when we restrict the sample to horizontal deals (See also Appendix Table B.3).

In the bottom panel of Figure 3, we focus on the subset of transactions involving OECD-based acquirers and targets. As expected, transactions involving acquirers in low-intensity sectors are not driven by energy price differentials. However, where the acquirer operates in a high energy intensity industry, deals are sensitive to energy prices with β_e between -0.32 and -0.35 (see also Appendix Table B.4). For deals with acquirers in medium energy-intensity sectors, energy price differences matter only for cross-border horizontal deals.

[33]The cutoffs have been chosen to balance the three groups, regarding both the number of sectors and the number of transactions observed in each group. Energy intensity is measured as the share of energy costs in the total real output of each sector as measured by value added. Energy use data is obtained from the IEA, which is then combined with our energy price index and UNIDO's sectoral value added to yield our energy intensity indicator. The mean energy intensity of each sector over the entire sample is presented in Appendix Figure A.5.

Figure 3: Effects of relative energy prices on M&A transactions by sectoral energy intensity



Notes: This figure shows the PPML estimates of coefficient β_e in specification (9) when interacting relative energy prices with an indicator of the acquiring sectors energy intensity being high ($> 4\%$), medium (1.5% to 4%) or low ($< 1.5\%$). Error bars represent 95% confidence intervals.

The fact that low and medium intensive industries also see a significant effect in the full sample but not the OECD-OECD subsample indicates that energy price gaps also matters (but to a lesser extent) for these sectors for OECD to non-OECD transactions where energy price gaps are larger.

Overall, our results reveal how the effects of energy prices on investment decisions are highly heterogeneous. Our baseline results in Section 5.1 suggests that on aggregate, relative energy prices matter for industrial investment location decisions, which is in line with the pollution haven hypothesis. Yet exploring geographical and sectoral heterogeneity reveals that the effect is concentrated in a well-delineated subset of transactions. Specifically, variations in energy costs across different sectors and countries can explain patterns of investment location only for cross-border and horizontal acquisitions in high energy intensity sectors within the OECD and for North-South deals. These subsets of transactions represent 19.7% of all transactions observed. Previous studies have found that carbon leakage risk is focused on a few subsectors of the economy. Our result quantifies this in relation to the risk of investment leakage.

5.4 Robustness checks

We test the sensitivity of our results to key assumptions. First, we control for the potential endogeneity of current-period sectoral energy prices in both acquirer and target countries by using the one-year lag of energy prices in the specification. Cross-border investments may result in increased (reduced) economic activity in the target (acquiring) country, thereby affecting energy demand and prices. We also relax the assumption that firms react to changes in energy prices within a year and consider an alternative hypothesis from the trade literature that firms respond to exogenous price or policy signals over a multiple year period (e.g. Head and Mayer, 2014). To test longer term effects, we first follow Hijzen et al. (2008) and aggregate our dataset over two, three and four-year intervals by taking the mean of the dependent variable and of each regressor[34] over the interval considered:

$$\overline{x}_t^{\tau} = \sum_{t'=t}^{t+\tau-1} \frac{x_{t'}}{\tau}, \text{ with } \tau \in \{2, 3, 4\} \tag{12}$$

The magnitude and significance of the effects of relative energy prices remain stable (Appendix Table B.5), and the estimate of β_e is not significantly different from the baseline model estimates. We then also use distributed lags in the main independent variables to understand how energy prices in previous years influence FDI (Appendix Table B.6). This shows that while firms' response to relative energy prices appear consistent in the short- and long-run, the contemporaneous effect drives the significance of our time windows results, suggesting limited long-term effects.

Second, we examine the sensitivity of our results to the energy price index. We replicate our results using an alternative energy price index from Sato et al. (2019). Specifically, we consider the variable-weight energy price level (VEPL), where the weight varies yearly to reflect the actual energy mix observed, and energy prices are observed at current market exchange rates. The magnitude and sign of the β_e estimated using VEPL are smaller but consistent with our main results (Appendix Table B.7). Using an energy price index with variable weights is expected to give rise to a downward bias on the effect of relative energy prices because sectors indeed switch between fuels in response to prices.[35]

Third, as some countries dominate global M&A activity, we test if the results are driven by a particular key country,[36] by excluding a country at a time on both the acquiring and target sides (Appendix Table B.8). The results for our relative energy price remain stable between -0.29 and -0.36.

Fourth, we consider additional sets of fixed effects: country-sector fixed effects (for both origin and destination country) which account for the time-invariant unobserved comparative advantage of countries in specific sectors, and sector-year fixed effects, which might account for global trends in sector-specific technological developments. The results are shown in Appendix Table B.9. In column (1), we complement country-pair FEs and acquiring and target country-year FEs with acquiring and target sector-year FEs.

[34] $x \in \{m_{ijkl}, e_{ijkl}, GDP_{ik}, GDP_{jl}, L_{ik}^{int}, L_{jl}^{int}, K_{ik}^{int}, K_{jl}^{int}\}$

[35] Further, we tested the sensitivity of the results to the choice of time period for the weights used for FEPI. In the baseline specification, weights are calculated using the average energy mix over the entire observation period. Results remain stable when weights are applied based on the energy mix observed in 2005.

[36] The top 5 target countries in our dataset being the United States (30% of all transactions observed), the United Kingdom (9%), Germany (8%), France (6%) and Japan (5%) and the rankings and proportions are similar on the acquiring side.

In column (2) we augment our main set of FEs with country-sector FEs. Column (3) shows the most stringent set of FEs combining country-pair, country-year, sector-time, and country-sector. Our key coefficient of interest remains highly statistically significant for all specifications. In terms of magnitude, including sector-year FEs yields an estimate similar to our main specification, while the introduction of country-sector FEs increases the estimate from -0.30 to -0.40 (although this difference itself is not statistically significant).

Fifth, as carbon leakage risk is understood to be not only a function of carbon intensity but also trade-exposure, we implement an additional robustness check replicating our main results table while controlling for trade exposure at the country-sector level. Using data obtained from Exiobase 3, we construct our indicator of trade exposure as:$\tau_{ik}^{exposure} = \frac{X_{ik}+M_{ik}}{VA_{ik}}$ where X_{ikt}, M_{ikt} and VA_{ikt} are sectoral exports, imports and value added respectively in sector k and country i. To avoid introducing potential endogeneity issues, we use the year 2000 as a benchmark. We find that our results remain qualitatively unchanged, albeit with a slightly larger magnitude on our main coefficient of interest (Appendix Table B.10).

Finally, we test the validity of using the number of deals to capture changes in foreign capital movements over time (see Appendix D). Unfortunately, the subset of our data for which we have deal values is small (less than 10% of our sample). Therefore, it is unsurprising that the effect of the energy price gap on deal values is found to be statistically insignificant. Yet, the coefficients have the expected sign. More extensive data on transaction values will help to yield more robust results.

6 Counterfactual carbon pricing simulation

We now explore whether these relative energy price effects are economically important. While more than forty countries have implemented a carbon pricing policy (World Bank, 2022), the price levels set by most of these initiatives fall short of the target range of \$40-\$80/tCO_2 recommended by the recent Stern-Stiglitz Commission (Stern and Stiglitz, 2017). This section presents results from a simple simulation of the potential impact on global M&A activity, if a leading climate coalition implements a carbon tax that leads to a CO_2 price gap of \$50/tCO_2, using our model of investment location (equation (6)) and the parameters estimated in section 5. We seek to quantify the degree to which relative CO_2 prices affect patterns of foreign investment. Three different policy scenarios representing increasing degrees of international collaboration are simulated: 1) the European Union unilaterally implements ambitious climate policy such that the CO_2 price in the EU is higher by \$50/tCO_2 than the rest of the world; 2) EU and OECD member countries, except the United States collectively implement ambitious climate policy and; 3) all countries in our sample implement carbon pricing at a similar level.[37]

The simulation involves the following steps. First, we calculate the increase in the energy price that results from the implementation of the carbon tax using the carbon content of fossil energy carriers and electricity. Our strategy for estimating the impact of

[37]Note that in all variants, we consider the gross impact in the absence of anti-leakage policies such as free allocation in emissions trading or border carbon adjustment (Morris, 2018). These measures would moderate the impacts described here.

relative CO_2 prices on investment activity is estimated as follows:

$$\frac{m_{ijkl}^*}{m_{ijkl}} = \left(\frac{e_{ijkl}^*}{e_{ijkl}}\right)^{\beta_{e,ij}} \frac{\Omega_{ijkl}}{\Omega_{ijkl}^*} \tag{13}$$

where the star denotes the counterfactual number of transactions, relative energy prices and multi-lateral resistance terms impacted by carbon taxation, and $\beta_{e,ij}$ are coefficient estimates from section 5.2 reflecting geographic heterogeneity. The second step involves computing an updated set of Ω_{ijkl}^* using the carbon tax augmented energy prices[38] before finally estimating the impact of the carbon tax on the number of cross-border transactions[39] using Equation (13). This methodology ensures that changing relative energy prices in a subset of countries modifies the multi-lateral resistance terms Ω_{ijkl} for the entire dataset. This is important because implementing a carbon tax in country j affects investments received from another country i both directly through changes to the relative energy costs, and indirectly through changes in the attractiveness of j against all other countries as measured by Ω_{ijkl}.[40] It is important to note, however, that this strategy does not yield general equilibrium effects and the results reflect lower bounds on the true magnitude of the effects.[41]

We report simulation results for 2010, which offers the widest coverage in our dataset. In the first scenario, investment activity targeting EU firms falls by 4.8% on average (Figure 4a and Appendix Table B.11). The effect is heterogeneous across the EU due to variations in energy mix and OECD/non-OECD status.[42] Other regions experience a 0.6% increase in the number of their expected inbound transactions. The effect is homogeneous in all regions outside the EU because of the conditional equilibrium approach adopted.[43] The average effect across all sectors masks heterogeneity across sectors. We find that the effect is magnified for highly energy-intensive sectors (7.6% on average) as expected and heterogeneous across EU Member States (see Appendix Figure B.1b).

In the second scenario, where other developed countries join the EU's climate action, except for the US, the negative impact is reduced in Europe to -4.1% (Figure 4b). In the case of a global carbon tax under the third scenario, investments into Europe barely change (-0.2%) (e.g. in Norway by 3.4% and in Sweden by 3.1%) but fall sharply in non-OECD, high carbon intensity countries such as China, India, Russia, and South Africa

[38]The calculation of Ω_{ijkl} requires information on both the acquiring and target sides. The reference cross-section includes more than 700,000 observations. Computing the multi-lateral resistance terms thus involves calculations on a 700,000 × 700,000 matrix, which is impractical on commodity hardware. Therefore, the algorithm was implemented on a high-performance Nvidia Tesla V100 GPU using the Google Compute Engine. This custom implementation reduced the time required to compute a single set of Ω_{ijkl} from 19 hours to a more manageable 30 min, thereby making the present simulations feasible.

[39]Only cross-border transactions are included in the computation of the counterfactual.

[40]By analogy with the structural gravity literature, a simpler approach that only considers the direct impacts resulting from the change in bilateral relative energy costs – term $\left(\frac{e_{ijkl}^*}{e_{ijkl}}\right)^{\beta_{e,ij}}$ in equation (13) – would yield *partial equilibrium* effects, while our approach is equivalent to what Yotov et al. (2013) label *conditional equilibrium* effects.

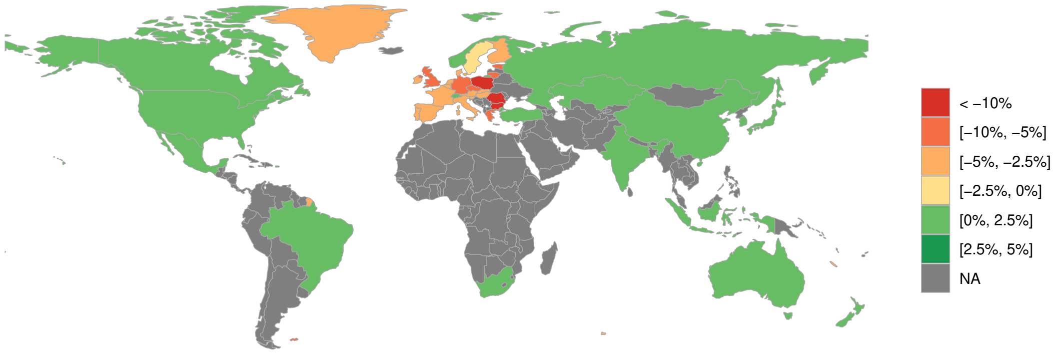
[41]In particular, we cannot consider the impact of the carbon tax on sectoral and aggregate economic activity or firm entry and exit in our framework. Taking into account the consequences of reduced foreign investments on domestic activity would further reduce the relative attractiveness of countries that implement a carbon tax, further increasing the negative impact of the tax on investment inflows. Detailed analysis of these general equilibrium aspects is left to future research.

[42]For example, the impact ranges from -0.8% in Sweden to -16.1% in Bulgaria.

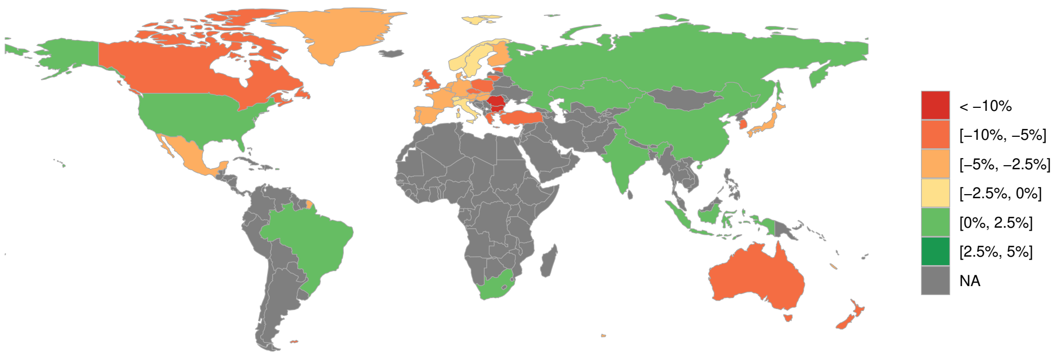
[43]The positive effect on each country's relative attractiveness is averaged into an aggregate impact by the adjustments in the multi-lateral resistance terms.

Figure 4: Simulated change in M&A deals in response to CO_2 pricing under three varying coalition scenarios

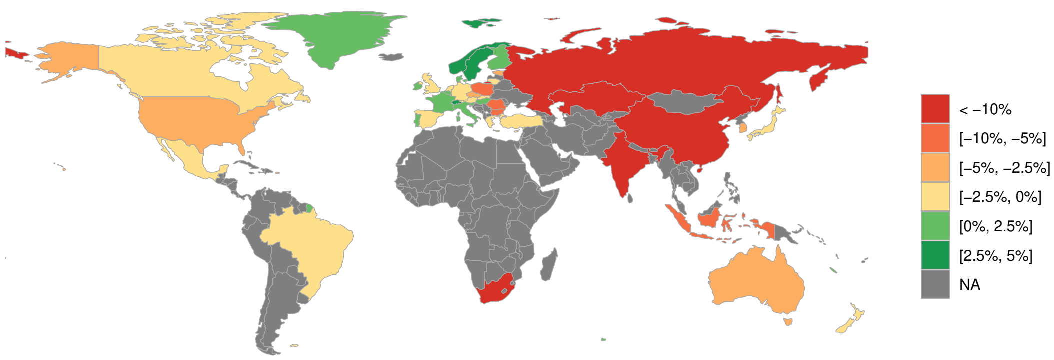
(a) Scenario 1: CO_2 price is higher by \$50/tCO_2 in the EU only



(b) Scenario 2: CO_2 price is higher by \$50/tCO_2 in the EU and OECD excluding the U.S.



(c) Scenario 3: CO_2 price is higher by \$50/tCO_2 in all countries in our sample



Notes: These maps show the simulation results on the percentage change in the number of firms acquired in M&A deals by country, in response to carbon pricing under three different coalition scenarios. The impact is expressed as the change in number of firms acquired in relative terms against a 2010 baseline. See text for full description of the simulation method.

(between 12% and 33%, Figure 4b). As an alternative representation of the results, we also show the share of domestic firms that engaged in M&As abroad as a result of carbon pricing in the three scenarios in Appendix Table B.12.

We conclude that while large CO_2 price gaps can impact investment location choices, the magnitude of the effect is modest for developed economies overall, with adverse impacts concentrated in the most energy-intensive sectors. This result holds even in the absence of anti-leakage measures such as free allocation of permits in emissions trading, particularly when other economies also impose similar CO_2 prices. This does not negate concerns about carbon leakage in energy-intensive industrial sectors, as we will discuss next.

7 Conclusion

Recent empirical literature recognises that exploiting the variation in the *relative* energy price between potential target and acquirer is more relevant and aligned with the theory that models FDI flows and firm location patterns as a function of international differences in factor endowments, which focuses on the *comparative* cost advantage (Helpman, 1984). For example, Garsous et al. (2020) use the difference between domestic and Chinese energy prices to proxy for relative energy prices and tests its effect on the international assets of firms in the OECD. Arezki et al. (2017) instead uses the gas price gap between the US and OECD-Europe as the main coefficient of interest to explain patterns of export, output, and other outcome measures following the shale gas revolution in the US. These are relatively crude measures of the relative price gap of energy. Instead, Manderson and Kneller (2020) uses a bilateral setting, the UK-US natural gas price gap and the overall energy price gap, using data from Sato et al. (2019), to assess UK firms' propensity to invest in the US and reduce production in the UK. These approaches are in contrast with previous work that exploited energy price variations over time within the target country (e.g. Panhans et al., 2016) to explain aggregated FDI flows.

To advance this literature, we adopt an empirical framework drawing on recent literature on the determinants of cross-border investments, which uses bilateral investment flows and a base model consisting of gravity-type covariates, borrowing from empirical bilateral trade literature. To the best of our knowledge, we are the first to adopt the dartboard model of M&A (Head and Ries, 2008) to derive a model linking location choice in bilateral FDI to relative energy prices. We collected global, detailed bilateral FDI data to implement the model. This extensive coverage of our data is a major contribution with high external validity of results, for example, compared to the UK-US study by Manderson and Kneller (2020).[44] In the context of the leakage and industrial offshoring debates, it is especially valuable that our sample covers key developing countries such as China and India, which are the most relevant countries.

Furthermore, the large sample size gives greater statistical power, which is important, because if any, the effects of energy prices on FDI tend to be small and may not be possible to detect with small sample data. In addition to limited geographical coverage, the lack of variation in other determinants of production location is problematic for identification. The bilateral structure with sufficiently disaggregated data that we use has a further advantage in that we can control for many confounding factors. This allows for the

[44] This study has the advantage of using microdata and an exogenous shock (the US Shale gas revolution)

estimation of regulatory effects that are purged of bias associated with country-pair and industry-specific trends. This is particularly important because, during this period, many factors (e.g., supply chain integration, trade agreements, technology changes) may have had differential impacts on sector-level FDI.

We have been able to provide a more complete and robust empirical assessment and a more nuanced understanding of the impact of *relative* energy prices on FDI location. For example, Manderson and Kneller (2020)'s finding that UK firms with high energy intensity are more likely to invest in the US following the shale gas revolution is consistent with our finding that FDI between OECD countries is sensitive to energy price differences in the case of cross-border horizontal deals. We can show that this is a special case, and cannot be generalised to non-horizontal deals or to deals involving low energy-intensive sectors.

Overall, our results suggest that while large energy and CO_2 price gaps can impact investment location choices, the magnitude of the effect is modest for developed economies, even in the absence of anti-leakage measures such as free allocation in emissions trading. This does not negate concerns about investment and carbon leakage in energy-intensive industrial sectors. For example, our findings that the effect of the energy price gap is particularly significant for North-South deals underscores the importance of covering non-OECD trade anti-leakage measures such as carbon boarder adjustment measures (CBAM), which raises multiple international equity concerns (Grubb et al., 2022). The fact that we find energy price differences also matter for OECD to OECD horizontal deals suggests the importance of harmonising climate policy stringency within industrialised nations, especially for the most energy-intensive sectors to prevent leakage. On the other hand, our finding that this effect is highly heterogeneous but modest overall supports previous findings that leakage protection such as free allocation should be targeted (e.g. Martin et al., 2014; Fowlie and Reguant, 2022) and used sparingly to reduce its downsides in weakening mitigation incentives for industry. Indeed, it suggest that rather than expending excessive political capital on pursuing specific leakage measures, resources may be better spent on efforts to establish a robust framework to support rapid industrial decarbonisation (e.g. Neuhoff et al., 2021; OECD, 2022).

Our analysis can be extended in several directions. The dataset could be augmented with more comprehensive data on the value of the transactions observed, to improve the quantification of the effect. Alternatively, an analysis focused on the subset of transactions involving listed companies, for which relevant covariates at the firm level are publicly available, could be conducted. Exploiting the information on the unrealized deals could also be explored. The model developed in this paper could be further extended to a full structural gravity model, which would allow the estimation of the general equilibrium effect of relative energy prices on industrial investment location. This and other extensions are left for future research.

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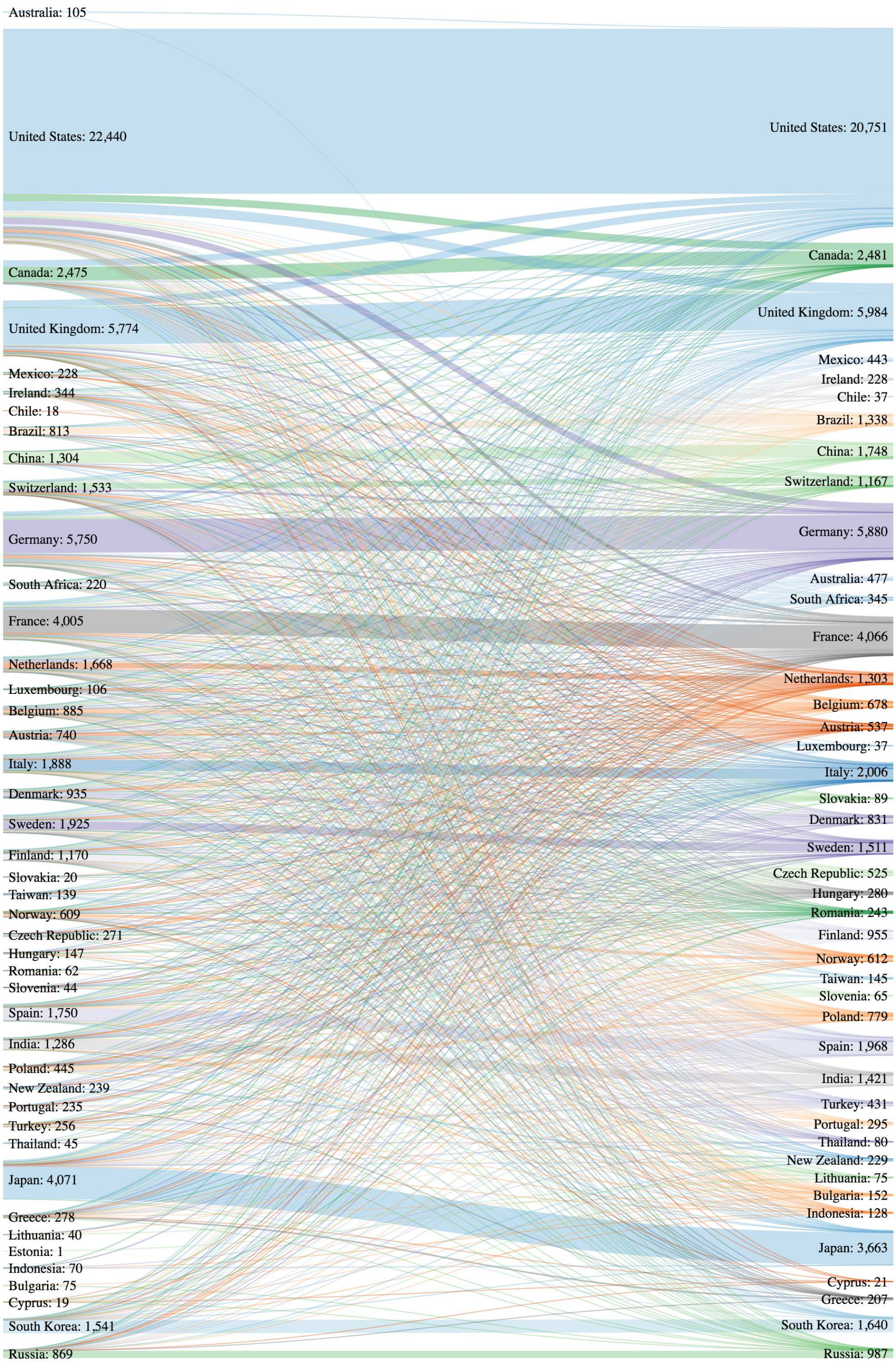
A Complementary descriptive statistics

Table A.1: Summary statistics

Variable	Mean	Std. Dev.	25^{th} perc.	Median	75^{th} perc.	Obs.
Bilateral						
Transactions	0.01	0.31	0.00	0.00	0.00	10,610,945
Energy price difference	-0.02	0.58	-0.38	0.00	0.33	8,876,420
Acquirer						
log GDP	21.84	2.55	20.45	21.77	23.07	10,610,945
Labor cost-share	0.56	0.20	0.46	0.59	0.69	10,422,960
Capital cost-share	0.15	0.11	0.09	0.13	0.19	10,422,960
Target						
log GDP	21.62	2.55	20.15	21.63	22.98	10,610,945
Labor cost-share	0.54	0.20	0.43	0.57	0.68	10,288,007
Capital cost-share	0.15	0.11	0.09	0.13	0.19	10,288,007

Notes: This table shows summary statistics over the sample period for M&A transaction numbers, relative energy prices, as well as the log of GDP, labour cost-shares and capital cost-shares in both the acquiring and target countries. Std. Dev. indicates standard deviation. Obs. indicates observation number.

Figure A.1: Number of transactions in the manufacturing sector by acquiring and target country (1995-2014)



Notes: This figure shows the flows of M&A deals by acquiring (left) and target (right) country, in terms of number of bilateral deals for our study period (1995-2014). *Source:* Thomson-Reuters Mergers and Acquisitions database.

Figure A.2: Map of total transactions by acquiring firm location (1995-2014)

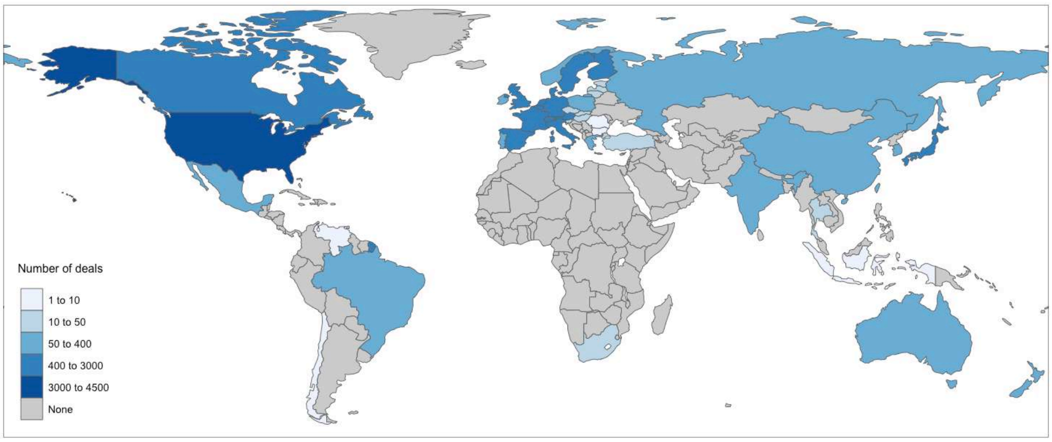
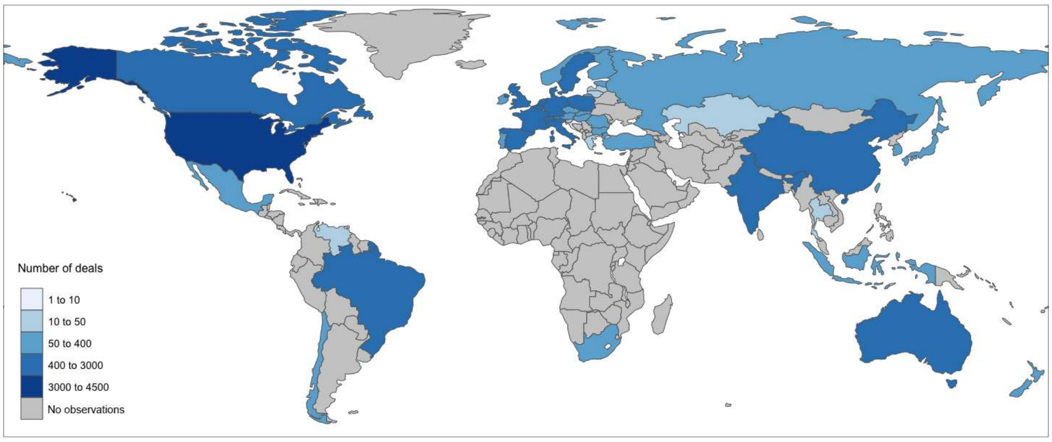
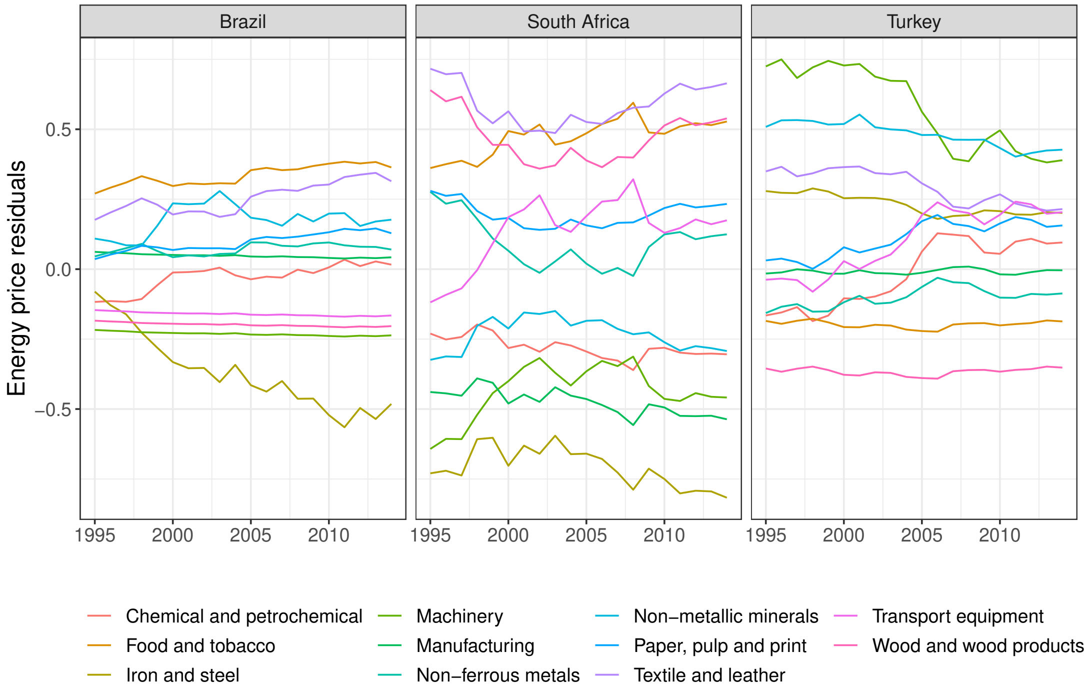


Figure A.3: Map of total transactions by target firm location (1995-2014)



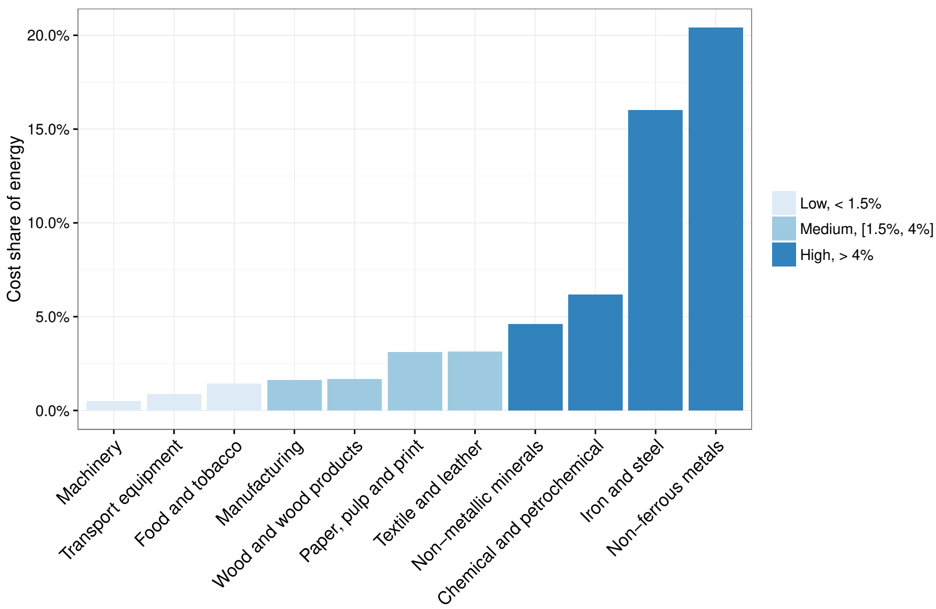
Notes: These maps show the spatial distribution of M&A deals by acquiring (A.2) and target (A.3) firm location (1995-2014). *Source:* Thomson-Reuters Mergers and Acquisitions database.

Figure A.4: Energy prices cross-sectoral variation in non-OECD countries (1995-2014)



Notes: This Figure shows the cross-sectoral variations in energy prices. Specifically we plot by sector, the residuals of the energy price index (FEPI) regressed on year fixed effects, for the period 1995-2014. *Source:* Author calculations using data from Sato et al. (2019).

Figure A.5: Mean cost-share of energy by sector (All countries, 1995-2014)



Notes: This figure shows by broad sector, the mean share of energy costs in the total real output as measured by value added. *Source:* Energy use data is obtained from the IEA and combined with the energy price index from Sato et al. (2019) and UNIDO's sectoral value added.

B Complementary results

Table B.1: Main results with origin and destination energy price entering separately

	All transactions			Acq. of Assets		
	All	All	Horizontal	All	All	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(E_{il,t})$	0.463***	0.472***	0.520***	0.590***	0.603***	0.591***
	(0.131)	(0.134)	(0.145)	(0.163)	(0.167)	(0.175)
$\log(E_{jl,t})$	-0.146	-0.157	-0.160	-0.124	-0.154	-0.155
	(0.128)	(0.132)	(0.133)	(0.160)	(0.165)	(0.163)
$\log(GDP_{ik,t})$	0.679***	0.656***	0.628***	0.698***	0.674***	0.643***
	(0.023)	(0.024)	(0.025)	(0.026)	(0.028)	(0.029)
$\log(GDP_{jl,t})$	0.654***	0.650***	0.637***	0.675***	0.671***	0.662***
	(0.021)	(0.022)	(0.023)	(0.024)	(0.026)	(0.027)
L^{int}	Yes	Yes	Yes	Yes	Yes	Yes
K^{int}	Yes	Yes	Yes	Yes	Yes	Yes
FTA	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	220,962	214,831	111,809	147,292	143,074	79,173
Observations	7,144,544	6,781,642	800,040	5,103,729	4,845,490	665,607

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table shows the PPML (with high-dimensional fixed effects) estimates of the effect of energy prices on the number of M&A deals, estimating equation (9). In contrast to estimating the effect of relative energy prices as is done in the baseline results (Table 2), the but acquiring and target country-sector energy price enters separately.

Table B.2: Impact of relative energy prices as a function of OECD membership

	All transactions		
	All	Cross-border	Horizontal
	(1)	(2)	(3)
$\log(e_{ijkl,t})$ (OECD to OECD)	-0.180	-0.181	-0.280**
	(0.123)	(0.121)	(0.130)
$\log(e_{ijkl,t})$ (OECD to non-OECD)		-0.499***	-0.529***
		(0.160)	(0.149)
$\log(e_{ijkl,t})$ (Non-OECD to OECD)		-0.729***	-0.069
		(0.229)	(0.228)
$\log(e_{ijkl,t})$ (Non-OECD to non-OECD)	-1.146***	-1.174***	-0.547
	(0.384)	(0.369)	(0.359)
$\log(GDP_{ik,t})$	0.665***	0.656***	0.629***
	(0.053)	(0.024)	(0.025)
$\log(GDP_{jl,t})$	0.657***	0.653***	0.640***
	(0.052)	(0.022)	(0.023)
$\log(L^{int}_{ik,t})$	0.184*	0.365***	0.320***
	(0.102)	(0.069)	(0.068)
$\log(L^{int}_{jl,t})$	0.140*	0.129**	0.079
	(0.082)	(0.052)	(0.048)
$\log(K^{int}_{ik,t})$	0.037	0.146***	0.108***
	(0.080)	(0.041)	(0.041)
$\log(K^{int}_{jl,t})$	0.026	0.085**	0.043
	(0.077)	(0.034)	(0.034)
FTA	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes
AIC	463,866	214,818	111,818
Observations	7,472,422	6,781,642	800,040

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents estimates from the same specification form and samples as columns (1)-(3) in Table 2. However, the explanatory variable $\log(e_{ijkl,t})$ is interacted with two variables indicating whether the acquiring (resp. target) firm is OECD-based or not. All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.2: Impact of relative energy prices as a function of OECD membership (cont.)

	Acq. of Assets		
	All	Cross-border	Horizontal
	(1)	(2)	(3)
$\log(e_{ijkl,t})$ (OECD to OECD)	-0.005	-0.226	-0.300*
	(0.088)	(0.148)	(0.153)
$\log(e_{ijkl,t})$ (OECD to non-OECD)		-0.653***	-0.665***
		(0.203)	(0.188)
$\log(e_{ijkl,t})$ (Non-OECD to OECD)		-0.845***	-0.043
		(0.271)	(0.267)
$\log(e_{ijkl,t})$ (Non-OECD to non-OECD)	-0.163	-1.219**	-0.383
	(0.501)	(0.549)	(0.473)
$\log(GDP_{ik,t})$	0.161***	0.674***	0.645***
	(0.061)	(0.028)	(0.029)
$\log(GDP_{jl,t})$	0.164***	0.676***	0.667***
	(0.058)	(0.026)	(0.027)
$\log(L^{int}_{ik,t})$	0.015	0.360***	0.331***
	(0.022)	(0.087)	(0.084)
$\log(L^{int}_{jl,t})$	0.009	0.157**	0.092
	(0.019)	(0.068)	(0.062)
$\log(K^{int}_{ik,t})$	-0.065	0.143***	0.103**
	(0.086)	(0.048)	(0.047)
$\log(K^{int}_{jl,t})$	-0.077	0.120***	0.063
	(0.086)	(0.043)	(0.041)
FTA	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes
AIC	88,493	143,071	79,181
Observations	20,710	4,845,490	665,607

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Impact of relative energy prices as a function of sectoral energy intensity

	All transactions		
	All (1)	Cross-border (2)	Horizontal (3)
$\log(e_{ijkl,t})$ (Low int.)	-0.266***	-0.241**	-0.283***
	(0.100)	(0.098)	(0.100)
$\log(e_{ijkl,t})$ (Med. int.)	-0.256**	-0.253**	-0.352***
	(0.106)	(0.116)	(0.121)
$\log(e_{ijkl,t})$ (High int.)	-0.448***	-0.423***	-0.357***
	(0.126)	(0.120)	(0.117)
$\log(GDP_{ik,t})$	0.665***	0.657***	0.629***
	(0.053)	(0.024)	(0.025)
$\log(GDP_{jl,t})$	0.655***	0.651***	0.637***
	(0.052)	(0.022)	(0.023)
$\log(L^{int}_{ik,t})$	0.185*	0.367***	0.319***
	(0.102)	(0.068)	(0.068)
$\log(L^{int}_{jl,t})$	0.140*	0.129**	0.079
	(0.082)	(0.052)	(0.049)
$\log(K^{int}_{ik,t})$	0.039	0.151***	0.109***
	(0.081)	(0.041)	(0.041)
$\log(K^{int}_{jl,t})$	0.027	0.088**	0.043
	(0.077)	(0.034)	(0.034)
FTA	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes
AIC	463,868	214,815	111,822
Observations	7,472,422	6,781,642	800,040

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table corresponds to the upper panel of Figure 3. It presents estimates from the same specification form and samples as columns (1)-(3) in Table 2. However, the explanatory variable $\log(e_{ijkl,t})$ is interacted with an indicator variable measuring whether the acquiring sector's energy intensity is high (> 4%), medium (1.5% to 4%) or low (< 1.5%). All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.4: Impact of relative energy prices as a function of sectoral energy intensity (within OECD)

	OECD to OECD transactions		
	All	Cross-border	Horizontal
	(1)	(2)	(3)
$\log(e_{ijkl,t})$ (Low int.)	-0.091	-0.094	-0.196
	(0.122)	(0.118)	(0.133)
$\log(e_{ijkl,t})$ (Med. int.)	-0.196	-0.195	-0.312**
	(0.136)	(0.150)	(0.154)
$\log(e_{ijkl,t})$ (High int.)	-0.324*	-0.321**	-0.348**
	(0.170)	(0.159)	(0.152)
$\log(GDP_{ik,t})$	0.665***	0.659***	0.631***
	(0.053)	(0.024)	(0.025)
$\log(GDP_{jl,t})$	0.657***	0.653***	0.641***
	(0.052)	(0.022)	(0.023)
$\log(L^{int}_{ik,t})$	0.185*	0.368***	0.319***
	(0.102)	(0.068)	(0.068)
$\log(L^{int}_{jl,t})$	0.140*	0.129**	0.080*
	(0.082)	(0.052)	(0.048)
$\log(K^{int}_{ik,t})$	0.039	0.152***	0.112***
	(0.081)	(0.041)	(0.041)
$\log(K^{int}_{jl,t})$	0.026	0.085**	0.041
	(0.077)	(0.034)	(0.034)
FTA	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes
AIC	463,785	214,757	111,815
Observations	7,472,422	6,781,642	800,040

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This tablecorresponds to the lower panel of Figure 3. It presents estimates from the same specification form as columns (1)-(3) in Table 2, estimated on the subset of transactions involving acquiring and target firms based in the OECD. However, the explanatory variable $\log(e_{ijkl,t})$ is interacted with an indicator variable measuring whether the acquiring sector's energy intensity is high (> 4%), medium (1.5% to 4%) or low (< 1.5%). All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.5: Robustness to time lag

	1-year lag	2-year averages	3-year averages	4-year averages
	(1)	(2)	(3)	(4)
$\log(e_{ijkl,t-1})$	-0.300***			
	(0.096)			
$\log(e_{ijkl,t})$		-0.340***	-0.343***	-0.363***
		(0.097)	(0.098)	(0.096)
$\log(GDP_{ik,t})$	0.661***	0.657***	0.656***	0.658***
	(0.053)	(0.054)	(0.053)	(0.054)
$\log(GDP_{jl,t})$	0.652***	0.647***	0.644***	0.647***
	(0.052)	(0.053)	(0.053)	(0.053)
$\log(L_{ik,t}^{int})$	0.189*	0.503***	0.557***	0.565***
	(0.104)	(0.103)	(0.112)	(0.113)
$\log(L_{jl,t}^{int})$	0.146*	0.478***	0.563***	0.550***
	(0.085)	(0.104)	(0.114)	(0.116)
$\log(K_{ik,t}^{int})$	0.033	0.122	0.143	0.143
	(0.080)	(0.089)	(0.092)	(0.095)
$\log(K_{jl,t}^{int})$	0.023	0.119	0.143	0.142
	(0.076)	(0.086)	(0.090)	(0.092)
FTA	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes
AIC	456,537	421,377	399,299	386,270
Observations	7,053,763	4,181,988	2,878,220	2,450,299

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This Table presents estimates from a specification and sample identical to that of column (1) in Table 2. Column (1) uses the 1-year lag of our energy price difference as dependent variable. In columns (2)-(4) we aggregate the dataset at 2-, 3- and 4-year time steps respectively, then estimate specification (9) as usual. While the number of observations is reduced by the aggregation procedure, the sample covered is identical in columns (2)-(4). All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.6: Impact of the distributed lag of energy price differentials

	All transactions			
	(1)	(2)	(3)	(4)
$\log(e_{ijkl,t})$	-0.679***	-0.585**	-0.623**	-0.729**
	(0.246)	(0.267)	(0.279)	(0.291)
$\log(e_{ijkl,t-1})$	0.363	0.363	0.429	0.569*
	(0.244)	(0.273)	(0.275)	(0.294)
$\log(e_{ijkl,t-2})$		-0.080	0.000	-0.104
		(0.228)	(0.280)	(0.287)
$\log(e_{ijkl,t-3})$			-0.098	0.298
			(0.242)	(0.297)
$\log(e_{ijkl,t-4})$				-0.320
				(0.276)
$\log(GDP_{ik,t})$	0.662***	0.662***	0.657***	0.649***
	(0.053)	(0.053)	(0.052)	(0.051)
$\log(GDP_{jl,t})$	0.654***	0.654***	0.650***	0.642***
	(0.052)	(0.052)	(0.051)	(0.050)
$\log(L^{int}_{ik,t})$	0.186*	0.178*	0.168*	0.165
	(0.103)	(0.102)	(0.101)	(0.101)
$\log(L^{int}_{jl,t})$	0.143*	0.138*	0.132	0.127
	(0.084)	(0.083)	(0.082)	(0.080)
$\log(K^{int}_{ik,t})$	0.035	0.029	0.022	0.021
	(0.080)	(0.079)	(0.077)	(0.075)
$\log(K^{int}_{jl,t})$	0.026	0.024	0.018	0.017
	(0.077)	(0.075)	(0.074)	(0.072)
FTA	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes
AIC	453,445	426,578	398,487	368,651
Observations	6,986,906	6,441,899	5,922,410	5,374,972

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This Table presents estimates from a specification and sample identical to that of column (1) in Table 2, but use of distributed lags in the main independent variables. Column (1) uses the 1-year lag of our energy price difference as dependent variable. In columns (2)-(4) we add 2-, 3- and 4-year lags of the energy price gap variable respectively, then estimate specification (9) as usual.

Table B.7: Main results using the VEPL energy price index

	All transactions			Acq. of Assets		
	All	Cross-border	Horizontal	All	Cross-border	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(e^{VEPL}_{ijkl,t})$	-0.197*	-0.169	-0.314***	-0.279**	-0.231*	-0.365**
	(0.110)	(0.107)	(0.120)	(0.136)	(0.132)	(0.145)
$\log(GDP_{ik,t})$	0.658***	0.654***	0.558***	0.671***	0.670***	0.583***
	(0.057)	(0.027)	(0.048)	(0.069)	(0.032)	(0.055)
$\log(GDP_{jl,t})$	0.648***	0.648***	0.562***	0.663***	0.669***	0.582***
	(0.055)	(0.024)	(0.046)	(0.067)	(0.029)	(0.054)
$\log(L^{int}_{ik,t})$	0.160	0.297***	0.194	0.300**	0.290***	0.325**
	(0.099)	(0.073)	(0.135)	(0.123)	(0.094)	(0.150)
$\log(L^{int}_{jl,t})$	0.131	0.117**	0.139	0.277**	0.141**	0.294**
	(0.082)	(0.053)	(0.109)	(0.117)	(0.071)	(0.148)
$\log(K^{int}_{ik,t})$	0.018	0.103**	-0.002	0.024	0.087*	0.004
	(0.086)	(0.045)	(0.061)	(0.102)	(0.051)	(0.067)
$\log(K^{int}_{jl,t})$	0.010	0.063*	-0.027	0.033	0.092*	-0.002
	(0.082)	(0.037)	(0.056)	(0.099)	(0.047)	(0.064)
FTA	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	422,647	187,312	178,478	282,613	125,145	128,233
Observations	5,804,212	5,223,577	683,605	4,312,137	3,753,565	592,072

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This Table presents estimates of coefficient β_e in specification (9), using the energy price index with time-variable sectoral shares (VEPL)to construct the dependent variable, $e^{VEPL}_{ijkl,t}$. We control for sectoral GDP, sectoral labour and capital intensity, and a rich set of fixed effects including country-pair, acquiring and target sector, acquiring and target country-year, and a free trade agreement indicator. All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.8: Robustness to the removal of the most represented countries in the dataset

	All transactions				
	Without the US (1)	Without the UK (2)	Without Germany (3)	Without France (4)	Without Japan (5)
$\log(e_{ijkl,t})$	-0.357***	-0.337***	-0.294***	-0.291***	-0.333***
	(0.081)	(0.108)	(0.104)	(0.103)	(0.105)
$\log(GDP_{ik,t})$	0.704***	0.651***	0.660***	0.664***	0.674***
	(0.040)	(0.057)	(0.059)	(0.056)	(0.055)
$\log(GDP_{jl,t})$	0.686***	0.637***	0.649***	0.654***	0.664***
	(0.039)	(0.056)	(0.057)	(0.055)	(0.054)
$\log(L^{int}_{ik,t})$	0.062	0.181*	0.189*	0.179*	0.312***
	(0.052)	(0.107)	(0.108)	(0.106)	(0.111)
$\log(L^{int}_{jl,t})$	0.051	0.142	0.141	0.141	0.245**
	(0.044)	(0.087)	(0.086)	(0.087)	(0.101)
$\log(K^{int}_{ik,t})$	0.001	0.033	0.025	0.042	0.075
	(0.049)	(0.091)	(0.081)	(0.088)	(0.087)
$\log(K^{int}_{jl,t})$	-0.003	0.023	0.018	0.025	0.060
	(0.045)	(0.087)	(0.077)	(0.084)	(0.082)
FTA	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes	Yes
AIC	324,795	406,625	401,345	418,085	436,104
Observations	6,945,400	6,873,098	6,829,170	6,888,019	7,060,944

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This Table presents estimates from a specification and sample identical to that of column (1) in Table 2. In columns (1)-(5), we remove from the sample (both on the acquiring and target sides) firms based respectively in the US, the UK, Germany, France and Japan. All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors are clustered at the acquiring-target country-sector pair level.

Table B.9: Main results with alternative FE structure

	All transactions		
	(7)	(8)	(9)
$\log(e_{ijkl,t})$	-0.300***	-0.405***	-0.391***
	(0.097)	(0.124)	(0.123)
$\log(GDP_{ik,t})$	0.656***	0.669***	0.665***
	(0.025)	(0.028)	(0.029)
$\log(GDP_{jl,t})$	0.652***	0.716***	0.720***
	(0.022)	(0.026)	(0.026)
$\log(L^{int}_{ik,t})$	0.383***	0.304***	0.325***
	(0.071)	(0.076)	(0.080)
$\log(L^{int}_{jl,t})$	0.140**	0.066	0.073*
	(0.055)	(0.041)	(0.043)
$\log(K^{int}_{ik,t})$	0.149***	-0.006	-0.001
	(0.042)	(0.037)	(0.037)
$\log(K^{int}_{jl,t})$	0.089**	0.029	0.031
	(0.035)	(0.030)	(0.031)
FTA	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes
Acq. sector-year FE	Yes		Yes
Tar. sector-year FE	Yes		Yes
Acq. country-sector FE		Yes	Yes
Tar. country-sector FE		Yes	Yes
AIC	214,832	211,865	211,900
Observations	6,770,753	6,377,096	6,368,056

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table B.9 presents estimates from our main specification used in column (2) of main results Table 2, using an alternate set of fixed effects. Column (7) complements country-pair FEs and acquiring and target country-year FEs with acquiring and target sector-year FEs. In column (8), we instead augment our main set of FEs with country-sector FEs. Column (9) comprises the most stringent set, combining country-pair, country-year, sector-time and country-sector. Standard errors are clustered at the country-sector pair level in all variants.

Table B.10: Controlling for country-sector-level trade exposure

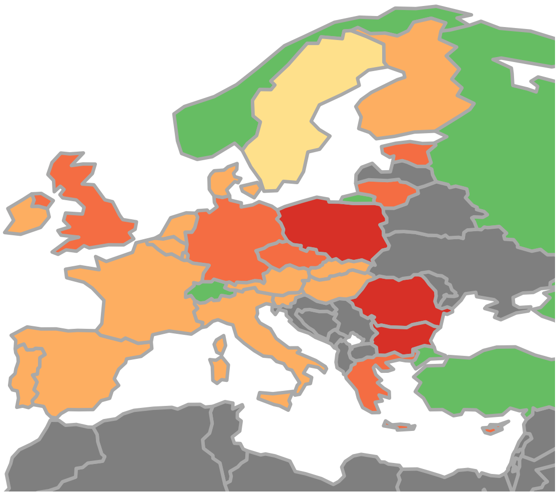
	All transactions			Acq. of Assets		
	All	All	Horizontal	All	All	Horizontal
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(e_{ijkl,t})$	-0.340***	-0.361***	-0.363***	-0.327***	-0.357***	-0.357***
	(0.106)	(0.106)	(0.104)	(0.120)	(0.120)	(0.120)
$\log(\tau_{ik}^{exposure})$	0.061**	0.077***	0.072**	0.052*	0.068**	0.059*
	(0.026)	(0.028)	(0.030)	(0.029)	(0.031)	(0.034)
$\log(\tau_{jl}^{exposure})$	0.026	0.025	0.009	0.019	0.019	-0.002
	(0.028)	(0.029)	(0.031)	(0.031)	(0.032)	(0.034)
$\log(GDP_{ik,t})$	0.694***	0.671***	0.639***	0.708***	0.687***	0.655***
	(0.024)	(0.026)	(0.026)	(0.026)	(0.028)	(0.029)
$\log(GDP_{jl,t})$	0.670***	0.666***	0.649***	0.680***	0.677***	0.663***
	(0.022)	(0.023)	(0.024)	(0.025)	(0.026)	(0.028)
$\log(L_{ik,t}^{int})$		0.394***	0.345***		0.380***	0.343***
		(0.075)	(0.071)		(0.090)	(0.085)
$\log(L_{jl,t}^{int})$		0.130**	0.076		0.163**	0.092
		(0.053)	(0.048)		(0.070)	(0.062)
$\log(K_{ik,t}^{int})$		0.139***	0.093**		0.132***	0.094**
		(0.042)	(0.041)		(0.047)	(0.046)
$\log(K_{jl,t}^{int})$		0.100***	0.050		0.121***	0.063
		(0.037)	(0.035)		(0.043)	(0.041)
FTA	Yes	Yes	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tar. country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	201,441	198,651	108,163	145,107	143,072	79,175
Observations	5,650,723	5,507,208	762,758	4,975,528	4,845,468	665,605

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

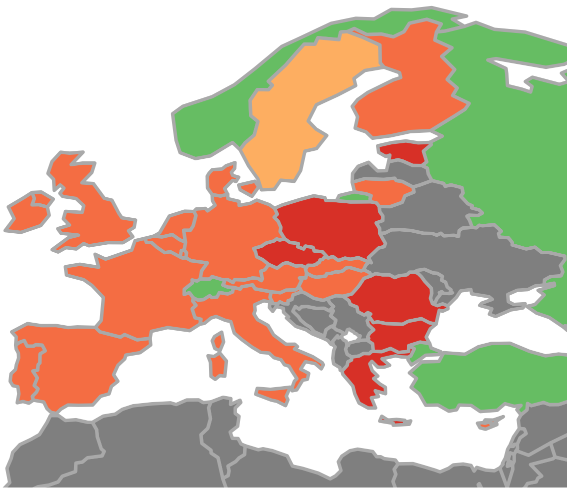
Notes: This Table presents estimates from a specification and sample identical to that of column (1) in Table 2, but additionally controlling for country-sector level trade exposure. The trade exposure indicator is constructed using data from Exiobase 3. See text for full details.

Figure B.1: The potential impact on M&A activity from carbon price gaps for high energy-intensive sectors only

(a) CO_2 price is higher by \$50/tCO_2 in the EU only, All sectors



(b) CO_2 price is higher by \$50/tCO_2 in the EU only, High energy intensity sectors



Notes: These maps show the simulation results on the percentage change in the number of firms acquired in M&A deals by country, in response to carbon pricing under three different coalition scenarios. Panel (a) shows the results for all sectors while Panel (b) shows the results when restricting the sample to deals within firms in high energy-intensive sectors only. The impact is expressed as the change in number of firms acquired in relative terms against a 2010 baseline. See text for full description of the simulation method.

Table B.11: Counterfactual simulation results by country

	EU-only	EU and OECD without the US	All
Australia	0.6%	-8.2%	-4.5%
Austria	-4.6%	-3.9%	0.0%
Belgium	-4.0%	-3.3%	0.6%
Brazil	0.6%	1.3%	-0.6%
Bulgaria	-13.0%	-12.4%	-8.9%
Canada	0.6%	-5.1%	-1.3%
China	0.6%	1.3%	-28.4%
Cyprus	-5.3%	-4.7%	-0.9%
Czechia	-7.2%	-6.6%	-2.9%
Denmark	-3.4%	-2.7%	1.2%
Estonia	-9.1%	-8.4%	-4.8%
Finland	-4.1%	-3.4%	0.5%
France	-3.5%	-2.8%	1.1%
Germany	-5.2%	-4.5%	-0.7%
Greece	-6.7%	-6.0%	-2.3%
Hungary	-3.5%	-2.8%	1.1%
India	0.6%	1.3%	-12.0%
Indonesia	0.6%	1.3%	-5.7%
Ireland	-4.1%	-3.4%	0.4%
Italy	-3.0%	-2.3%	1.6%
Japan	0.6%	-3.9%	-0.1%
Kazakhstan	0.6%	1.3%	-33.7%
Lithuania	-6.5%	-5.8%	-2.0%
Luxembourg	-4.2%	-3.5%	0.3%
Mexico	0.6%	-4.2%	-0.4%
Netherlands	-5.0%	-4.3%	-0.5%
New Zealand	0.6%	-6.1%	-2.4%
Norway	0.6%	-0.5%	3.4%
Poland	-10.5%	-9.8%	-6.2%
Portugal	-3.8%	-3.1%	0.7%
Romania	-12.9%	-12.3%	-8.8%
Russia	0.6%	1.3%	-15.7%
Slovakia	-4.8%	-4.1%	-0.3%
Slovenia	-3.8%	-3.1%	0.8%
South Africa	0.6%	1.3%	-33.0%
South Korea	0.6%	-7.3%	-3.6%
Spain	-4.7%	-4.1%	-0.2%
Sweden	-1.5%	-0.8%	3.1%
Switzerland	0.6%	-1.0%	2.9%
Taiwan	0.6%	1.3%	-13.0%
Turkey	0.6%	-5.0%	-1.2%
United Kingdom	-5.8%	-5.1%	-1.4%
United States	0.6%	1.3%	-4.7%

Notes: This table shows the simulation results on the percentage change in the number of firms acquired in M&A deals by country, in response to carbon pricing under three different coalition scenarios. The impact is expressed as the change in number of firms acquired in relative terms against a 2010 baseline. See text for full description of the simulation method.

Table B.12: Impacts of the implementation of a \$50/tCO_2 carbon tax on the number of domestic firms involved in M&A as an acquirer

	EU-only	EU and OECD without the US	All
Other OECD	0.6%	-5.6%	-1.9%
European Union	-4.8%	-4.1%	-0.2%
BRICS	0.6%	1.3%	-22.6%
Other non-OECD	0.6%	-1.8%	-6.8%
Japan	0.6%	-3.9%	-0.1%
United States	0.6%	1.3%	-4.7%

Notes: This table shows the simulation results on the percentage change in the number of firms that are involved in M&A deals as an acquirer by country or country groups, in response to carbon pricing under three different coalition scenarios. The impact is expressed as the change in number of firms acquiring in relative terms against a 2010 baseline. See text for full description of the simulation method.

C Sectoral correspondence and classifications

Table C.1: Correspondence between ISIC 3.1 and IEA sectors

ISIC 3.1 Code	ISIC 3.1 Name	IEA Sector
15	Food and beverages	Food and tobacco
16	Tobacco products	Food and tobacco
17	Textiles	Textile and leather
18	Wearing apparel, fur	Textile and leather
19	Leather, leather products and footwear	Textile and leather
20	Wood products (excl. furniture)	Wood and wood products
21	Paper and paper products	Paper, pulp and print
22	Printing and publishing	Paper, pulp and print
23	Coke,refined petroleum products,nuclear fuel	Chemical and petrochemical
24	Chemicals and chemical products	Chemical and petrochemical
25	Rubber and plastics products	Manufacturing
26	Non-metallic mineral products	Non-metallic minerals
2710	Iron and steel	Iron and steel
2720	Non-ferrous metals	Non-ferrous metals
28	Fabricated metal products	Machinery
29	Machinery and equipment n.e.c.	Machinery
30	Office, accounting and computing machinery	Machinery
31	Electrical machinery and apparatus	Machinery
32	Radio,television and communication equipment	Machinery
33	Medical, precision and optical instruments	Machinery
34	Motor vehicles, trailers, semi-trailers	Transport equipment
35	Other transport equipment	Transport equipment

Table C.2: IEA sectors definitions

IEA	ISIC rev. 4
Iron and steel	241, 2431
Chemical and petrochemical	20, 21
Non-ferrous metals	242, 2432
Non-metallic minerals	23
Transport equipment	29, 30
Machinery	25, 26, 27, 28
Mining and quarrying	07, 08, 099
Food, beverages and tobacco	10, 11, 12
Paper, pulp and printing	17, 18
Wood and wood products	16
Construction	41, 42, 43
Textile and leather	13, 14, 15
Industry	22, 31, 32

D Transactions value

Here, we assess our strategy to test the influence of energy prices on the *number* of transactions between two country-sector pairs. We want to know if measurement error is a serious concern when using this count variable to capture changes in foreign capital movements over time. This may be an issue if, for example, there is little correlation between the number and size of deal values. However, if there are systematic patterns, for example, the number of deals generally increases over time while the size of the deals also increases, then our empirical strategy to use the number of deals as a dependent variable and control for unobserved heterogeneity by year using year fixed effects is sound.

To test this, we use a small subset of our data where deal values are consistently reported. These deals occur between publicly listed companies and account for less than 10% of the transactions we observe (see Table D.1). Firms acquiring privately held companies are under no obligation to reveal the value of their acquisitions; hence, reporting is patchy. Previous papers using the Thomson-Reuters M&A dataset to assess determinants of FDI flows also use deal counts generally while recognising the issue, but have not thoroughly questioned this strategy (Hijzen et al., 2008; Feito-Ruiz and Menéndez-Requejo, 2011; Dowling and Aribi, 2013).

Table D.1: Transaction values coverage

Firm ownership		Share of	Share of transaction values
Acquirer	Target	all transactions	observed within category
Private	Private	47%	22%
Public	Private	41%	49%
Private	Public	3%	64%
Public	Public	9%	84%

Source: Thomson-Reuters Mergers and Acquisitions database

Results are reported in Table D.2. We find the expected sign for β_e. The magnitude of the estimate is larger on all transactions (-0.44 *vs* -0.32), but smaller on acquisition of assets (-0.18 *vs* -0.32). However, in all cases the point estimates of β_e fail to reach statistical significance. More extensive data on transaction values will be needed to confirm these preliminary findings.

Table D.2: PPML estimates of the effects of relative energy prices on the values of M&A transactions

	All transactions		Acquisition of assets	
	(1) Baseline	(2) Cross-border	(3) Baseline	(4) Cross-border
log $e_{ijkl,t}$	-0.438	-0.321	-0.181	-0.128
	(0.405)	(0.382)	(0.410)	(0.396)
log $GDP_{ik,t}$	0.261*	0.329**	0.585***	0.641***
	(0.136)	(0.167)	(0.121)	(0.109)
log $GDP_{jl,t}$	0.521***	0.664***	0.694***	0.755***
	(0.153)	(0.152)	(0.120)	(0.114)
FTA	Yes	Yes	Yes	Yes
Country-pair FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes
Sectoral FE	Yes	Yes	Yes	Yes
Pseudo-LL	-18,288,076	-8,665,322	-5,731,126	-3,107,450
Deviance	47,268	38,852	37,090	27,787
Observations	5,246,776	5,048,648	4,755,583	4,557,754
Transactions	37,287	7,349	37,287	7,349

All results estimated with a Poisson Pseudo-Maximum Likelihood estimator. Standard errors in parentheses. All standard errors clustered by acquiring-target country-sector pairs.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$